Computer Communications 154 (2020) 313–323

Contents lists available at ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

Review

Applications of Artificial Intelligence and Machine learning in smart cities

Zaib Ullah [a,*], Fadi Al-Turjman [b,c], Leonardo Mostarda [a], Roberto Gagliardi [a]

[a] Computer Science Division, University of Camerino, 62032 Camerino, Italy
[b] Artificial Intelligence Department, Near East University, Nicosia, Mersin 10, Turkey
[c] Research Center for AI and IoT, Near East University, Nicosia, Mersin 10, Turkey

ARTICLE INFO

Keywords:
Smart city
5G and B5G communication
UAVs
Intelligent Transportation System
Smart grids
Cyber-security
Internet of Things
mmWave communication

ABSTRACT

Smart cities are aimed to efficiently manage growing urbanization, energy consumption, maintain a green environment, improve the economic and living standards of their citizens, and raise the people's capabilities to efficiently use and adopt the modern information and communication technology (ICT). In the smart cities concept, ICT is playing a vital role in policy design, decision, implementation, and ultimate productive services. The primary objective of this review is to explore the role of artificial intelligence (AI), machine learning (ML), and deep reinforcement learning (DRL) in the evolution of smart cities. The preceding techniques are efficiently used to design optimal policy regarding various smart city-oriented complex problems. In this survey, we present in-depth details of the applications of the prior techniques in intelligent transportation systems (ITSs), cyber-security, energy-efficient utilization of smart grids (SGs), effective use of unmanned aerial vehicles (UAVs) to assure the best services of 5G and beyond 5G (B5G) communications, and smart health care system in a smart city. Finally, we present various research challenges and future research directions where the aforementioned techniques can play an outstanding role to realize the concept of a smart city.

Contents

1. Introduction

According to the reports [1,2], by 2050, the global urban population is expected to reach 66% or 70% respectively. This amount of surge in urbanization will have drastic impacts on cities' environment, management, and security. To efficiently handle the meteoric growth in urbanization, many countries have proposed the concept of smart cities to effectively manage the resources and optimize energy consumption. The smart cities projects can precisely deal with assuring the green environment by developing and adopting low carbon emission technologies. Many nations (e.g., US, EU, Japan, etc.) around the globe have proposed and realizing the smart cities projects to efficiently accomplish the possible looming challenges. To meet the requirements of a smart city, efficient utilization of information and communication technologies (ICTs) are highly necessary [3–6] to adequately administer

* Corresponding author.
E-mail addresses: zaibullah.zaibullah@unicam.it (Z. Ullah), fadi.alturjman@neu.edu.tr (F. Al-Turjman), leonardo.mostarda@unicam.it (L. Mostarda), roberto.gagliardi@unicam.it (R. Gagliardi).

https://doi.org/10.1016/j.comcom.2020.02.069
Received 25 December 2019; Received in revised form 5 February 2020; Accepted 23 February 2020
Available online 2 March 2020
0140-3664/

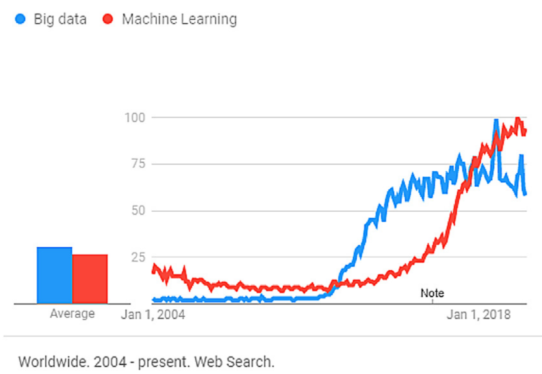

Fig. 1. This figure (obtained from google trends) shows an era of Big Data and ML from 2004 to January 2020.

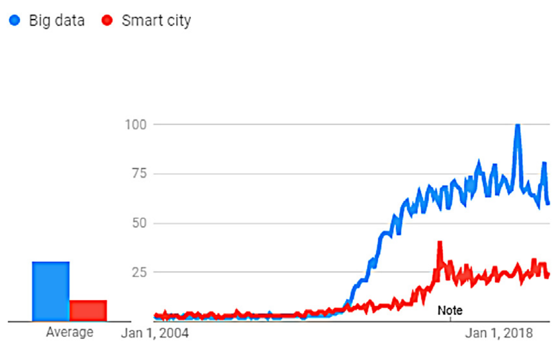

Fig. 2. The popularity of smart city concept and big data over the given period particularly after 2012.
Source: Google trends

the data analysis, data communications and effective implementation of complex strategies to ensure the smooth and secure operation of a smart city.

The IoT is the most important and significant constituent part of most of the smart city applications, that are responsible for generating an immense amount of data [7,8]. In the presence of such amounts of big and complex data, its difficult to precisely decide the most accurate and efficient actions. The best possible analysis of the big data can be carried out using advanced techniques like Artificial intelligence (AI), Machine learning (ML), and Deep Reinforcement Learning (DRL) to reach an optimal decision [2,9]. The preceding techniques take a long-term objective into consideration and can lead to the best possible or near-optimal control decisions [10]. The accuracy and the precision of the aforementioned techniques can be further enhanced by increasing the amount of training data to strengthen their learning capabilities and hence the automated decision efficiencies [11]. In [12], the authors have shown that the concept of smart cities realization and the use of advanced data analysis techniques for Big Data have surged approximately in the same era. The concept of smart cities, IoT, Blockchain, Unmanned aerial vehicles (UAVs) and the use of AI, ML, and DRL-based techniques in various applications are still in the evolutionary phase and would offer more opportunities in the future (see Figs. 1–3).

