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A review of machine learning techniques for optical wireless communication in intelligent transport systems

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Abstract: Intelligent Transport Systems (ITS) are crucial for safety, efficiency, and reduced congestion in transportation. They require efficient, secure, high-speed communication. Radio Frequency (RF) technologies like Fifth Generation (5G), Beyond 5G (B5G), and Sixth Generation (6G) are promising, but spectrum scarcity mandates coexistence with Optical Wireless Communication (OWC) networks, which offer high data rates and security, forming a strong foundation for hybrid RF/OWC applications in ITS. In this paper, we delve into the application of Machine Learning (ML) to enhance data communications within OWC systems in ITS. We commence by conducting an in-depth examination of the data communication prerequisites and the associated challenges within the ITS domain. Subsequently, we elucidate the compelling rationale behind the convergence of heterogeneous RF technologies with OWC for data communications in ITS scenarios. Our investigation then pivots towards elucidating the indispensable role played by ML in optimizing data communications via OWC within ITS. To provide a comprehensive perspective, we systematically evaluate and compare a spectrum of ML methodologies employed in OWC ITS data communications. As a culmination of our study, we proffer a set of valuable recommendations and illuminate promising avenues for future research endeavors that warrant further exploration within this critical intersection of ML, OWC, and ITS data communications.

Key words: machine learning; optical wireless communication; free space optics; visible light communication; intelligent transport systems, 5G, B5G, 6G

1 Introduction

Intelligent Transportation System (ITS) refers to a broad range of services and applications that enables the efficient functioning of vehicles to address transport challenges such as high crash rates, which can result in deaths and injuries, and traffic congestion that can have detrimental economic and environmental impacts. ITS consisting of Internet of Things (IoT) device, Radio Frequency (RF) technologies and Artificial Intelligence (AI) applications have the potential of addressing global social ills arising from road accidents and traffic congestion. There are many dimensions of ITS which receive plenty of attention from researchers[1]. There have been surveys that have been performed such as in Ref. [2] where authors provided state of the art of how Machine Learning (ML) technologies have been applied across a broad range of ITS services and applications. Another study considering how context-aware machine learning has been incorporated in ITS to enhance decision-making regarding factors like location, time, weather, road conditions, etc., was presented in Ref. [3]. In this paper, we explore a different perspective in ITS in which we focus our efforts on data communications in Optical Wireless Communication (OWC) for ITS. To

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the best of our knowledge, we are not aware of studies that have been performed to date which properly scrutinize this topic.

With the massive amount of heterogeneous data generated by IoTs deployed in vehicles and Road Side Units (RSUs), high data communication with ultra low-latency is of utmost importance in ITS to enable real-time decision-making that can translate into saving lives and improving the quality of life. New RF technologies such as Fifth Generation (5G) networks, Beyond 5G (B5G), and future Sixth Generation (6G) networks, have the potential to deliver massive connectivity, high-speed data communication, and ultra low latency, which are some of the requirements for a modern ITS system. OWC has also appeared as one of the candidate technologies that will most like work in tandem with these latest RF technologies to realize high performance solutions to ITS. In fact, it is envisaged that future networks will likely comprise RF technologies that will be complemented by OWC and in some cases RF technologies will converge towards OWC. However, OWC technologies are Line-of-Sight (LoS) technologies that require direct communication between transmitter and receiver for efficient communication. Machine learning, a branch of AI, is considered a powerful tool that can analyze large amounts of data generated in vehicular networks and yield models with high performance. Thus, it has the capability to handle the enormous amounts of data generated in ITS environments as well as having the power to offer predictive solutions learned from training data. In this paper, we investigate the role of ML in enhancing data communication for OWC in ITS. We aim to review current ML techniques used for Autonomous Vehicles (AV) and ITS focusing on the OWC perspective in 5G/B5G/6G networks. Specifically, our contributions are as follows:

- Review the requirements and challenges for OWC focusing on data communications for Free Space Optics (FSO) and Visible Light Communication (VLC) in AV and ITS.
- Provide a review of related work on ML techniques for addressing OWC challenges to data communication requirements in ITS.
- Perform a comparison and analysis of ML methods for data communications in OWC applications for ITS.
- Offer future research directions and recommendations for ML-based data communications in OWC for ITS.

The rest of the paper is organized as shown in Fig. 1. Section 2 presents ITS data communications requirements and challenges. Section 3 discusses convergence of RF technologies towards OWC methods to meet data communications requirements in

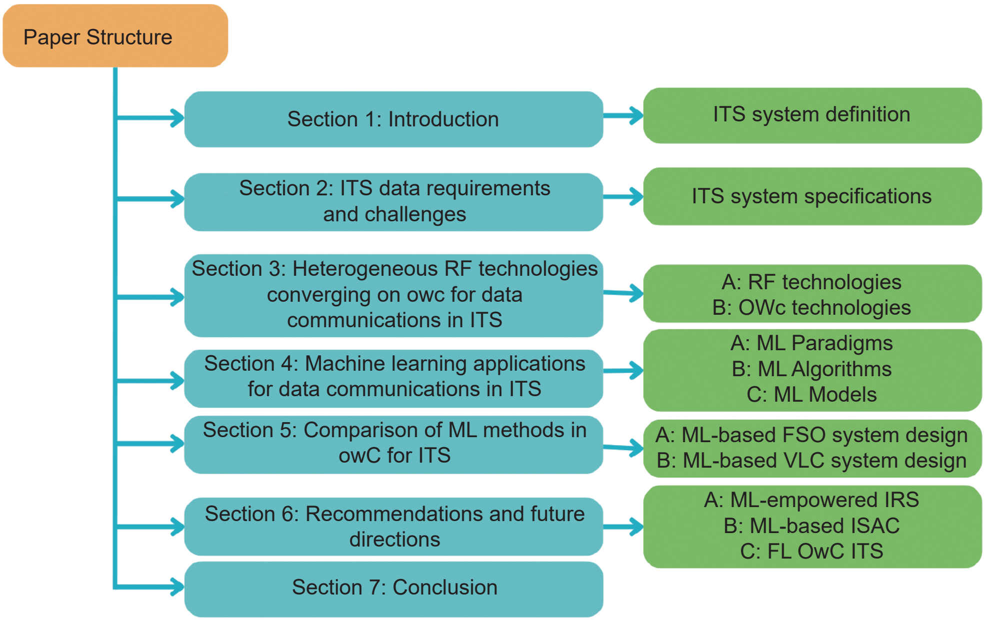

Fig. 1 Organization of paper.

ITS. Section 4 discusses ML techniques for data communications in OWC ITS. Section 5 offers comparison and analysis of ML techniques for data communications in OWC ITS. Section 6 presents future directions and recommendations, and Section 7 concludes the paper.

2 ITS data communications requirements and challenges

The ability of ITS to prevent accidents and injuries depends on reliable, accurate, instantaneous real-time communication between the Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V), or Vehicle-to-Everything (V2X) in general[4, 5]. This makes data communication a topic of vital importance in ITS. Studies exploring data communication requirements in ITS go back as far as in Ref. [6] in which the authors identified an ITS architecture consisting of six typical subsystems encompassing various components such as vehicles, RSU, public management center, traffic management center, and emergency management center. The authors identified basic RF communication requirements and different types of data that are likely to flow in an ITS network. In Ref. [7], the authors explored standards of communication in ITS like the IEEE 802.11p including latest developments such as Dedicated Short Range Communication (DSRC) and IEEE 1609 Wireless in Vehicular Environments. A discussion of fully distributed technologies versus central cellular networks as well as security and privacy in inter-vehicular communication is also offered. The authors of Ref. [8] noted that ITS data can be sourced from multiple sources such as traffic sensors, cameras, GPS, and cell phone tracking. To produce better inferences and enable better decision-making from this data, the authors provided a study of data fusion techniques that facilitate real-time accurate traffic data operation monitoring, route guidance, and incidence detection. The authors also discussed how data fusion in ITS supports Near Real-Time (NRT) advanced traveller information, advanced driver assistance, network control, crash analysis and prevention as well as traffic monitoring, forecasting, and accurate position estimation. With the advent of the IoTs, the authors of Ref. [9] provided an account of an ITS system based on IoTs. Su and Chen[9] designed an IoT-based ITS architecture, which consists of five essential layers: a perception layer, an information processing layer, a network layer, a business support layer, and an application layer. This architecture encompasses functionalities such as command and control, as well as decision support. In this paper, we can define an ITS as comprising of a perception layer, a physical layer, an application layer and a data communications layer as depicted in Fig. 2. A survey on network optimization for ITS involving IoVs was conducted in Ref. [10]. The authors emphasize that the efficiency of IoVs depends on connectivity and

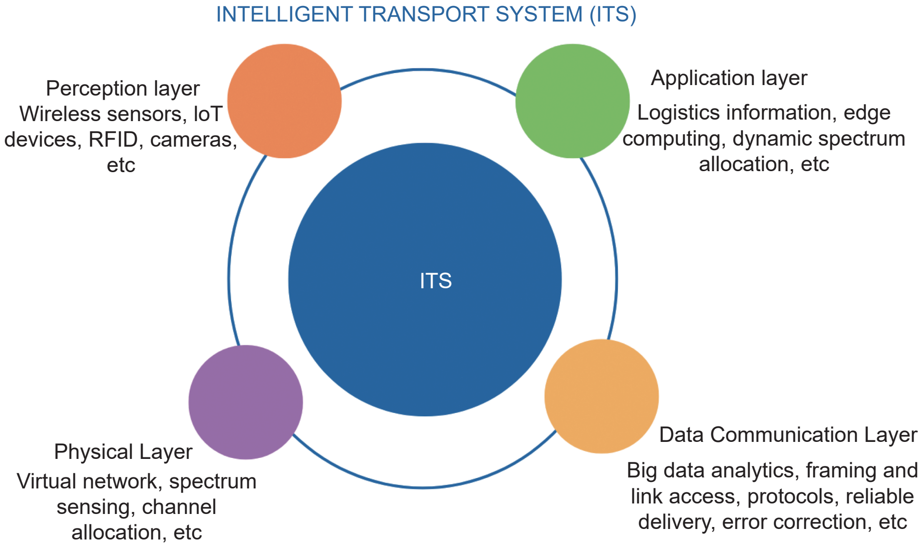

Fig. 2 Intelligent transport system adopted in the paper.

proceed to discuss a wide range of issues concerning IoVs such as applications, architecture, communication technologies, routing, naturally-inspired network optimization techniques and commonly used simulation tools in IoVs. A study of internet of vehicles and connected smart vehicles communication system towards autonomous driving was conducted in Ref. [11]. The authors reviewed various V2X technologies and proposed a novel planning scheme for internet connected and autonomous vehicles. Principal components and how they should be distributed and function in their considered architecture including a holistic view of hardware and software architecture involving an in-car gateway were presented. Arooj et al.[12] scrutinized architectures, taxonomies and open challenges in big data processing and analysis in internet of vehicles. Their rigorous survey of current research works in IoVs reveals that big data can play a vital role in providing sound and valuable predictions and they also provide a comprehensive analysis of methods, tools and techniques for applying big data in IoV. Finally, key challenges in IoV, followed by recommendations and open research dimensions involving big data in IoV are highlighted.