In smart cities project, various sectors like Intelligent transportation, cyber-security, smart grids (SGs), and UAVs-assisted next-generation communication (5G and B5G), etc. are playing a vital role. All the preceding sectors of a smart city is highly influenced by Big data analytic and effective use of AI, ML, and DRL-based techniques that can enhance their efficiency and scalability in a smart city project. The modern intelligent transportation system (ITS) is highly influenced by ML and DRL-based techniques to realize self-driving vehicles, ensure security of connected vehicles, efficient passengers hunt, and safe travels. In [14], the authors have conducted a survey where the role of

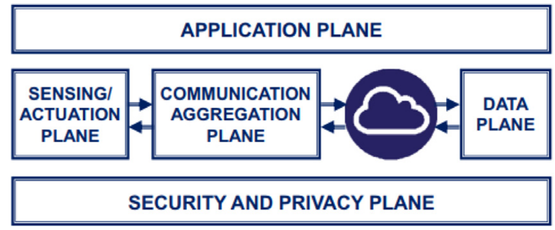

Fig. 3. A generalized architecture of smart city applications, composed of environment sensing, communication protocols, data transmission, and security and privacy. The significance of the security plane in smart city applications is clearly shown [13].

DRL-based protocols on ITS has been discussed. Cyber-security is the most important and significant aspect of a smart city that can realize the ideal concept of a smart city. To realize the security plane shown in figure [13], an extensive, dynamic, and vigorous cyber-security plane must be designed and sketched to all the constituent parts of the proposed architecture. The role of AI, ML and DRL based techniques in cyber-security is outstanding and has significantly impacted almost all the sectors of a smart city. In [15], the authors have surveyed an in-depth role of ML and DRL techniques in cyber-security of IoT devices that play a fundamental role in smart city applications. The energy generation, management, and consumption is an essential feature of a smart city and big data analytics have a noteworthy impact on ICT-based SGs operations (see Table 1).

The impact of AI on our daily life activities is increasing day by day. AI is rapidly changing the nature of our daily jobs, impacting the traditional approach of human thinking, and interaction with the environment. How should the new regulations be designed to safeguard the current and future generations from the negative aspects of AI and maximize its positive impacts over humanity? Moreover, how AI-assisted policies and regulations should be developed to ensure social and economic development [16,17]. In [18], the authors proposed an efficient crime detection system for a smart city, based on DRL and neural networks, to efficiently identify and analyze any criminal activity. Similarly, the authors in [19] proposed an ML-based architecture that can be used to predict incident and generating response before its happening.

In this work, we have provided the most recent development regarding AI, ML, and DRL-based applications in various sectors of smart cities. We have focused to review the role and impacts of the preceding techniques on the most important aspects of smart cities e.g., ITS, cyber-security, SGs, UAVs-assisted 5G and B5G communication, and smart health care. The literature review of various ML and DRL techniques has been carried out in Section 2. Section 3 provides in-depth details of ITS, Section 4 offers a detailed study of recent innovations in cyber-security, and Section 5 summarizes innovative development regarding energy generation and management in smart cities. Section 6 offers the most recent review of ML and DRL based UAV applications in 5G and B5G communication. Similarly, Section 7 focus on innovations in the smart health care sector, Section 8 outlines future research challenges, trends and solutions, and finally, the Section 9 concludes the review.

2. Machine learning: A brief overview

Machine learning methods are divided into three categories i.e., supervised, unsupervised and RL. The RL uses algorithms from all branches in the different scenarios as given in Fig. 4 [20]. Here we briefly introduce supervised and unsupervised learning with examples. Further, we will present RL and its major algorithms.

In supervised learning, a dataset of input and target values is used to train the Artificial Intelligence (AI) network to find a mapping function to map input data to output. Supervised learning is further divided

Table 1
Acronyms used in this article.

Acronym	Text	Acronym	Text	Acronym	Text
ML	Machine Learning	DRL	deep reinforcement learning	UAV	Unmanned Air Vehicle
UAV	Unmanned Air Vehicle	UAS	Unmanned Aerial System	BS	Base Station
MDP	Markov Decision Process	Relay-BS	Relay Base Station	UE	user equipment
LTE	Long Term Evolution	AI	Artificial Intelligence	R&d	Research and development
DS	Delivery System	RMS	Real-time multimedia streaming	ITS	Intelligent transportation systems
RL	Reinforcement Learning	TD	Temporal Difference	MC	Monte Carlo systems
DP	Dynamic Programming	LoS	Line of Sight	ESN	echo state network
ELM	Extreme Learning Machine	QoE	quality-of-experience	CSI	Channel State Information
SGs	smart grids	ICT	information and communication technology	US	United States
EU	European Union	IoT	Internet of Things	MEC	mobile edge computing
DNN	Deep Neural Network	GPS	Global Positioning System	ECC	edge cognitive computing
ANN	Artificial Neural Network	PMUs	phase measurement units	PLC	power line communication

into regression and classification. Some famous examples of supervised learning are linear regression, support vector machine and random forest.

In unsupervised learning, there is no guidance available, only a non-labeled and non-classified input dataset is being provided and used to train the AI network to find hidden patterns, answers, and distributions. Different types of unsupervised learning problems are clustering and association. A few examples are the k-means and auto-encoder algorithm.

Markov Decision Process (MDP) Most of the RL problems are based on the Markov Decision Process (MDP). The objective of an MDP is to search for optimal solutions to sequential decision problems (SDP). In the case of stochastic SDPs, an MDP cannot provide absolute solutions but can help in offering an optimum or the best solutions among all possible solutions. An MDP model is defined by a set of states, a set of actions, a transition model, and a reward function. Reward and transition depend upon the current state, chosen action, and next resulting state.

Reinforcement Learning (RL) The goal of the RL agent is to improve its long term aggregated reward based on its many interactions with the given environment. The part of the RL algorithm who does interactions and learns is known as an agent. An agent achieved this objective through an optimal policy. A policy is a sequence of actions for a given set of states and optimal policy is one that maximizes the overall long-term reward. The critical task for an agent is to exploit the already know actions and at the same time, to explore new actions which may provide better reward over the existing best actions. The balance between exploration and exploitation is a central issue in the RL setup i.e., a balance between maximizing reward from known moves or to search for new horizons which may even give a better outcome. Generally, RL algorithms can be divided into two types i.e., Model-based and model-free. Model-based RL algorithms use function approximator and are considered as sample efficient. However, an important issue in the RL framework is a generalization and model-based algorithms generalization for probabilistic, complex and models with high dimensions are not good. Different techniques to solve model-based RL problems include value function, policy search, return function and transition models. Monte Carlo (MC) and Temporal Difference (TD) are model-free RL algorithms. The Q-Learning and SARSA techniques which will be explained later are examples of TD method.

Dynamic programming (DP) developed by Richard Bellman in the middle of twenty century, is a computer programming and mathematical method used for optimization problems. DP is a recursive method that sequentially breaks down a complicated and complex task in simpler and small problems. DP approach is model-based which requires the full observable knowledge of the environment. Therefore, in some RL problems where given environment model is an MDP model, DP is used to find an optimal policy by using value iteration or policy iteration method

Monte Carlo (MC) method Monte Carlo (MC) method uses randomness for the solution of problems. First-visit MC and every-visit MC are two different MC techniques. First-Visit MC is the average of the returns by following the first visits to a state during a set of episodes while the average of the returns following all the visits to a state during a set of episodes is the Every-Visit MC. The main advantages of MC over DP are, (i) It can be used with sample models. (ii) MC algorithms are efficient and easy to implement. (iii) MC learns optimal solutions through direct interaction.

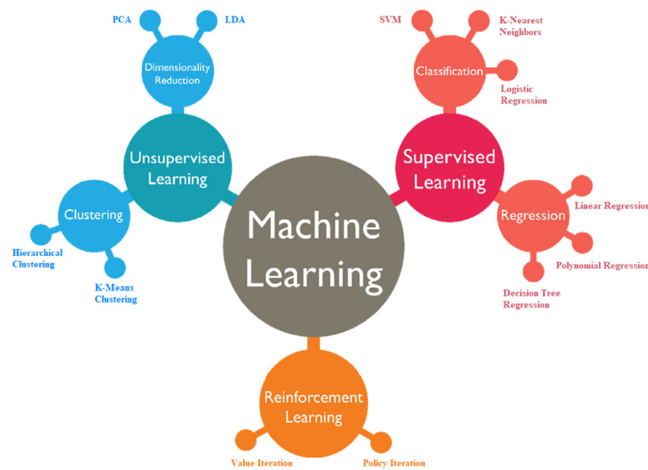

Fig. 4. Classification of machine learning techniques.

Temporal difference methods A problem in MC techniques is that for an update one has to wait till the end of an episode and this problem can be solved by Temporal difference (TD) methods, a class of model-free RL algorithm TD method learns by bootstrapping from the current value function estimation. In general, TD is used for prediction of a quantity that depends on the given signal's future values but in the RL framework, it is used for a prediction about long-term future rewards. It is one of the most widely used methods for the evaluation of the policy. The two major TD based algorithms are Q-learning and SARSA briefly explained in the following.

SARSA State-Action-Reward-State-Action (SARSA) proposed by [21] as 'modified Q-learning' due to its similarity to Q-learning and later Sutton [21] called it SARSA is active RL-TD control case method. It is similar to Q-learning except that SARSA is an on-policy learning algorithm. As clear from its name, the update is based on 'State-Action-Reward-State-Action'. So it learns the optimal Q-value from the results of action performed by following the present policy instead of the greedy ones.

Q-Learning The Q-learning technique is suggested to be used as a DRL approach in a stochastic environment. Q-learning is a model-free, off policy and forward learning TD algorithm [21] for control. Q-learning algorithm learns the optimal policy by using off policy i.e. learning by observation. In Q-learning, the next action a' is selected for maximum Q-value of next state which is a greedy policy and it does not follow the present policy i.e. it is off-policy learning. We can also speed up the convergence in Q-learning and SARSA by using eligibility traces. The preceding protocol efficiency becomes poor in case of discrete actions and a large number of repeated states. Most often, the Q-learning technique requires function approximations.

actor–critic algorithm The actor–critic technique is based on popular RL algorithms. It is a hybrid method consisting of value function and policy. The critic part of the algorithm estimates the value function whereas, the actor updates the policy in accordance with critic feedback. This type of method stands between policy-based methods and value-based methods; i.e., it estimates both policy and value function. It applies to small state–action spaces as well as to large action-state spaces. The objective of the preceding technique is to associate the actor-only and critic-only techniques. To learn a value function, the critic method utilizes the simulation and an approximation framework. The value function is then used to update the actor's policy values to enhance efficiency [22].