To meet increasing data communication traffic demands in vehicular networks, 5G, B5G, and 6G networks with transmission rates of up to 1 Tbit/s (Tbps) have emerged as attractive RF technologies[13]. Two widely employed methods of enhancing the transmission rate are improving spectrum efficiency and increasing transmission bandwidth[14]. One of the popular technologies on improving spectrum efficiency in B5G and 6G deployments is massive Multiple Input Multiple Output (MIMO). To increase spectrum bandwidth, Millimetre Wave (mmWave) and terahertz frequency bands have appeared as alluring candidates as shown in Refs. [15, 16]. Considering the amount of data generated by IoTs and other multiple sources in ITS, the authors of Ref. [17] presented a study on the applications of big data in ITS. After highlighting sources of big data in ITS like GPS, video cameras, and sensors, they identified supervised and unsupervised ML methods that can help enhance decision-making in public transport service planning, traffic prediction and accident analysis. Based on the diverse data sources in ITS, the authors in Ref. [18] proposed data-driven models that can learn and adapt for efficient operation of ITS assets, systems and processes. They described a data modelling pipeline for ITS that defines characteristics, engineering requisites, and other intrinsic challenges regarding data fusion, adaptive learning, and model evaluation. They concluded their study by outlining functional requirements for data-based actionable models. In Ref. [19], the authors considered ways of distributing large-size data in IoVs using a dedicated ad hoc network to reduce reliance on 5G/6G resources. A content-centric data distribution scheme based on a heterogeneous network consisting of Short range OFDM Wideband Communication (SOWC) with ultra-high data rate and IEEE 802.11p was designed. The proposed approach which involves cache node selection is shown to achieve improved maximum link capacity, average delay, and penetration ratio. Adhikari et al.[20] provided a roadmap of next generation wireless 6G-enabled vehicular networks. Their studied illuminates ITS requirements such as continuous demand for Ubiquitous Mobile Ultra Band (uMuB), Ultra-High Density Data (uHDD) and Ultra-High-Speed Low Latency Communication (uHSLLC). Despite its recent launch in 2019, 5G falled short of meeting these criteria, thus clearing the path for 6G technology, which is poised to be fully supported by artificial intelligence, offering extensive wireless coverage in rural areas, and ensuring secure communication. Recent 5G architectures and developments can only achieve 20 Gbit/s (Gbps) upload and 10 Gbps download with approximate delay of 10−50 ms[21] while AI-enabled 6G can accomplish up to 1 Tbps in upload and download with a minimized delay of 1 ms. Thus, 6G is capable of meeting the stringent ITS requirements of reliable connectivity of fast moving vehicles. The authors in Ref. [20] also provide illustrative use case scenarios for 6G applications in the context of edge-centric Internet of Vehicles (IoV). A study of 6G for V2X communications considering enabling technologies, challenges, and opportunities is presented in Ref. [22]. Issues concerning privacy and trust in the internet of vehicles were contemplated in Ref. [23]. The authors highlighted that even though new services in IoVs, such as parking space identification, platooning, and intersection control are expected to improve traffic congestion, efficiency, and safety, the proposed end-user services utilize private information with little consideration for the impact on users and third parties. Thus privacy and trust issues within the IoVs give rise to four fundamental concerns: privacy of personal information, trust, consent to provide information, and multi-party privacy. When contemplating whether end-user services necessitate voluntary or involuntary data sharing, Zavvos et al.[23] emphasizeed critical research challenges and propose approaches to tackle them. This focus includes evaluating the trade-offs between privacy and service functionality, automating consent negotiations, fostering trust in the IoV ecosystem and its constituent services, and resolving privacy conflicts involving multiple parties.

Envisaging that 6G communication systems will fulfil requirements of next-generation V2X (capability to support hyper-fast, ultra-reliable, and low-latency massive information exchange), the authors of Ref. [22] outlined key enabling technologies including new materials, advanced algorithms, and innovative system architectures necessary to attain the technological goals. With the vision that machine learning will play a vital role for advanced vehicular communication and networking, Noor et. al[22] reviewed recent advances of machine learning in 6G vehicular networks and finally discuss open challenges, maturity and ways of enhancing areas of these technologies. The authors of Ref. [24] outlined how AI will fuel the evolution of 6G mobile networks in vehicular networks leveraging on technologies such as software defined networks, network function virtualization, multi-access edge computing, and current vehicular networks. Opportunities and challenges that will be faced in integrating 6G into vehicular networks were also hinted. In an I2V network, 6G can also be employed to improve the maintenance of the infrastructure. For instance, in Ref. [25], the authors demonstrated how 6G connected vehicle framework with DL data fusion can support infrastructure maintenance. A hierarchical framework that uses CNN to fuse image and sensory data to detect potholes and a demonstration of how this approach has potential to facilitate large-scale real-time FL road surface condition monitoring and adaptive resource allocation for road infrastructure maintenance was introduced. UAV-enabled ITS 6G communications for IoVs were considered in Ref. [26]. The authors proposed a computing-communications intelligent offloading scheme to offload tasks in an energy-efficient manner. In their scheme, large data nodes are selected as Task Gathering Nodes (TGNs) in which UAVs fly to first resulting in reduced distance and energy. Kilanioti et al.[27] studied ITS networks in B5G and 6G networks and reveal the importance of edge-located solutions as well as the role of Integrated Sensing and Communication (ISAC) in vehicular networks. The authors also deliberated on the potential deployment of technologies within the mmWave frequency band in ITS and acknowledge the substantial research interest directed toward cell-free massive MIMO systems as a prospective technology for upcoming 6G systems in ITS.

3 Heterogeneous RF technologies converging on OWC for data communications in ITS

3.1 RF technologies in ITS

RF technologies have surfaced as front-runners to meet stringent ITS requirements. When studying trends in ITS communication in Ref. [28], the authors exposed the importance of efficient communication between RSUs and the Traffic Management Centre (TMC), RSU to vehicles, as well as inter-vehicular communication. Introduced as Wireless Access in Vehicular Environments (WAVE) and ratified as IEEE 802.11p[29], the Dedicated Short Range Communications (DSRC) standard is one of the RF methods that was proposed for vehicular communication. However, it encountered formidable competition from Cellular Vehicle-to-Everything (C-V2X) technologies operating within the 5.9 GHz spectrum band, a frequency allocation specifically designated for ITS across various regions worldwide. One of the advantages of C-V2X compared to DSRC is that it can accomplish higher coverage, capacity, scalability, range and number of supported devices. These are very attractive qualities for C-V2X with longer range capability directly translating into earlier alerts for drivers to maneuver dangerous situations.

Earlier implementations of C-V2X employed Fourth Generation (4G) Long Term Evolution (LTE) versions such as LTE-M and Narrow Band-IoT (NB-IoT)[30, 31]. However, 4G implementations still fall short of meeting the high ITS performance demands in terms of low latency and high data communication. The advent of 5G technologies has significantly boosted C-V2X as shown in Refs. [32–34]. These comprehensive surveys outline the role that 5G has played in advancing RF technologies in ITS. Another study of the role of 5G in ITS was considered in Ref. [35] in which the authors considered various roles of 5G within the context of smart cities emphasizing applications in utilities, industrial, and mobility based scenarios that include autonomous driving and vehicular communication. In Ref. [36], it is indicated that the integration of better data transmission rates in 5G with high mobility IoVs enables improved performance, safety, as well as the introduction of infotainment, and new business use cases in Vehicular Ad-hoc Networks (VANETS). A study of how data is disseminated in a 5G based IoV network was performed in Ref. [37]. The authors explored data communication methods based on smart control, social networks, and traditional approaches. Finally, they proposed a 5G IoV architecture composed of a cloud computing layer, edge layer, and an IoV layer with a target of developing a low maintenance, low latency, scalable, mobility supportive, heterogeneous data communications network. In addition to 5G enhancing the performance of RF applications compared to prior techonlogies, it is revealed in Ref. [38] how 5G enabled V2X communications can help protect Vulnerable Road Users (VRUs). The study reviews various features of VRU protection systems such as collision avoidance and detection, cooperative perception, and alert dispersal in ITS. It also emphasizes the need to constantly improve VRU safety solutions in terms of latency, reliability, scalability and localization accuracy. Although Ref. [39] still appreciates the advantages of near real-time monitoring brought by 5G in their analysis of applications of 5G to ITS, the shortcomings of 5G were vividly illuminated in Ref. [40]. The authors highlighted huge aggregated traffic volumes, on-demand provisioning of high capacity in geographical locations, and need for quick reconfigurability of transport resources as some of the challenges of 5G implementations in ITS. In this regard, meeting the ultra-low latency requirements poses a challenge when architecting backhaul networks for 5G, necessitating the adoption of high-speed optics.

Even though 5G deployments in ITS are as recent as 2019, efforts to develop the next generation of wireless networks aimed at addressing apparent 5G ITS challenges are already underway[41–43]. These studies provide insightful understanding of 6G wireless communication requirements, features, applications, critical enabling technologies like AI, intelligent surfaces, cell-free massive MIMO as well as security and privacy techniques. Shen et al.[44] presented their vision of 6G consisting of five facets namely, next generation architectures and services, next generation networking, IoTs, wireless positioning and sensing, and DL applications in 6G. Further building blocks towards 6G network development offering detailed description of air interface, transmission technologies, and paradigm shifts like exploration of all spectra including mmWave, THz, and optical frequency bands were presented in Refs. [45, 46]. On top of elevated network security that will be present in 6G networks, authors accentuate the importance of AI/ML technologies in dealing with big datasets generated by heterogeneous networks, diverse communication scenarios, wide bandwidths and new service requirements.

Needless to say, radio spectrum is a scarce resource. New innovative technologies in ITS place even further pressure already limited spectrum. Reference [47] highlights the need for co-existence and inter-operation of DSRC and C-V2X scenario while the need for spectrum regulation in ITS is shown in Ref. [48]. In their study, the authors clearly stipulated currentd and possible future ITS spectrum regulations for RF technologies in a heterogeneous ITS ecosystem for different countries. This huge demand for spectrum resources in ITS together with the other rigorous performance requirements of high data communication and ultra low latency has launched a relentless exploration for innovative technologies that can address these needs.