Bayesian methods In DRL, an agent attains different rewards from various states and is certain to enhance the reward with the passage of time. The agent trains itself to switch to the states with the highest rewards while avoiding the least reward-based states. Its the uncertainty information of environment that plays a vital role in maximizing the reward. The Bayesian models provide an analytical architecture to evaluate and examine a model uncertainty at a sufficient computational cost [23]. Bayesian methods can be a solution to the exploitation–exploration dilemma due to their ability to capture uncertainty in learned parameters and avoid over-fitting. A few famous methods used for Bayesian approximations are Myopic and Thompson Sampling. Thompson sampling can be used to solve the problem of exploration–exploitation.

Deep Q Network TD algorithm especially Q-learning is one of the widely used algorithms in RL but it has a lack of generality issues in large state space. In previous methods, we store value function in the look-up table or matrix. For example, in Q-learning, we store the Q table in a two-dimensional array. For environments with large state space and many associated actions, it is difficult to visit and estimate value function for all states. With the introduction of RL based on neural network for function approximation, it is possible to overcome the issue of generalization. The Deep Q-Network (DQN) [21] uses a Neural Network to estimate the value function in large state space. The training of the network is done by using the Q-learning update rule

3. Intelligent transportation system

The ITS is a joint application of advanced sensors, control systems, and ICT that generates big data and has effectively impacted the future of ITS and the concept of smart cities [24]. The AI, ML, and specifically the DRL techniques are playing a vital role to precisely monitor and estimate the real-time traffic flow data in an urban environment which is a key element for a sustainable ITS [25,26]. In the following, we briefly overview the most recent developments in ITS that would play a significant role in a smart city realization.

In [27], Veres et al. established a detailed study to investigate the role of ML and DRL to various issues e.g., assessing traffic flow, fleet management, passengers hunt, channel estimation in MEC, estimating the possibilities of accidents, etc., in ITS that can be efficiently utilized in smart cities. In [14], the authors developed a study based on DRL techniques and edge analytics in ITS that focus on issues (e.g., trajectory design, fleet management, and cyber–physical security, etc.) that can play a vital role in the development of smart cities. In this [28] article, the authors have proposed an enhanced driving behavior decision-making technique in a heterogeneous traffic environment based on DRL. This approach consists of a data preprocessor that converts data into a hyper-grid matrix, a two-stream DNN(deep neural network) to extract the essential latent features, and a DRL approach to attains an optimal policy. The performance of the proposed scenario has been validated through simulation results using various traffic scenarios for connected vehicles. The authors in [29] focus on the arising security issues with mobile edge computing (MEC). To successfully handle the possible security threats, a DRL based approach is proposed to learn various attacking possibilities through unsupervised learning. The comparative analysis of the proposed model with the contemporary ML-based protocols has been carried out. The performance shows that the proposed technique attains a 6 percent extra gain in accuracy. In [30], the authors utilized a DRL based approach to predict short term traffic flow in a highway. They conducted a study based on the Deep Long-Short Term Memory Recurrent Neural Network (LSTM-RNN) for data analysis of Gyeongbu Expressway (South Korea) to predict congestion. The experimental results yielded a significant response in predicting the short-term traffic flow in highway systems. In [31], the authors conducted a study to efficiently use GPS trajectories data of Taxis in an area for passengers hunting. The proposed efficient and effective recommendation system (TRec) is based on the structure of DNN. In TRec, the passenger's hunt is accomplished as: the taxi drivers are the learning objects, to foresee the road status, and the assessment of net earning. The proposed recommendation system (TRec) is evaluated by using a real dataset that confirms its efficiency and effectiveness. In [32], the authors proposed an innovative prediction technique based on the LSTM (long short-term memory) network to predict various parameters of a wireless communication channel and ensure optimum system performance. The LSTM network has the capability to arrange the auspicious information in an array that provides ease in analyzing the Spatio-temporal correlation among different parameters of the communication channel. The efficacy of the proposed model in the given scenario has been validated by the simulation results. In [33], the authors utilized a DRL technique to develop a smart offloading system for vehicular edge computing. The authors implemented a finite Markov chain to model the communication and computation states and developed a joint optimization problem based on task and resource management to enhance the users' Quality of Experience (QoE). The proposed NP-hard problem is further divided into two sub-problem to handle it efficiently and its effectiveness has been validated through numerical results. In [34], Ye et al. developed a DRL-based innovative decentralized resource allocation technique for V2V communication that can also be employed in unicast and broadcast environments. According to the proposed technique, an independent vehicle or v2v link can decide on its own to search for an optimal power level for data transmission and sub-band irrespective of waiting for global information. The simulation results illustrate that each user or agent efficiently learn to comply with the stern latency requirements on v2v links and optimize the interference in V2I (vehicle-to-infrastructure) communications. In [35], the authors coined the DRL based techniques as a solution to model the traffic flow. The stacked auto-encoder model is proposed and implemented to learn the various aspects of traffic flow and trained in a greedy layer-wise manner. The performance of the proposed technique to foresee the traffic flow surpassed the efficiency of existing techniques. The fast and swift movements of UAVS, ease in its deployment, increasing payload capabilities, long endurance and low manufacturing cost have made it a significant part of ITs of smart cities. The preceding auspicious aspects of UAVs have realized its role in ITS from blood delivery to parcel delivery. The ML and DRL techniques are playing a significant role in optimizing UAV's trajectory, energy consumption, and efficiency in ITS. In [36], the authors proposed a traffic-aware technique to facilitate UAVs deployment in a vehicular environment to improve the quality of service. The deployed UAVs acts as MEC nodes in an environment of traffic congestion and related events. The proposed protocol performance has been validated through simulation results. The authors in [37], proposed a DRL based decentralized architecture of airborne UAVs aimed to provide coverage services to mobile users in a defined region. The objectives of the proposed model are to maximize the coverage of areas of interest, optimize the energy consumption of UAVs, maintain the inter-connectivity of UAVs, and limit the airborne UAVs within the area of interest. The superior performance of the proposed model is validated through simulation results. The authors in [38], explored the opportunity of utilizing UAVs for downlink transmission for vehicles with maximizing throughput. The proposed model is based on the MDP problem, exploring various transition states of UAVs and vehicles. The DDPG algorithms based on three different DRL techniques were suggested to efficiently study the energy consumption of flying UAVs. The performance of the proposed model is studied in a more realistic environment and verified through simulation results.

4. Cyber-security

A smart city is supposed to consists of safe, secure and reliable interconnected sensors, actuators, and relays to gather, process and transmit data to assure trusted and efficient digital services. This interconnectivity of various devices has opened up cyber-security issues that need to be alleviated [39]. Most of the data is generated by Cloud-based IoT devices that perform a vital role in different applications of smart cities [40].

In [41], the authors have developed a brief survey to explore various essential and significant aspects of a smart city. Some of the discussed vital challenges are ensuring privacy and security of data, safeguarding networks against any possible cyber-attack, encouraging mature and responsible data share culture, and convenient use of AI, ML, and DRL techniques. In [13], Hadi et al. conducted an extensive survey to study different research problems and corresponding solutions to the concept of smart city architecture from communication, privacy and security perspective. They primarily focused on exploring the range of challenging issues arises during the integration of existing communication protocols, sensors, actuators, and infrastructure. In [15], Mohammad et al. established an extensive study and explored the role of ML and DRL techniques from an advanced security perspective of IoT and recently introduced security threats. The authors reviewed ML and DRL protocols for potential IoT security, advantages, limitations, and proposed possible research directions. In [42], Riccardo et al. organized a review to investigate the role and possible opportunities by implementing ML and DRL techniques in the healthcare sector and Bioinformatics. They explored various challenges and proposed solutions to efficiently use ML and DRL-based technologies in the state-of-the-art healthcare domain. In [43], the authors utilized the self-taught potential and capabilities of DRL techniques to explore the latent pattern from the training dataset to differentiate between the normal and anomalous traffic. They proposed a distributed deep learning-based approach to detect and identify the cyber attacks in IoT applications in smart cities. The efficiency of the proposed technique is superior to the shallow models-based approach. In [44], the authors focused on the security of IoT devices in the smart city and proposed a Random Forest ML-based architecture called Anomaly Detection-loT (AD-IoT) system. The proposed technique can efficiently identify any sort of suspicious activity happening at the distributed fog nodes using machine learning-based dataset evaluation. In [45], the authors proposed an innovative DRL-based architecture to safeguard the digital infrastructure of a smart city against any sort of cyber intrusion. The proposed model identifies the intruders in an early stage based on their data behavior and the network can be safeguarded in advance. The preceding model can help in developing a range of secure and confidential applications in materializing the smart city concept. In [46], the authors presented an ML-based secure computational offloading framework in the Fog-Cloud-IoT environment to optimize latency and energy consumption. The proposed framework is based on the Neuro-Fuzzy model that ensures data security at the gateway and IoT devices decide the favorable fog nodes for computation offloading using Particle Swarm Optimization (PSO). The proposed framework has a better performance in terms of latency minimization. In [47], the authors proposed the architecture of edge cognitive computing (ECC) network and explored the key problems. Moreover, the ECC architecture was established for dynamic and active service migration. The preceding ECC architecture is based on cognitive mobile user's practice and usual behaviors. The performance analysis of the ECC framework shows that it has superior efficiency over traditional computing architecture. In [48], the authors proposed a DRL-based Online Offloading technique to develop binary decision offloading capabilities from experience. In binary offloading mechanisms, each task is either performed locally at the node level or entirely offloaded to a MEC device. The proposed model rules out the need to solve complex optimization problems and enormously lower the computational complexity, particularly in large scale networks. The proposed protocol achieves near-optimal performance and significantly reduces the computation time. In [49], the authors envisioned ML-based secure cloud service for connected vehicles that provide identifications of cyber attacks and fulfill the user's QoS and QoE. The intrusion detection mechanism is based on three phases e.g., traffic data analysis, compression, and classification mechanisms to differentiate between the trusted and malicious service requests. The system performance has been validated through simulation results. In [50], the authors explored various security challenges faced by airborne UAVs, used for ITS and proposed an ANN-based approach to nullify such challenges. The proposed model enables the UAVs to frequently utilize the system resources while assuring the real-time safety of airborne UAVs during different assigned missions e.g., ITs, real-time data streaming, and UAVs-assisted cargo delivery. The preceding technique performance has been validated through simulation results. The authors in [51] focused on the GPS spoofing attack where counterfeit signals can circumvent the UAVs and their ground controllers. They proposed ML-based ANN to identify and uncover the GPS spoofing attacks. In the proposed technique the GPS signals are characterized on the basis of various aspects like SNR, Doppler shift, and signal pseudo-range. The proposed protocol uncovers the GPS spoofing attacks with a high probability and with a low false alarm. In [52], the authors developed a DRL-based technique to thwart jamming attacks against airborne UAVs. The proposed technique is modeled irrespective of the jammer geographic location, channel model, and the UAV channel model. This technique decides the UAVs trajectory and level of power transmission based on assessing the UAV transmission quality. The simulation results show that the aforementioned technique improves the QoS of the deployed mission-specific UAVs.