3.2 OWC technologies in ITS

Optical wireless communication has emerged as one of the promising candidate technologies on which 5G/B5G and 6G technologies converge to realize their desired performance demands. In Ref. [49], the predestined evolution of the latest RF technologies is laid bare. The authors presented free space optics, terahertz systems, photonic integrated circuits, massive MIMO, multi-core fibers among some of the technologies that will be pillars of 5G/B5G and 6G. They showcased applications of some of these technologies on mobile fronthaul systems based on millimeter 5G and motivate the need for heterogeneous solutions in these environments. This role of OWC in 5G/6G is further clarified in Ref. [50]. In the spirit of providing high capacity and security, massive and reliable connectivity and ultra low latency, authors demonstrate how OWC technologies like optical camera communication, light fidelity, VLC and FSO will be effective solutions in 5G/6G and IoT deployments. The intimate relationship between RF and OWC is scrutinized in Ref. [51] to prove the convergence of wireless and optical networks in future communication networks. With increasing popularity of technologies like AR/VR, AI and holographic communication, it is explained how RF and OWC cooperation and alignment can enable smooth and seamless high-speed, low latency communication. Another account aimed at cementing understanding of RF and Optical convergent access technologies toward 6G is offered in Ref. [52]. After showing how the integration of RF technologies with OWC will be essential in building a strong infrastructure by discussing requirements and use cases, the authors turned their attention to key enablers for 6G networks. Some of the key enabling technologies they identify are THz and sub-THz communication, VLC, FSO, new antenna designs, power-over-fiber deployments, and the application of ML in the physical layer of future networks. Table 1 provides a summary of existing challenges and mitigation approaches for current OWC applications in ITS.

As revealed in Refs. [50, 58], apart from frequent handovers, flickering (fluctuations in brightness of light undetected by human eye), atmospheric loss is also one of the major challenges in 5GB/6G OWC networks. In outdoor environments, bad weather conditions such as rain, snow, or fog can result in scattering, refraction, reflection, or absorption of optical signals. This can lead to significant communication link degradation and ultimately deterioration of performance of OWC networks. These technologies are also Line-of-Sight (LoS) technologies depending on direct line of sight between Transmitter (Tx) and Receiver (Rx) with performance decreasing in Non-Line-of-Sight (NLoS) scenarios. Some of these challenges of OWC in ITS are depicted in Fig. 3 for both VLC and FSO in an ITS setup. In Ref. [59], the authors provided a detailed summary FSO requirements to meet some of the ITS communication applications such as cooperative driving, infotainment, and traffic efficiency and safety. They accurately summarized latency, reliability, and range requirements for different FSO use cases in ITS.

Table 1 Summary of current methods to mitigate challenges of FSO applications in ITS.

Feature	Challenge	Mitigation approach	Reference
Transmitter/Receiver	Tx/Rx misalignment	Application of ATP mechanisms to achieve LoS	[53–55]
Channel	Atmospheric turbulence	Aperture averaging, Waveform correction techniques (AO)	[54]
Transmitter/Receiver	Beam divergence loss	Applying diversity: using smaller receiver apertures to create multiple copies of signal mutually uncorrellated in time, frequency and space	[56]
Channel	Atmospheric scattering and absorption	Diversity, hybrid FSO/RF	[57]

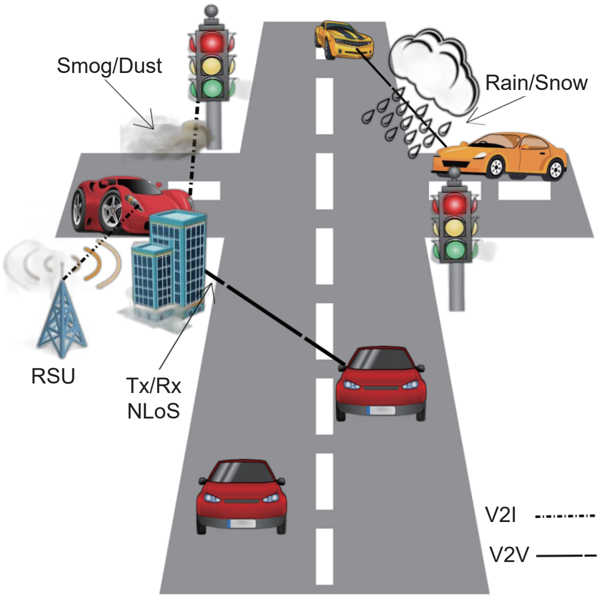

Fig. 3 Typical outdoor challenges of OWC in ITS.

As the recognition of how RF technologies can be enhanced by OWC unfolds, a burgeoning interest in the integration of light-based technologies for data communication within the domain of ITS, is evident through various conducted studies on this topic. In Ref. [60], the concept of light fidelity (Li-Fi) on smart communication between vehicles and traffic signals as well as V2V is outlined. The authors discussed Li-Fi implementations in V2V and in direct and indirect emergency vehicle to traffic signal communication as well as limitations of the technology. Due to their higher data rates, increased data security, and energy efficiency, OWC technologies have also been considered viable candidates for future V2X networks. The most recent FSO and VLC research endeavors in ITS are depicted as follows.

3.2.1 Free space optical communication

Free Space Optical (FSO) is a LOS technology that utilizes invisible beams of light to transmit data in free space. An overview and analysis of trends in FSO communication is provided in Ref. [61]. After presenting a background of FSO communication, the authors reflected on key aspects of FSO design and limitations of FSO. On top of natural drawbacks caused by weather conditions like rain, snow and haze, they also brought to attention other channel impairments such as physical obstacles like flying birds as well as environmental complexities in the form of smoke from industries, dust from construction sites, or transmitted light losing intensity due to spreading of light over distance (optical beam attenuation). They motivated that due to its cost-effective, easy deployment, and high bandwidth ability, the technology will likely be employed extensively in future next generation communication systems. A historical account of FSO from its early implementations to its current deployments is presented in Ref. [53]. The authors presented a timeline of telecommunication systems from versions of wireless transmission of radio waves to early 2000 s deployments. They discussed principles underlining FSO communication, followed by a review of atmospheric, space, and underwater FSO communication channels as well as temporal challenges in FSO communication systems such as fog, smog, rain, snow, sand-wind. They highlighted the current methods of mitigating these challenges as aperture averaging, Acquisition, Tracking, and Pointing (ATP), and waveform correction. Aperture averaging is a common method of reducing power fluctuations using appropriate sizes of averaged Receiver (Rx) apertures. Smaller apertures are likely to result in smaller collection area and received signal power variance based on link range and value of atmospheric turbulence strength. It is essential to have onboard ATP systems to improve beam centroid stability on detector planes in long-range terrestrial, inter-satellite space missions. Such ATP systems can be fabricated using commercially available micro-scale tip/tilt platforms. Waveform correction techniques such as Adaptive Optics (AO)-based phase compensation help improve reliability of FSO communication systems in the presence of atmospheric turbulence fluctuations which contribute to phase disturbances along the propagation path. FSO optical multiplexing methods like Wavelength Division Multiplexing (WDM), Subcarrier Multiplexing (SCM), and VVLC are discussed with the study concluding in a review of FSO space optical communications and next generation FSO communication networks.

An overview of the potentials and challenges of FSO in ITS is offered in Ref. [59]. The authors explained adaptive illumination schemes, communication improvement using Mode Division Multiplexing (MDM) and WDM, and how integrated sensing and communication contributes to traffic efficiency and safety. Kaymak et al.[54] presented a comprehensive survey on ATP mechanisms for mobile FSO communications. They highlight the importance of ATP mechanisms in their application to align FSO transmitter and receiver to attain LOS required for effective operation of FSO communication and categorize ATP mechanisms according to their functionality, use cases, implementation technologies, and discuss their advantages and disadvantages. Some of the ATP mechanisms discussed are gimbal-based, mirror-based, adaptive optics, liquid-crystal, hybrid ATPs such as gimbal-mirror, RF-FSO, and other ATP mechanisms to complete their study. In Ref. [55], the authors developed a proof of concept prototype to demonstrate automatic realignment of electronic steering of FSO transceivers in MANETS. They considered FSO structures consisting of multiple transceivers mounted on a spherical shape with angular diversity and address the problem of automatically detecting and maintaining LOS alignment among adjacent multi-transceiver FSO structures. They showed how using multiple directional transceivers and an auto-alignment mechanism can enable maintaining optical wireless links in a mobile setting with minimal disruptions and overhead. Work considering FSO transmission performance enhancement with a motive of sustaining high capacity 5G services is outlined in Ref. [62]. The authors presented a mixed FSO and fiber network to tackle nonlinearity factors and enrich system capacity and range. They investigated the effect of fiber non-linearities, FSO pointing errors, and co-channel interference on FSO performance and evaluate their model in terms of Cumulative Distribution Function (CDF), outage probability, Peak-to-Average Power Ratio (PAPR), and Bit-Error-Rate (BER). They demonstrated improved performance of their model compared to current approaches using simulations. In Ref. [63], a comprehensive survey of hybrid FSO communication networks to achieve 5G backhauling connectivity is presented. The authors commenced their study by carefully reviewing the fundamentals of FSO and comparing it with other backhaul communication systems such as optical fiber, microwave radio, coaxial cable. They then considered hybrid Decode-Forward (DF) FSO/RF MIMO systems aimed at providing larger channel capacity and data rates. They also examined numerous dual-hop mixed RF/FSO topologies and compare relay-assisted models. Focusing on a hybrid FSO/RF multiuser system model, they studied a plethora of switching schemes and algorithms in hybrid FSO/RF links. In Ref. [64], Internet of Drones (IoDs) is highlighted to have the potential of enhancing performance of FSO networks. Combined with Deep Reinforcement Learning (DRL), drones in IoDs can help alleviate atmospheric turbulence challenges experienced by FSO links by serving as relays in FSO networks thus overcoming mobility and buffer restrictions.