5. Smart grids

In smart cities, big data is playing a significant role in revolutionizing the operational structure of SGs and efficient energy utilization [53]. The SGs are based on modern Information and communication systems, IoT devices and voluminous data [54].

In SGs, the heterogeneous data arrives from different sources that can be effectively analyzed and used for adequate management and operational decisions. In smart cities, big data analytics has the potency to enhance the safety of power grids, decision making of power-sharing, management, and power grids performance. However, the recent trend shows that SGs are making effective use of smart meter big data for different applications like load assessment and prediction, baseline estimation, demand response, load clustering, and malicious data deception attacks [55–59]. The phase measurement units (PMUs) big data analysis are mainly used for state estimation, dynamic model calibration, and transmission grid visualization [53]. In [60], the authors have established a recent study that explores a variety of big data-assisted applications in SGs. In [61], the authors have analyzed the role and applications of 5G communication in SGs. A detailed study of the existing and futuristic 5G communication architectures from SGs perspective has been presented. In [62], the authors have developed an extensive survey that depicts the role of ML and DRL techniques in SGs related applications and their performance in cyber-security of SGs are discussed in detail. In [63], the authors have reviewed various applications of DRL techniques regarding fault analysis, transient stability, load forecasting, assessment of new power generation, and power grid control. In [64], the authors proposed a model that considered the shared energy resources and ML-based techniques as an integrated part of the SGs system that helps in finalizing the complex logical decisions based on provided data. The ML-based model maintains the system performance in an efficient manner and steers the power to critical loads during adverse and unfavorable environments. In [65], the authors proposed a Deep Long Short-Term Memory (DLSTM) model to forecast the price and demand for electricity for a day and week ahead and tested it using real electricity market data. The model performance was evaluated using Normalized Root Mean Square Error (NRMSE) and Mean Absolute Error (MAE) as benchmark parameters. The proposed DLSTM model surpassed the existing standard methods in terms of accurate prediction of price and load forecasting. In [66], a well-measured building simulation prototype was established to study and analyze the impact of demand response (DR) policies under different time-dependent electricity costs. Two DR protocols, the rule and ML-based were employed to control and regulate a joint system of heat pump and thermal storage. The two protocols were trained and tested using metered data to reach an optimal decision regarding energy consumption, cost, environment, utility, computation, and prediction model. In [67], the authors proposed the concept of an autonomic ML platform that helps in developing the decision factors during the development of ML-based applications. The preceding platform can be used to develop high-level learning by optimizing the number of complex designs and expert interruptions. The proposed platform performance can be efficiently used in smart cities, particularly in ML-based applications regarding database management. In [68], the authors have proposed an intrusion detection and position finding mechanism using ML and power line communication (PLC) modems in SGs. The PLC modems continuously monitor the CSI and report any deviation caused by the suspected intruder. The proposed protocol can help in monitoring energy consumption. The authors in [69], proposed the design of ISAAC (see Table 2) security testbed for SGs systems. It is a cross-domain, re-configurable, and distributed platform that emulates the data of operational power facility. Researchers can test and evaluate their cyber-security solutions using the ISAAC platform. In [77], the authors have developed a study that presents various challenges faced by the cyber-security and ML-based techniques in SGs. The authors in [78], proposed a DRL-based technique called deep-Q-network detection (DQND) to counter data integrity attacks in AC power systems. The proposed protocol is implemented over the central and targeted network to master the optimal defense policy during the training phase. The experimental results show that the aforementioned protocol performance is superior to benchmark protocols in terms of speed and detection accuracy. In [79], the authors proposed a DRL-based innovative technique to inspect the power line system using UAVs. The proposed model efficiently detects various flaws in power lines e.g., fractures in poles, rot and woodpecker damages, etc. The experimental results show that the proposed technique has an effective role in smart monitoring of the power lines that further contributes to the efficiency of SGs. In [80], the authors employed the Pan-Tilt-Zoom (PTZ) camera to monitor the SGs and power lines to enhance the efficiency of SGs and nullify the chances of possible disasters. The authors in [81] focused on using DRL-based UAVs for wind turbine monitoring. They established a system to analyze the UAVs acquired images and assess the damage suggestions. The accuracy of the proposed model is almost equal to the human-level.

Table 2
Use of ML and DRL techniques in SGs based applications.

References	Year	Approach	Summary
[70]	2019	Anomaly detection algorithm	ML on physical data is used for identification of cyber–physical attacks.
[71]	2019	Simple fuzzer and DRL technique	To reduce the computational complexity of testing process.
[72]	2019	DRL-based intrusion detection system (IDS)	To stop cyber attacks on SGs, the proposed model utilizes the generation of blocks using short signatures and hash functions.
[73]	2019	ML	Designing anomaly detection engine for large-scale SGs, that can distinguish between actual fault and cyber intrusion.
[74]	2019	DRL techniques	Analysis of energy efficiency and delay issues in HetNets for SGs data communication under different delay constraints.
[75]	2019	DRL	Effective utilization of the energy storage appliances with varying tariffs structures.
[76]	2019	DRL and DNN	To help the service providers in acquiring energy resources from different customers to balance the energy variation and improve SG reliability.

6. DRL based UAVs applications in 5G and B5G communication

The increasing demands of high data rates, high-reliability, and low latency have led the existing mobile wireless communication system towards 5G and B5G communications. To achieve the aforementioned objectives, AI, ML and particularly the DRL-based techniques have been identified as the most effective tool to deal with the various complex communication issues involving high-volumes of network data [48,82–84]. Although the preceding techniques have played an important role in 5G communication but in the following, we will emphasize more on the UAVs role in 5G and B5G communication that would further play a crucial role in smart city creation and sustainability.

The authors in [85] proposed an innovative paradigm to efficiently analyze and detect cyber-attacks in 5G and B5G communication networks. The DRL techniques are employed to assess the network traffic by analyzing different aspects of network flows. In [86], the authors presented a technique to identify cyber-attacks in 5G and IoT networks. The proposed technique is based on a deep auto-encoded dense neural network protocol that efficiently detects various cyber-intrusions.

Despite having auspicious applications, UAVs still faces many unsolved challenges. For example, LTE cellular coverage is not omnipresent, particularly in the sky. In LTE, serving BS antennas are downtilted and primarily designed for serving ground UEs. Even in 5G and B5G communication, its hard to have ubiquitous sky coverage due to its architecture, interference & LoS related issues and economic challenges. Moreover, UAVs supported communications have some restraint e.g., formulating a perfect model need realistic consideration of an end to end communication, path loss model, channel & antennas model and terrain or environment model, etc. Most importantly, many optimization problems in advanced communication systems are highly non-convex and hard to solve efficiently.

ML-based approach known as DRL can be the best choice to efficiently deal with various kinds of such complex challenges e.g., avoiding aerial UAVs collision by learning UAVs flying dynamics, UAVs landing over mobile platforms, UAVs identification based on number of rotors, data acquisition and image processing techniques based estimation of soil moisture content & plants identification in precision agriculture, joint optimization problem based on UAV flight trajectory and schedule of getting updated data from GTs, etc. In the following, we present a brief summary of few such research efforts to tactfully handle many such UAVs oriented problems. In [87], Challita et al. proposed a deep (RL) framework using echo state network (ESN) for trajectories optimization of many airborne UAVs. The proposed framework facilitates UAVs in alleviating interference at GBSs and optimizing data communication latency. In the proposed framework, each UAV is an independent player and individually & jointly learns its trajectory, transmission power level, and association vector. To ensure UAVs optimal trajectories and related resources, ESN based DRL algorithm was proposed. According to the author's claim, this is the first-ever attempt of using ESN based DRL approach for UAVs communication to enhance the improvement between energy efficiency, latency and interference induced at GBSs. In [88], Herald et al. proposed a framework where UAV carries a BS and acting as a constituent part of users serving the network. The reinforcement Q-learning system is utilized to enhance sum rate during the airborne state. In [89] Challita et al. utilized ESN based DRL algorithm to steer UAV and optimize interference level at ground BSs. Machine and deep learning are best used in pattern recognition and can offer suitable research direction in UAVs classification and identification using radar technology (see Table 3)

6.1. DRL based UAVs-assisted mmWave communication

The UAV-supported WSNs can withstand higher data rate communication in case of using mmWave bandwidth for wireless communication. The shorter wavelength of mmWave offers helps in an efficient arrangement of tiny antennas over a single chip to develop beamforming antenna arrays and ideal for UAVs-assisted communication. Moreover, the directional nature of the mmWave beam help in reducing interference and enhance data security [99]. Fig. 5 [99] shows an airborne UAV providing mmWave communication-based network coverage and depicts that a mmWave link can be blocked even by a human presence. In this subsection, we are presenting a brief overview of DRL and its applications in 5G mmWave communication. Various efforts have been made to develop different key techniques to alleviate existing challenges and improve mmWave communication. In the following, we will focus on different DRL based approaches to design efficient UAV-assisted 5G mmWave communications. Fadi et al. [91] proposed a framework to employ an optimal number of UAVs to provide cost-effective 5G network coverage in a given area. The problem is modeled using linear optimization equations and efficiently solved through genetic and simulated annealing (SA) algorithms. In [92], Meng et al. proposed a communication system, consist of UAV-based dynamic BS. The UAV is equipped with a movable cylindrical antenna to provide omnidirectional coverage. Moreover, the traditional attitude estimation technique was replaced with the attitude estimation mechanism using a deep neural network to develop a more reliable communication link. The proposed method efficiency has been verified, using simulation experiments based results.