3.2.2 Visible light communication

Visible light communication enables dual use of automotive and road side infrastructure lighting for both illumination and communication purposes by utilizing the modulation of light intensity of LEDs to transmit information. A comprehensive survey of vehicular visible light communications is provided in Ref. [65]. The authors presented V-VLC concepts and architectures, applications, and regulatory requirements for automotive lighting systems. They delved into various aspects of V-VLCs such as system architecture, transmitter front-end characteristics, LED-based exterior automotive lighting as well as multiple factors that influence V-VLC communication. Finally, the authors discussed channel models, simulation tools employed in V-VLCs as well as open research directions. An investigation into how to achieve omnidirectional coverage in visible light communication for connected vehicles is performed in Ref. [66]. Considering channel modelling based non-sequential ray tracing to quantify the capability of receiving signals in different cases, the authors evaluated the performance of a vehicular VLC system in different road types and traffic scenarios. Their experiments show that deployment of nine photodetectors with carefully determined locations is adequate for creating quasi-omnidirectional for both V2V and V2I connectivity. An exploration of visible light and reconfigurable intelligent surfaces for beyond 5G V2X communication networks at road intersections is done in Ref. [67]. The authors proposed employing hybrid Vehicular Visible Light Communication (V-VLC/V-RF) with relaying and Reconfigurable Intelligent Surface (RIS) to improve communication range for urban V2V communication. A stochastic geometry based analytical framework is employed to analyze the performance of the proposed solutions with numerical results showing considerable improvement in outage and throughput while ensuring low latency compared to conventional V-RF with relaying. In Ref. [68], a study of latest technologies in visible light communications in intelligent transport is conducted. The authors outlined the benefits of VLCs such as significant energy consumption reduction due to simultaneous illumination and data communication. VLCs also offer high data security, utilize unregulated visible light spectrum and are immune to electromagnetic interference. However, they also identify the influence of environmental factors (e.g. fog, vehicular exhaust, dust storms, etc.) and excessive light from the sun and other sources as some of the challenges that receivers might fail to register signals transmitted from LEDs/LDs thus degrading VLCs performance. Another factor that limits the transmission range of VLCs is the fact that visible light cannot pass through solid objects. The authors highlighted that there is still room for developing hybrid VLC-RF systems that embrace the merits of both technologies. An extensive survey on hybrid RF/VLC systems applications is done in Ref. [69]. An elaborate study of both RF and VLC technologies detailing their principles of operation as well as their advantages and disadvantages is presented. The authors then outlined work that has been done on hybrid systems involving RF/VLC systems highlighting various aspects such as resource allocation, performance analyses issues, network experimentation implementations, applications, and conclude their study by presenting future research directions that could be pursued in that area. A cascaded FSO-VLC communication system is proposed in Ref. [70]. The FSO-VLC system consists of multiple VLC access points catering for end users connected via a Decode and Forward (DF) relay to the FSO backhaul link. Assuming an FSO link affected by path-loss, pointing errors and atmospheric turbulence, and VLC downlinks statistically characterized by random user positions, they derived closed form expressions of OSNR Probability Density Function (PDF) and Cumulative Distribution Function (CDF).

4 Machine learning applications for data communications in OWC for ITS

The has been growing interest in applying ML in analyzing large amounts of data generated in vehicular networks to generate models with good performance. ML has been widely applied as outlined in the following studies. An overview of machine learning applications in vehicular networking is presented in Ref. [77]. The authors illustrated how machine learning can be utilized to address vehicular networking issues like mobility and handover management, routing decision making, resource management, and energy efficiency. Finally, they reflected on challenges of ML applications in vehicular networks such as the need for distributed learning and multi-agent cooperation for ML methods due to data being store in different units, implemented ML methods complexity issues and interpretability and trust for ML methods in vehicular networks. A study of machine learning in vehicular networks is conducted in Ref. [78]. An extensive review of core machine learning concepts is offered and is followed by a discussion of data-driven decision making in vehicular networks including traffic flow prediction, network flow control and local data storage. Intelligent wireless resource management methods such as distributed resource management, virtual resource management and load balancing are outlined to control scarce resources like spectrum, transmission power, storage. Learning dynamics in vehicular networks, method complexity and distributed representation are highlighted as open issues that warrant further attention. Liang et al.[79] considered a machine learning framework as an approach towards intelligent vehicular networks. They identified distinctive characteristics of high mobility vehicular networks and motivate using machine learning to address resulting challenges especially its applications in learning dynamics of vehicular networks and making informed decisions to optimize network performance. They focused on the application of reinforcement learning in managing network resources as an alternative to other prevalent optimization approaches.

Some of the challenges faced by OWC technologies in ITS identified in Tables 1 and 2 can be mitigated using ML techniques[80]. Considering FSO and VLC, each table specifies a challenge associated with each part of the OWC communication link and the current methods in literature that have been employed to address it. In Ref. [80], clear examples of how ML techniques like Convolutional Neural Networks (CNNs) can be used for image recognition in ITS, how Recurrent Neural Network (RNN) can be applied for sequential data analysis, and how Generative Adversarial Networks (GANs) can be employed for data augmentation to expand training sets from rare experimental data are outlined. With this perspective, studies examining the utilization of ML to enhance the performance of data communications in OWC ITS are presented as follows. For completeness, we consider studies spanning ML paradigms, algorithms and models in OWC ITS.

4.1 Machine learning paradigms

4.1.1 Supervised learning

Supervised learning refers to a group of ML methods trained under supervision using labelled data for purposes of classification, regression, and prediction. The following works outline studies in ITS in which supervised learning has been applied. In Ref. [81], methodologies of enhancing the performance of a FSO communication system using ML for 5G/6G and IoT applications are outlined. The authors noted that heterogeneous nature of traffic and service quality parameters in 5G and Beyond (5GB) and 6G networks presents numerous challenges and identify FSO as one of the promising candidate technologies to deliver higher data rates with low power consumption. However, the performance of FSO is degraded by weather, pointing errors and turbulence. They proposed SVM based decoding for OOK modulated FSO signals and test their models under various atmospheric weather conditions such as fog, rain, snow, and other factors like turbulence and pointing errors. Using simulated numerical results, they showed how their proposed schemes address channel impairments due to turbulence and pointing errors. An ML method to effectively predict V2I link lifetime and vehicle’s next cell for software defined vehicular networks is proposed in Ref. [82]. The authors presented a supervised ML method based on random forests to estimate the time duration that a vehicle remains connected to a cell using the vehicle’s position, speed, and Network Attachment Point (NAP). They evaluated their method using a dataset from a Luxembourg network operator to show their approach achieves a minimum Mean Absolute Error (MAE) of 3.52 s for a narrow coverage cell and short lifetime values and a maximum MAE of 50 s for a wide coverage cell and higher link lifetime values. When studying ML applications for short reach optical communication, Xie et al.[83] showed that most commonly used ML algorithm in that environment is supervised learning. They continued to demonstrate how supervised learning plays a part in constructing Artificial Neural Networks (ANNs), CNNs, and RNNs. Although the study of supervised learning for noisy optical signal estimation in Ref. [84] is done for underwater OWCs,

Table 2 Summary of current methods to mitigate challenges of VLC applications in ITS.

Feature	Challenge	Mitigation approach	Reference
Transmitter/Channel	Robustness to noise	Narrowing FOV	[71]
Receiver	Communication range	Using receiver optical lenses	[72]
Transmitter/Receiver	Enhancing mobility with LoS	Using more photo-detectors and active receiver control	[73]
Transmitter/Receiver	Visible light positioning	Repetitive OOK sequence to determine phase difference of arrival	[74, 75]
Receiver	Increasing data rate	Using camera-based receivers	[76]

it does spark interest regarding the significance of such approaches for data communications in OWC ITS. Esmail et al.[85] outlined FSO channel monitoring using machine learning. They considered predicting three channel parameters (noise, turbulence, and pointing erros) in FSO links related to Amplified Spontaneous Emission (ASE). After highlighting performance of predicting FSO parameters using Asynchronous Amplitude Histogram (AAH) and Asynchronous Delay-Tap Sampling (ADTS) histogram features, they compared the performance of Support Vector Machines (SVM) and CNN regressor using ADTS histogram features. Finally, they investigate the capability of CNN regressor in predicting the considered channel parameters for three different speeds.

4.1.2 Unsupervised learning

Unsupervised learning is a group of ML techniques that train on unlabelled data to identify patterns through methods such as clustering, anomaly detection, density estimation, finding associations. Unsupervised learning has been applied in ITS as shown in the studies below. In Ref. [86], data, models, and algorithms for smart transport planning are presented. The authors examined how clustering analysis can be applied in trip distribution, generation and traffic zone division. Another study considering unsupervised learning in smart traffic management is offered in Ref. [87]. An online incremental big data smart traffic management platform based on unsupervised learning, DL, and DRL is proposed to handle high frequency unlabelled data from heterogeneous data sources. A deployment of unsupervised learning DL for GPS transportation mode identification is presented in Ref. [88]. Noting that massive geospatial data from GPS sensors is often unlabelled, the authors firstly pretrain a deep Convolutional Autoencoder (CAE) using fixed-size trajectory segments. They then attached a clustering layer to the CAE's embedding layer and keep retraining the clustering model to strike a balance between the model's reconstruction and clustering losses.

4.1.3 Reinforcement learning

Reinforcement Learning (RL) is an ML method based on rewarding agents for desirable actions and penalizing them for unfavourable actions. Several works have considered the application of reinforcement learning combined with Mobile Edge Computing (MEC) for data communication in ITS. In Ref. [89], the authors designed a deep reinforcement learning task computation offloading model in a heterogeneous vehicular network considering multiple stochastic tasks to address efficient and reliable data communication to maintain low latency. They proposed an adaptive computation offload method based on deep reinforcement learning to obtain a trade-off between cost of energy consumption, cost of data transmission delay, and avoid the curse of dimensionality caused the complexity of the continuous action space involving time-varying wireless channels and bandwidth. The authors in Ref. [90] explored resource allocation in V2X communications based on Multi-Agent Reinforcement Learning with Attention Mechanism (AMARL). They modeled the problem as a multi agent reinforcement learning process where each link is considered as an agent, all agents intercommunicate with the environment, and each agent allocates spectrum and power through its Deep Q Network (DQN). Their experimental results show that their AMARL approach satisfies requirements of high rate V2I links and low latency to V2V links with good adaptability to environmental changes. Wang et al.[91] highlighted that device-to-device offloading is visualized as a promising paradigm to efficiently transmit data in AVs at reduced network delay and processing time. Consequently, they formulate a cost minimization problem by exploiting Markov Decision Process (MDP) framework and propose dynamic reinforcement learning scheduling algorithm and deep dynamic scheduling algorithm to solve the offloading decision problem. Reinforcement learning is also recommended for hybrid RF/VLC networks[92].

4.2 Machine learning algorithms

4.2.1 Distributed learning for data communication in ITS

Sixth generation networks are anticipated to achieve higher data rates that would enhance the performance of ITS. In Ref. [93], the authors provided an overview of distributed machine learning techniques for 6G networks. They highlighted some 6G challenges regarding device energy consumption, mobile edge computing, terahertz communication, and ML related challenges. To demonstrate the importance of ML in 6G communications, they focused their study on two distributed ML paradigms, Federated Learning (FL) and Multi-Agent Reinforcement Learning (MARL). They also discussed applications of the two algorithms in a myriad of applications including non-terrestial networks, mobile wireless networks, power systems, and vehicular networks. This need to exploit distributed learning techniques to handle massive interconnected networks that generate heterogeneous data at network edge is also explicitly shown in Ref. [94]. In Ref. [95], the authors presented a comprehensive review of Transfer Learning (TL) algorithms and how TL can be applied in different wireless communication domains. They motivated requirements needed for realization of 6G communication such as high efficiency (e.g. high transmission rates, high capacity, large-scale data processing), seamless integration, and innovation technologies like AI and OWCs. They then illustrated various examples of application of TL in wireless communication and eventually reveal the mutual relationship between TL and 6G communication. In ITS, one of the concerns is data security and privacy of user information. ML algorithms rely on training data from vehicles in a V2X network. FL possesses the capability of preserving user privacy and data security as user data is not transmitted but the global model is updated after users have locally trained their models. A performance analysis and mechanism design of FL with unreliable clients is done in Ref. [96]. The authors modeled unreliable behaviours of clients and investigate the impact of such clients on models by deriving a convergence upper bound on the loss function based on gradient descent updates. They then designed a defensive mechanism named Deep Neural Network-based Secure Aggregation (DeepSA) and perform experiments to validate their method while comparing it to other defensive mechanisms. An exploration of privacy preserving FL for UAV-enabled networks is also presented in Ref. [97].

Most ITS scenarios require instantaneous decision making as it can prevent accidents and deaths. FL prevents the transmission of actual data to the central server, this enables reduction communication overhead costs as well as lowering latency in V2X networks making it a good candidate for application to ITS. FL applications in 6G can achieve Massive Ultra-Reliable Low Latency Communications (mURLLCs) and are also scalable[98]. As shown in Ref. [99], FL has advantages in wireless communications compared to other distributed algorithms. The authors of Ref. [98] presented performance and requirements for FL in 6G such as mURLLCs, scalable architecture, human-centric services. They also outlined motivations for applying FL in wireless networks like resource management, user behaviour prediction, channel estimation and signal detection. They finally explored open challenges of the relationship between FL and emerging technologies like how high propagation attenuation in terahertz band can affect convergence analysis, or how FL can be used in satellite communication to optimize the beam and location of the satellite. A development of an efficient communication FL approach for vehicular edge computing in 6G communication networks is offered in Ref. [100]. The authors proposed a three part FedCPF customized local training strategy for vehicular clients to achieve convergence in fewer communication rounds. A two-layer FL with heterogeneous model aggregation supporting 6G IoVs is investigated in Ref. [101]. With the aim of developing a more efficient and accurate object detection learning strategy while preserving data privacy and keeping communication overheads at minimum, the authors designed a multi-layer FL heterogeneous model selection and aggregation scheme involving individual vehicles and RSUs. They evaluated their proposed method to illustrate how it achieves better precision, recall and F1 score in addition to better scalability with larger RSUs.

4.3 Machine learning models

4.3.1 Deep learning

DL-based methods continue to be a subject of interest in ITS applications. DL methods need vast amounts of data to perform efficiently and with immense data generated in ITS, there is potential to incorporate them to address ITS challenges. In Ref. [102], the authors presented a motivation of how DL can be utilized to solve ITS challenges. Firstly, they reviewed a spectrum of ITS domains in DL can be applied ranging from defense, healthcare, agriculture, and security. They proceeded to show how DL can be integrated in ITS through lane detection, road sign detection, traffic light detection, and pedestrian detection. Finally, they highlighted how DL can be used for other ITS challenges such as object detection, multi-object tracking, and activity recognition that help prevent accidents for both pedestrians and other vehicles. In Ref. [103], the authors also highlighted the challenges faced by DL for pedestrian detection in ITS. They noted that to be effective, DL applications in ITS have to be fast and accurate enough to be deployed in real-time life-saving scenarios. They proposed a depth wise separable convolution and single shot detector framework using OpenCV activation maps to develop a DL method to solve pedestrian detection in ITS. In an effort to curb pedestrian fatalities the authors of Ref. [104] studied how to predict pedestrian intentions to cross the road. They developed a CNN model combined with depth sensing camera to estimate pedestrian orientation and distance from the vehicle. Their model detects 2D higher human body keypoints and translates them into 3D using depth information. Eventually every change in pedestrian movement pattern toward the road is translated into warning for the driver. A comprehensive survey of DL application for autonomous vehicle control is presented offered in Ref. [105]. Focusing on vehicle control rather than perception based studies which include object detection, the authors conducted different comparative analyses relating to computation, architecture selection, and adaptability and generalisation. Another ITS control based study concentrating on DRL based Traffic Signal Control (TSC) is presented in Ref. [106]. The authors discussed different problem formulations, RL parameters, and simulation environments. They provided an extensive overview of multi-agent and DL RL approaches for TSC. A study of optimal deployment of UAVs in VLCs using DL is made in Ref. [107]. They formulated the optimization problem considering joint UAV deployment, user association, and power efficiency while satisfying illumination and communication requirements. They devised an ML framework involving Gated Recurrent Units (GRUs) with CNNs, divided the optimization problem into two-subproblems, and then solved it using a low-complexity iterative algorithm.

A study of ML to DL perspectives in optical communications is conducted in Ref. [80]. The authors focused their efforts in shedding light how appropriate Deep Neural Networks (DNNs) should be used based on the nature of the problem and specialized data types involved to generate suitable DL-enabled solutions in optical communications. Therefore, they recommended using CNNs for image data, RNN for sequential data, end-to-end learning for joint optimization with DL-based channel model, generative adversarial network for data augmentation, and deep reinforcement learning network automation. Osman et al.[108] developed a method of enhancing the reliability of communication between V2X based on deep learning for providing efficient road traffic information. Their model is targeted at determining required optimum interference power to enhance connectivity, comply with Quality of Service (QoS) constraints and improve communication link reliability. Considering distribution and density of vehicles, average length, and minimum safety distance between vehicles, they focused on fulfilling best four QoS metrics (achievable data rate, packet delivery, packet loss rate, average end-to-end delay). After mathematically formulating the optimum interference power as a constrained optimization problem, they trained their deep learning model and show how their model improves road traffic information efficiency and increases road traffic safety. An investigation of using deep learning to predict traffic in V2X networks is performed in Ref. [109]. The authors proposed a deep learning algorithm based on unidirectional Long Short-Term Memory (LSTM) to predict traffic in V2X networks. Their simulation results reveal that the highest prediction accuracy was achieved with 4 packets/s of transmitted data with models having 14 packets/s having the lowest prediction accuracy. Work considering DL-enabled Intelligent Reflecting Surfaces (IRS) is provided in Ref. [110]. The need for secure, robust, and efficient communication in vehicular networks gives rise to 6G communication and IRS have emerged as one of the technologies composed of reflecting elements able to intelligently configure incident signals to and from vehicles. The authors investigated DL-enabled IRS ITS performance metrics such as energy efficiency and spectral efficiency including channel estimation. They also brought to light challenges of deploying DL-enabled IRS in ITS such as delays in training the learning algorithms and other challenges in application to different ITS environments like long distance and public transportation scenarios. Deep learning methods for enhancing FSO are presented in Ref. [111]. Aiming to mitigate the effects of atmospheric effects such as turbulence and thermal noise that inhibit the propagation of ON/OFF Keying (OOK) FSO communication, the authors propose and experimentally validate a CNN to reduce BER of FSO. As a post-processing technique their method allows combination with current error correction and demodulation methods. Efforts to develop low complexity and cheap DL channel estimation methods in FSO communication systems are made in Ref. [112]. The authors investigated combinations of DL and conventional structures and compare the combinations in Gamma-Gamma atmospheric turbulence.

4.3.2 Generative adversarial networks

It can be challenging and costly to perform data imputation with high accuracy as it requires large and diverse traffic data. To address some of the challenges of OWC in ITS GANs can be considered to improve decision making capability of ML techniques. GANs can be employed for data generation, traffic modelling, traffic prediction and traffic control[113]. The authors of Ref. [113] investigated the potential roles of GANs in parallel transportation in terms of traffic generation, modelling, prediction and control and note that there is still work to be done in using GANs to augment real-world datasets to solve practical problems more effectively. In Ref. [114], the authors proposed network-scale deep traffic prediction model that combines adversarial training and CNNs to predict traffic as an alternative to common traffic prediction models that use statistical methods incapable of capturing nonlinear, stochastic, time-varying characteristics of urban transportation systems. Noting the difficulty of procuring accurate traffic information, the authors of Ref. [115] proposed that massive traffic-related information spread in social media can be converted into useful traffic data using GANs. They propose a Text-to-Traffic Method (T^2GAN) that combines historical traffic data with semantic information collected from social media to ultimately construct a heterogeneous dataset. Human behavior prediction and simulation in ITS is critical for safety and efficiency. In Ref. [116], Kuefler et al. explored how to imitate driver behavior such as lane change rates using GANs. They applied Generative Adversarial Imitation Learning (GAIL) method first introduced in Ref. [117] to model human highway driving behavior. However, they highlighted outstanding challenges in capturing the entire range of human driving behavior in a single neural network as drivers change their style depending on scene context. GANs in combination with other ML methods to address OWC challenges especially in NLoS situations.

5 Comparison and analysis of ML methods in OWC for ITS

Appreciating that OWC technologies will be indispensable in future RF technologies supporting data communications in ITS, is important to consider how ML techniques can be incorporated in their design to optimize their performance. To improve the systematic performance of both FSO and VLC, it is important to study how ML can be implemented in designing OWC transmitter, channel and receiver components. To start with, let us consider a comparison of ML methods in terms of learning strategy and delay in applications for data communications in ITS in Table 3. Although quantitative values of the delay for each learning strategy is not provided, the qualitative delay values for

Table 3 Comparison of machine learning applications for data communications in ITS.

ITS functionality	Feature	ML method	Strategy	Delay	Reference	Contribution
Traffic efficiency	Low latency V2I links, max. sumrate V2V links	MADRL	Deep reinforcement learning	High	[90]	Joint spectrum and power allocation to maximize sumrate of V2V links
Traffic efficiency	Sumrate maximization	DNN	Deep learning	High	[118]	Solve power allocation using DNN and WMMSE
	Traffic Prediction	LSTM	Deep learning	High	[109]	Propose unidirectional DL LSTM algorithm to predict traffic in V2X network
Traffic efficiency	V2I lifetime prediction	RF	Supervised learning	Medium	[82]	Predict V2I lifetime and vehicle's next cell
Traffic efficiency	Vehicle environment identification	CNN, DL	Deep learning	High	[119]	Use receiver side CSI and CNN to identify vehicular environment
Traffic safety	High data rate, energy consumption	FL, MARL	Distributed learning	Low	[93]	Apply FL and MARL terahertz communication
Traffic safety and reliability	mURLLCs	FL	Distributed learning	Low	[98]	Outline applications of FL in user behaviour prediction, channel estimation and signal detection
Traffic efficiency and safety	Optical signal analysis	CNN	Distributed learning	Low	[80]	Optical channel performance monitoring and impairment diagnosis
Data security	Unreliable FL clients	DNN, FL	Distributed learning	Low	[96]	Propose a defensive mechanism (DeepSA) to deal with unreliable clients
VLC/RF network architecture design	High data	FL	Distributed learning	Low	[120]	Identify requirements for convergence between AI and 6G, potential challenges, trends and key research problems
ITS VLC network design	Design considerations	FL	Distributed learning	Low	[121]	Consider FL architectures in VLCs, model aggregation methods, client selection and scheduling, communication efficiency
Cooperative driving	High-precision positioning	FL	Distributed learning	Low	[122]	Use FL, social IoTs and CEC to achieve high-precision position correction with user privacy
Energy efficiency	Sustainable ITS	ANNs, KNNs, DNNs, SVMs, DRL	Deep learning	High	[123]	Solve low-margin optical design, power optimization and RWA
Preserving privacy	Privacy	FL	Distributed learning	Low	[97]	Privacy preserving FL for UAV-enabled networks focusing on joint scheduling and resource allocation

MADRL: Multi-agent Deep Reinforcement Learning, WMMSE: Weighted Minimum Mean Square Error, RF: Random Forest

the learning strategies (low, medium, high) are based on the perception that deep learning based methods generally need significantly more data to be trained before they can be deployed while distributed learning based methods like federated learning which are locally trained at the network edge can achieve convergence faster and hence lower latency in general. Similarly, supervised learning-based strategies can be considered to have medium delay as they will not require as much training as deep learning based methods. Table 3 also provides a summary of various ITS functionalities in which the different ML methods have been applied. From the reference studies outlined in the table we can deduce that FL based methods have lower delay compared to other ML methods, and are able to offer increased data security and privacy, making them suitable to ITS scenarios with such requirements[93, 97, 98, 120].

Consider the following detailed examples of specific applications of ML algorithms in OWC data communication. In Ref. [83], the authors revealed that in short-reach LoS optical communications (ITS V2X communications included) ML algorithms can play a vital role both at the system-level and network-level. At the system level, ML methods are often used in signal processing for signal reception and detection after the signal has propagated through highly nonlinear optical communication channels. From the network level perspective, ITS OWC data networks encounter challenges from increased data switching and routing. Although the emergence of reconfigurable network topologies like Elastic Optical Networks (EONs) have improved network reliability, heterogeneity, capacity, etc.[124], there still exists increased complexity from both the data plane and control plane points of view[125]. With their ability to learn and adapt to highly dynamic ITS OWC network environmental changes, ML approaches can handle a myriad of scenarios including unforeseen situations that can be incorporated into the ML algorithm during the design process[126]. An additional example in Ref. [127] shows how ML methods can be merged with Software-Defined Networks (SDNs) to address routing and wavelength assignment problems in WDM systems.

In Ref. [128], the authors provided a justification of how utilizing ML algorithms can immensely assist in tackling nonlinearity problems in the OWC system when compared to traditional methods. Nonlinearity in OWC systems often arises due to inherent nonlinearity in LED devices, nonlinearity of channel, nonlinearity of PIN device at receiving end as well as nonlinearity of amplifiers[129]. As an example of how traditional methods have been employed to address nonlinearity challenges in OWC systems, Ref. [130] proposes using linear post-equalization together with nonlinear post-equalization algorithm (Volterra) in Carrier Free Amplitude-Phase (CAP) modulation scenarios which showed satisfactory results. However, the implementation of such traditional approaches encounter huge complications in OWC applications as the computational complexity of Volterra becomes significantly high as the nonlinearity complexity increases. In their study, Ghanem et. al[128] vividly explained how ML algorithms aid in tackling various OWC implementation issues such as pre- and post-equalization, specifically, how Density-Based Clustering Algorithms (DB-SCAN) help in anti-jitter effects, and how Gaussian Kernel Deep Neural Network (GK-DNN) help with nonlinear suppression. With this perspective, studies reflecting how ML algorithms are applied in designing each component of OWC systems are outlined below.

5.1 ML-based FSO system design considerations in ITS

5.1.1 FSO transmitter

For efficient FSO communication in ITS some of the main FSO transmitter design considerations as identified in Ref. [57] are driver circuit, modulator and collimator. Since FSO depends on LoS for effective communication, there have been efforts to improve the performance of ATP mechanisms. There has also been increasing interest in developing ML based switching methods when designing transmitter driver circuits. In Ref. [131], the authors investigated ML methods for predicting RSSI of atmospheric channel for a hybrid FSO/RF system. Based on the RSSI, they studied the application of decision trees and decision trees with AdaBoost regressor to implement hard switching method from primary FSO communication to secondary RF based communication.

5.1.2 FSO channel

The authors of Ref. [132] explored DL-based channel estimation in an FSO communication system. Their proposed low complexity DL methods are deployed in an FSO MIMO system for constellation shaping, detection, and joint constellation-shaping detection.

5.1.3 FSO receiver

In Ref. [133], the authors proposed ML methods for predicting quality factor of FSO systems with multiple transceivers. To address FSO performance degradation due to adverse weather conditions, they proposed four ML techniques, namely, multi-linear regression, SVMs, decision tree regression, and random forest regression. Using synthetic data they evaluate the performance of the models and note that decision tree and random forest models demonstrate high coefficient of determination (R^2) and low Mean Square Error (MSE) compared to other models. An investigation of error analysis for FSO using ML is done in Ref. [134]. Considering OOK for various detection approaches, the authors proposed ML approach compare its performance for soft and hard decicions in Avalanche Photodiode (APD) Input-Dependent Gaussian Noise (IDGN) and Input-Independent Gaussian Noise (IIGN). They derive soft values for IDGN and IIGN, evaluate optimum and sub-optimum detection thresholds and demonstrate the performance of their proposed ML method. In Table 4, a summary of ML techniques that have be used for different parts of FSO communicaton system is provided.

5.2 ML-based VLC system design considerations in ITS

The VLC system can typically be divided into five components based on function namely, VLC transmitter, driving circuit, VLC channel, receiver circuit, and VLC receiver[135]. ML methods are often applied in the VLC transmitter and receiver. In this section we will consider how ML techniques are used to enhance some of these components to improve the performance of the ITS VLC system.

5.2.1 VLC system design

The effect of nonlinear distortion in a VLC system can significantly degrade its performance. Different factors that give rise to nonlinearity in a VLC system are distributed across its components. For instance, in the transmitter LEDs have nonlinear transfer function implying a nonliear relationship between the voltage and current (a violation of Ohm’s law) resulting in illumination power and controlling device power not directly proportional. Channel nonlinearity can also lead to significant signal fading effects. At the receiver, the saturation effect of Photodiodes (PDs) and APDs can produce received signal clipping. An attempt to address nonlinearity caused by LEDs in VLCs using ANNs is presented in Ref. [136]. the authors considered a Wiener−Hammerstein model for nonlinearity strengths in three dynamic regions to propose an ANN based equalizer to compensate for the nonlinearities. They compared the performance of their proposed method with that of conventional methods such as Volterra series-based equalizer and memory orthogonal polynomial based equalizer. In Ref. [137], an exploration of an LED nonliearity Probability Bayesian Learning (PBL) mitigation scheme is done. The proposed PBL regression method is demonstrated to have better performance when commpared to Time Domain Averaging (TDA) in terms of reduced training overhead as well as spectral and computational efficiency. In VLC systems, jitter is also one of the common challenges that causes signal distortion. The authors of Refs. [138, 139] proposed Two Dimensional Density Based Spatial Clustering Applications (2D-DBSCAN) as well as 3D-DBSCAN algorithms to equalize PAM and QAM signals thus removing jitter caused false decisions to improve overall system performance. Nonlinearity in VLC systems can result in a mismatch of constellation points ultimately leading to a misjudgement of the received signal. Errors in phase estimation in VLC systems are often generated by phase deviations in the received signal created by nonlinearity. In Ref. [140], the authors explored phase estimation of 8-QAM modulations based on K-means clustering in Underwater VLC (UVLC). They investigate four special shaped 8-QAM constellations in a single carrier UVLC and evaluate the performance of their proposed method via experiments.

5.2.2 VLC transmitter

In the transmitter, the following processes are usually

Table 4 Summary of machine learning FSO design techniques for applications in ITS.

ITS functionality	Target feature	ML technique	Reference	Contribution
FSO Tx/Rx for traffic safety	Predicting quality factor	MLR, SVMs, DT, RF	[133]	Propose ML methods for predicting Quality Factor of FSO systems with multiple transceivers
FSO Channel for traffic efficiency	Channel estimation	DL	[132]	Explore DL-based channel estimation in an FSO communication system
	Channel impairments and pointing errors	SVM	[81]	Propose SVM based decoding for OOK FSO signals

performed; Digital Signal Processing (DSP) involving coding binary data, modulation, pre-equalization (where required), up-conversion, and then generating digital signal to be sent to driving circuit[135]. An account of a DL-assisted visible light positioning scheme for vehicles with an image sensor is presented in Ref. [141]. At the transmitter a hierachical encoding method is used to support both short-distance and long-distance communication after firstly using DS8-PSK encoding for short-distance communication and Manchester coding for long-distance communication. An ANN is then employed to predict the location of the vehicle and a CNN used at the receiver.

5.2.3 VLC Channel

OWC channel models based on deterministic and stochastic methods often do not account for mobility induced ambient light, optical turbulence and effects of road reflections on characterization of the communication channel. In Ref. [142], a method of machine learning based channel modelling for vehicular visible light communication is developed. Authors propose alternative machine learning based schemes to obtain accurate VVLC channel loss and Channel Frequency Response (CFR). They demonstrate synthesis of ML based VVLC channel model frameworks through MultiLayer Perceptron (MLP) feed-forward neural network, Radial Basis Function Neural Network (RBF-NN) and random forest ensemble learning algorithms. Predictor and response variables are collected through practical road measurements and used to train and validate proposed models for various conditions. In Ref. [143], an investigation of how to efficiently predict link outage in mobile optical communications is conducted. After highlighting how user mobility leads to signal quality deterioration in LoS links, the authors presented a DL based approach to predict outage events in LoS links. They developed a dataset by generating channel gain representations in optical wireless networks where VLC is used in downlink and infrared communications is applied in uplink. They proposed a channel predictor that forecasts burst outages or signal recoveries in upcoming frames using a deep recurrent neural network implementing LSTM. In V2V communication, ambient light noise is one of the major contributors to performance degradation. In Ref. [144], an ML based filter applying K-Nearest Neighbour (KNN) is employed as a de-noising scheme to combat the effects of solar radiation on V2V VLC links. Assuming a VLC receiver installed in the taillights of the vehicle, they develop a KNN adaptive filter that is able to reduce the effect of sunlight intensity by adjusting cascading films before APDs and is also able to modify the FOV angle to achieve the desired BER. In Ref. [145], the authors developed a DL-based method for selecting between RF and VLC bands in D2D communication with an aim of maximizing energy efficiency while minimizing outage at the same time. Based on the knowledge only receiver power and sum interference from D2D transmitters in a multi-user scenario, they proposed deep neural network for making initial band selection and then using a fast heuristic algorithm to make further band selections. They validated their method through simulations to demonstrate that it reaches close-to-optimal performance and has less complexity, and energy efficiency compared to existing solutions. An in-band channel modelling strategy based on DL in end-to-end visible light communication is presented in Ref. [146]. The authors proposed a DL autoencoder to mitigate the influence of Low-Frequency Noise (LFN) and low signal-to noise data when training channel model in their considered End-to-End (E2E) framework. They demonstrate that their approach achieves 1.875 Gbps transmission which is under 7% Hard-Decision Forward Error Correction (HD-FEC), is robust to signal bias and amplitude variations.

5.2.4 VLC receiver

The VLC receiver also involves DSP processes such as differential operations, down-conversion, post-equalization (if necessary), demodulation and decoding. After decoding the transmitted binary data, performance metrics such as BER can be computed to evaluate the overall performance of the entire VLC system. In Ref. [147], the authors presented a V-VLC receiver design based on a biologically inspired micro genetic algorithm for automotive applications. Their proposed μGA determines the alignment of maximum received signal strength (RSSmax) instead of monitoring the signal strength of each angle. Although μGA does offer a method of redirecting the receiver to reach RSSmax, it suffers from early convergence. A study of a DL based optical camera communication (OCC) is conducted in Ref. [148]. The authors identified major challenges that impact the performance of OCC systems in vehicular communications as white noise from ambient light and blur caused by vehicular vibration during mobility, camera focusing issues and weather conditions. They proposed a hybrid spatial phase shift keying based end-to-end channel coding, neural network based decoder and AI error correction method as well as a You Only Look Once (YOLOv2)-based object detection algorithm for real-time tracking to address the identified OCC system challenges. A detailed summary of how ML methods have can be utilized in improving the performance of each part of the VLC communication system is offered in Table 5.

Table 6 outlines a comparison of deploying V2X communication technologies in ITS applications. From the table, it can be inferred tha not only do RF technologies have higher power consumption as compared to OWC technologies but are also more complex to implement due to the need to install numerous base stations that need to be installed to operate the small cell nature of 5G/6G architectures. FSO also presents challenges in terms of its high cost and high complexity for ITS applications. This shows that VLC still remains the most viable option when it comes to V2X communications. In Table 7, real-world experimental validation of the effectiveness of ML algorithms in ITS applications is presented. Studies outlined show that there is significant improvement in average speed and congestion when machine learning algorithms are employed compared to instances when they are not applied. There is also a 5% reduction in accident rates in cases where ML algorithms are utilized for traffic safety warnings. A notable 30.8% traffic congestion is observed in scenarios where ML

Table 5 Summary of Machine Learning VLC Design techniques for applications in ITS.

ITS functionality		Target feature	ML technique	Reference	Contribution
Overall VLC system design					
		Nonlinear mitigation	ANN	[136]	Offer ANN based equalizer for nonlinearity mitigation
		Nonlinear mitigation	PBL	[137]	Present PBL based nonlinearity mitigation for VLCs
		Jitter Compensation	2D-DBSCAN, 3D-DBSCAN	[138, 139]	Propose density based spatial clustering for equalizing PAM and QAM signals
		Modulation format identification			
		Phase Estimation	K-means	[140]	Propose a K-means clustering phase estimation for UVLC
		Phase Estimation	SVM	[149]	Present an SVM based multi-CAP phase estimation technique for VLCs
Transmitter	Green V2X communications	Minimize transmit power, RF uplink rate	FL	[150]	Propose a lightwave power transfer method to mitigate energy challenges in FL wireless networks
	Traffic efficiency	Low latency	FL	[151]	Employ compression methods to reduce transmitting FL parameters through user selection and resource allocation
	Long-distance communication	Long-distance communication, High accuracy positioning, LED dimming	ANN	[141]	Propose a DL-assisted IS-based visible light positioning scheme
Channel	VLC communication efficiency	Accurate VVLC channel loss and CFR	MLP and RBF-NN	[142]	Propose ML methods to obtain accurate VVLC channel loss and channel frequency response
	VLC communication reliability	LoS link outage prediction	deep LSTM based RNNs	[143]	Propose channel predictor based on deep LSTM RNNs to predict outages and signal recoveries

Table 6 Comparison of deploying different V2X communication technologies in ITS applications.

Description	RF (5G/6G)	VLC	FSO	Reference
Range	<100 m	<100 m	<1 km	[59]
Data rate	~Gbps	~100 Mbps	~Gbps	[59]
Power consumption	25 mW	2.3 mW	1 mW	[152](RF), [153](VLC), [154](FSO)
Cost	Medium	Low	High	[155](RF), [156](VLC), [157](FSO)
Complexity	High	Low	High	[35](RF), [156](VLC), [158](FSO)

Table 7 Real-world experimental validation of effectiveness of ML algorithms in ITS applications.

Target feature	Reference	Optimization effect of using ML algorithms
Traffic flow: Average speed	[159]	20% increase in average speed in city experiment before and after application of ML algorithm
Traffic flow: Congestion index	[159]	15% decrease in congestion in city experiment before and after application of ML algorithm.
Path Planning	[159]	10% improvement in user satisfaction for navigation systems using ML algorithms.
Traffic safety early warning	[159]	5% decrease in accident rate in regions using SL for traffic safety warnings.
Traffic prediction	[160]	Almost 100% prediction accuracy at 0.38s prediction speed using supervised learning classification tree algorithms for speeds less than or equal to 65km/h.
Adaptive traffic light control	[161]	Developed regression based methods show 30.8% reduction in traffic congestion tested on real-world UK national road traffic data.

methods are used for adaptive traffic light control. Thus, it is evident from these studies that there are great benefits that are reaped from applying ML algorithms in ITS applications.

6 Recommendations and future direction

6.1 Machine learning empowered IRS for OWC Data communication in ITS

Intelligent reflecting surfaces are described as real-time controllable reflect-arrays with massive number of low-cost passive elements intended to introduce a phase shift to incoming signals before propagation towards their destination[162]. The target of IRS is to create a smart propagation environment with a target of improving system performance. In Ref. [163], IRS is identified as one of the promising technologies to enhance 6G connectivity by generating intelligent and controllable wireless environment with ubiquitous connectivity, deep connectivity and holographic connectivity. It can accomplish fine-tuned 3D massive beamforming through intelligent control of the wavefront (e.g. phase, amplitude, frequency, polarization, etc). This opportunities for 6G enabled V2X communication are further explored in Ref. [164]. The authors brought to light multiple use cases for IRS enabled V2X communications like optical beamforming, mmWave and THz, physical layer security, and ML techniques. Perhaps the untapped potential of ML techniques in handling intrinsic and complicated resource allocation and signal processing in IRS V2X communication is the one that stands out in all the uses. Echoing similar sentiments the authors of Ref. [165] presented a study of IRS in vehicular communications making strenuous efforts to highlight impact of IRS-aided aerial vehicular communications involving UAVs. Sejan et al.[166] presented a comprehensive account of ML enabled IRS applications in 6G wireless networks. Focusing on DL-based IRS-enhanced communication, they considered a plethora of use cases regarding optical IRS placement, dynamic hybrid beamforming, IRS for IoT networks, EDGE intelligence, and hybrid communication implementations involving VLCs. Another investigation of DL-enabled IRS in ITS focusing on how to improve spectral efficiency, energy efficiency, and how to enhance computational performance of DL algorithms in such environments is done in Ref. [110]. A platoon scheduling scheme is designed in Ref. [167] to improve training performance of an FL IRS based system in vehicle platooning networks. Multiple platoons cooperate in training a shared FL model in a cost-effective and energy efficient manner through joint platoon scheduling, bandwidth allocation and phase shift using IRS to maximise number of vehicles scheduled in a platoon. Overall design and application considerations of IRS in B5G networks is contemplated in Ref. [168]. Even in their interest to develop Smart Radio Environments (SREs), they acknowledged the immense impact of AI/ML solutions in optimizing IRS networks to optimize system performance. Having reviewed these works, we believe that application of ML in IRS to improve data communications in OWC ITS is still worth further investigation in the future. In Fig. 5a, an example of how ML-based IRS can be applied to aid V2V communication in NLoS scenarios.

6.2 Integrated sensing and communication

ML posseses numerous capabilities to enhance Integrated Sensing and Communication (ISAC) process regarding extracting and leveraging temporal and spatial patterns, solving complex optimization patterns and approximating complicated models. Some of the ML benefits in joint sensing and communication are outlined in Ref. [169]. The three major areas of ML applications in ISAC worth highlighting are the following.

6.2.1 Sensing aided communication

Future wireless communication systems are likely to operate in higher frequency waves such as mmWave and terahertz due to enormous available bandwidth at these frequencies that enables higher data rates. OWC technologies such as FSO and VLC depend on aligning narrow beams at the transmitters and receivers although such alignment is influenced by the locations of transmitters/receivers and the geometry of the surrounding environment. One of the challenges that arises in such scenarios is high beam training overhead. To overcome this challenges, ML approaches such as the adoption of DNNs to learn and approximate complex models could provide promising data-to-beam solutions to address beam prediction challenges. Since they operate in mmWave and terahertz frequencies, OWC technologies require LoS links which are very sensitive to blockages. Objects that obstruct LoS links can result in significant signal attenuation and abrupt link disconnections. Using beam switching techniques or reactive hand-off methods can lead to high latency overhead. Employing traditional methods such as multi-connectivity methods in which the user is connected to multiple base stations even if one link is connected can result in underutilized network resources and eventual poor overall network performance. ML methods can produce proactive sensing aided blockage and hand-off predictions. In this regard, DL methods can be applied on sensing data to predict future LoS link blockages, their time and duration before they happen. ML based link blockage prediction can enable proactive beam switching and hand-off decisions which can enhance vehicular network reliability and lower latency aspects. In Ref. [170], a study illustrating the application of ML for sensing aided beam and link blockage and hand-off prediction is outlined based on the real world dataset in Ref. [171].

6.2.2 Communication aided sensing

As motivated in Ref. [172], the concept of communication aided sensing is born out the fact that transmitted communication signals that are back-scattered/reflected from various objects in the environment can be opportunistically utilized for sensing tasks like positioning, object detection/tracking and imaging. However, it can be difficult to achieve high quality sensing of received communication signals as the components of underlying communication signals and systems such as frame structure, preamble, and other hardware might not be optimized for sensing functions. This is where ML has the potential to optimize communication aided sensing using DNN data-driven characteristics to accomplish sensing goals without explicitly modelling various components of communication hardware. Thus, even though it might be difficult to handle multiple propagation paths and interference in traditional signal processing methods, ML techniques can approximate underlying complex models and leverage derived solutions from multiple paths to extend sensing resolution and range. Another interesting application of communication aided sensing is using multiple communication transmitters to achieve better sensing performance in terms of range and angular resolution. Designing joint sensing solutions for distributed systems that account for synchronization requirements, control overhead and other complex design problems in joint sensing functions might be challenging. To address these, data-centric ML techniques can enable distributed sensing using communication signals and hardware without needing to accurately model these systems. New distributed learning approaches[173] such as federated learning and transfer learning facilitate the application of distributed sensing devices to allow integration of information gathered from different locations. They also enable scalability of distributed sensing functions while preserving data privacy and restraining system complexity.

6.2.3 Joint sensing and communication

There are instances where it is desirable to perform Joint Sensing and Communication (JSC) to simultaneously meet communication (e.g. data rates, latency, and reliability) and sensing objectives. However, trade-offs between sensing and communication systems requirements can make achieving JSC difficult. This can be due to issues like ADC/DAC quantization hardware limitations, rapidly changing communication channels or peak-to-average power ratio constraints in OFDM systems. By embracing data-driven approaches ML methods have the potential to learn to solve JSC waveform optimization design challenges using multi-objective techniques that produce site-specific JSC waveforms that adapt to deployment scenarios. In full-duplex mode where where JSC functions operations concurrently, DNNs can immensely contribute to self-interference cancellation by learning transmit/receive beamforming patterns for self-interference nulling and help reduce self-interference cancellation complexity. ML methods can also be employed to tackle resource optimization by intelligently allocating sensing and communication tasks based on prior user activity.

6.3 Federated learning for data communication in OWC ITS

Considering the fast changing wireless channel environment due to high mobility in vehicular networks and the fact that most data is generated at the network edge (e.g. vehicles and base stations) in vehicular networks, it can be challenging to combat latency in ITS. Apart from the associated costs of transferring data to a remote cloud environment, there are also underlying issues such as privacy and security that also present hurdles for training ML models in ITS. FL has recently been identified as one of the promising solutions as models train locally and only update the global model parameters without the need to transfer actual data. Therefore, there is a need to further investigate the potential of FL in data communications in ITS. The authors of Ref. [174] proposed a Federated Deep Learning Intrusion Detection System (IDS) using GANs (FEDGAN-IDS) to detect threats in IoT systems. They propose a distributed GAN over IoT devices which acts as classifiers and trains using augmented local data. They validate the performance of their proposed method to other standalone IDS. Their work motivates future research efforts to investigate the performance of GAN-based FL techniques in OWC ITS networks.

One of the areas that has received significant attention is the application of FL in hybrid RF/VLC channel estimation. In Ref. [175], a joint channel estimation and feedback for mmWave systems based on FL is developed. Considering a massive MIMO system, authors propose an FL Channel State Information (CSI) estimation and feedback scheme in which each user trains the local model using local dataset and exchanges model parameters with the base station. Their proposed CSI estimation and compression and CSI recovery network shows satisfactory numerical results. In Ref. [176], the authors discussed how a Visible Light Integrated Positioning and Communication (VIPAC) framework can be formulated to incorporate positioning tasks for sensing device and channel estimation for communication device in unified architecture. They employ FL in their multi-user cooperative VIPAC scheme and demonstrate how their approach improves positioning performance and channel estimation in spatiotemporally nonstationary environments compared to existing schemes. Considering a 5G context, Ref. [99] explores applications of distributed learning, specifically FL in wireless communication like edge computing and caching and spectrum management. The authors emphasized that one of the essential considerations of FL in wireless communications is convergence time which is not only influenced by computation time of local learners and aggregator but also by the communication time between them which in turn depends on wireless channel quality. Thus, when optimizing the model, for instance, making the trade-off between reducing model complexity and its accuracy, the quality of the wireless channel should be contemplated given the time-varying nature of the wireless channels. These works show that there is still room for investigating the great potential of applying FL in hybrid RF/VLC networks.

In Fig. 4, we present an ITS roadmap for recommended technologies and ML techniques based specifically on our focused perspective of data communication in OWC for ITS. In resonance with the adopted ITS definition in Fig. 2, we illustrate how ITS data communication based on OWC technologies, specifically VLC and FSO, can be employed as the means to satisfy the identified ITS requirements, challenges and functionalities and prescribe ML techniques according to literature that best accomplish each ITS scenario. For instance, latency requirement in ITS can be achieved using VLC and federated learning[98−100].

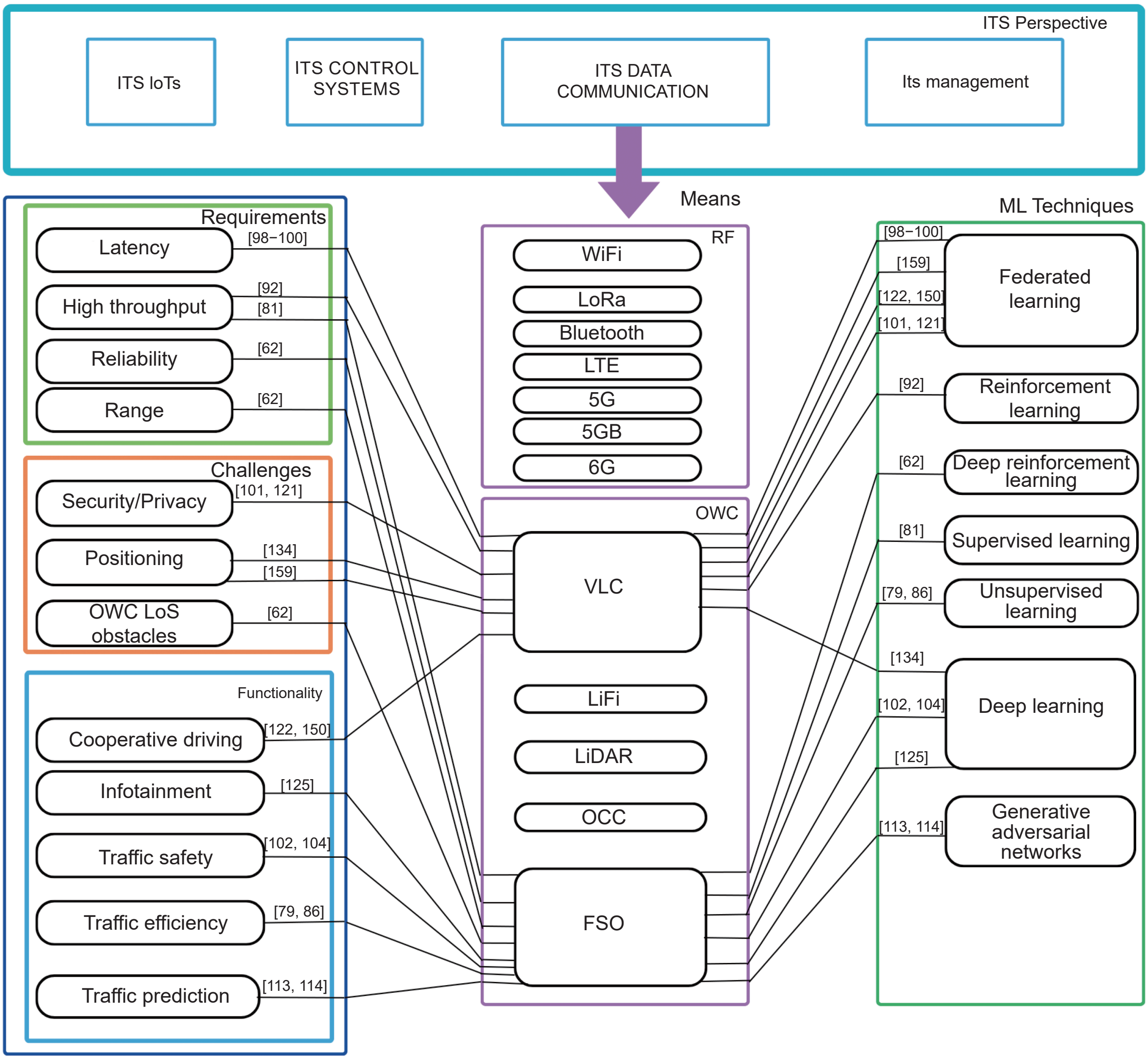

Fig. 4 ITS roadmap for recommended technologies and ML approaches.

Examples of how ML techniques such as FL (b) can be used to enhance Visible Light Positioning (VLP) is demonstrated in Fig. 5. VLP is increasingly becoming one of the most important topics of research as more cars now have VLC LEDs fitted in their headlights and taillights, making it a low-cost implementation technology. VLP can immensely improve optimization of numerous ITS applications such intelligent platooning, traffic efficiency and safety. In this figure we illustrate how each Base Station (BS) reports its locally trained model containing vehicle positioning information to a global FL server. An example of how this information can be helpful is in optimizing hybrid RF/OWC switching in NloS situations. In Fig. 5c, an example of how datasets from image sensors mounted on cars communicating with RSUs (e.g. streetlamps) following works like Ref. [177] can be augmented using GANs. In ITS it is difficult to procure experimental datasets and GANs are gaining attention from researchers to augment datasets that have been experimentally to improve channel estimation for VLP purposes.

7 Conclusion

In ITS, RF technologies such as 5G, B5G and 6G have emerged as front-runners in their potential to meet the requirements of massive connectivity, high data communication, and ultra low latency. ITS RF technologies can be complemented with OWC technologies such as FSO and VLC which are able to satisfy high data communications requirements, thus creating a convergent heterogeneous communication networks. To address some of the challenges of OWC deployments in B5G and 6G heterogeneous networks, machine learning algorithms are recognized as highly valuable solutions. In this paper, we have reflected on how ML approaches can be embraced to address some of the OWC challenges caused by adverse weather conditions and NLoS scenarios. We also considered how ML techniques can be implemented in designing various components of OWC systems to enhance their performance, and hence better meet ITS requirements. We have also highlighted future research directions with potential for further investigation and provided an ITS ML road-map that can be applied when working with various aspects of ITS.

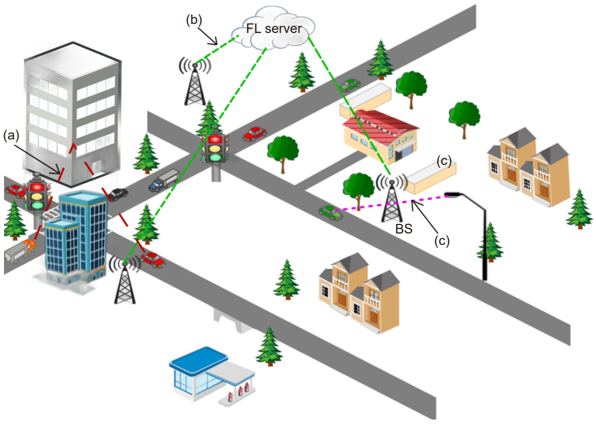

Fig. 5 Examples of ML applications in OWC ITS: (a) intelligent reflecting surface at intersection in NLoS scenarios, (b) federated learning based VLP ITS, (c) GANs-based channel estimation data augmentation for VLP.

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