6.2. UAV positioning for throughput maximization and data offloading

In [93] et al. proposed cache-enabled UAVs in a cloud radio access network (CRAN) environment to optimize the quality-of-experience (QoE) of users devices. The proposed model utilizes human behavior and daily routine pattern to establish user–UAV associations, UAVs optimal position, and data to cache at UAVs for efficient utilization. The authors utilized the ESNs technique to efficiently predict users behaviors (e.g., mobility, content request) based network availability and user information. Based on the preceding information, the authors derived the UAVs optimal position and content to be cached at UAVs. In [94] Zhang et al. proposed a framework to predict UAVs deployment as relay-BS to assist cellular BS in case of a hot spot or users high congestion scenarios. To model cellular data pattern and the possibility of network congestion, ML techniques based on wavelet decomposition and compressive sensing is utilized. The contract matching problem was proposed to assign an optimal number of UAVs to the predicted data demanding zones. Simulation results confirm that the proposed UAVs predictive deployment significantly improves the overall performance of ground BSs in hot spot regions. In [95], Yirga et al. proposed utilization of multi-layer perceptron (MLP) and long short term memory (LSTM) techniques to predict optimal UAV location to enhance user throughput and system performance. The system performance is evaluated by the joint utilization of preceding techniques (e.g., MLP and LSTM) for regression tasks and K-means clustering protocol for generating classes. The comparative analysis study shows that the proposed approach offers an accurate UAV position and enhances user throughput.

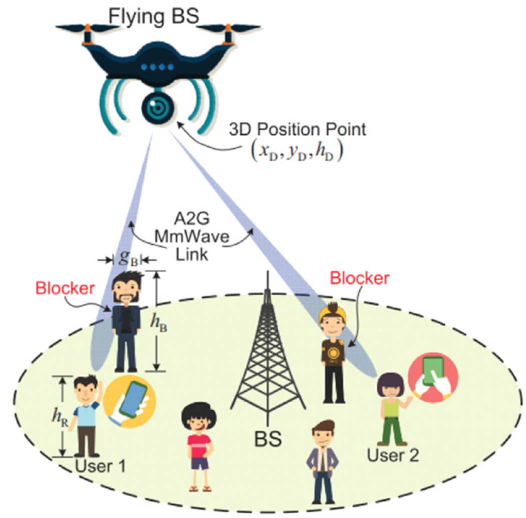

Fig. 5. Depiction of airborne UAV providing mmWave communication based network coverage and mmWave link blockage.

7. Smart city health care and machine learning

With the advent of advanced sensors, high-performance IoT devices, cloud computing, and an increase in data rates have led to extensive use of AI, ML, and DRL techniques in advanced health care mechanisms known as health intelligence [100–102]. The preceding techniques are playing a vital role in disease diagnosing [103], cure prediction, social media analytics for a particular ailment, medical imaging [104,105]. In the following, we are briefly discussing the most recent research trends and activities regarding health care in smart cities.

The authors in [106] have developed a review to study the role of 5G communication in the health care system, the required techniques, hardware, architecture and analyze the key objectives. Their primary contributions are focused around the 5G-based health care architecture and constituents technologies, a taxonomy of communication protocols and technologies, and network layer issues (e.g., routing, scheduling, and congestion control, etc.)imminent to IoT based health care systems. The authors in [107] produced an in-depth study regarding Big data analysis using AI, ML, DRL applications in health care systems. The authors explore various advantages of the aforementioned techniques regarding complex data analysis, classification, diagnosis, disease risk, best treatment, and patient survival predictions. However, the use of the preceding techniques poses many challenges (e.g., precise model training, addressing the real clinical issues, doctors understanding of the data analysis tools and data under study, and care for defined ethical considerations) that need to be adequately addressed. In [108], the authors rule out the notions that in futuristic health care systems, AI would entirely replace doctors and mention about four domains

Table 3
Use of DRL algorithms in UAVs oriented applications.

References	Year	Approach	Summary
[90]	2019	ANN	UAVs connectivity, security, and secure operations.
[87]	2018	ESN-based DRL framework	Trajectory, latency, & interference optimization.
[88]	2019	Q-learning	UAVs as BS to improve sum-rate .
[89]	2018	DRL algorithm	UAVs utilization for interference optimization.
[91]	2019	Genetic and Simulated annealing (SA) algorithms	Optimal number of UAVs to ensure 5G communication
[92]	2019	Attitude estimation mechanism using a DNN	Improvement in network coverage.
[93]	2017	ESN technique to model users behaviors	Improvement in Quality of Experience (QoE).
[94]	2018	ML techniques	Assisting cellular BSs in high congestion zones.
[95]	2019	MLP and LSTM techniques	UAVs optimal positions to maximize data throughput.
[96]	2019	Q-learning and MDP	Optimal decision to charge sensor nodes, data collection, and UAVs hovering speed.
[97]	2019	Q-learning and ESN technique	Joint optimization of power control and sum-rate.
[98]	2018	DRL	UAVs handover issue and improvement in data rate.

(e.g., patient monitoring, administration, health care mediation, and clinicians decision) where the preceding techniques can play a significant role. The development of an efficient AI-enabled system would be based on realistic data of the aforementioned area [108]. In [109], the authors discuss the perception of using AI for drug discovery purposes that will reshape the research and drug development methodologies of the existing pharmaceutical industry. In [110], the authors have outlined various potential AI, ML, and DRL protocols that can enhance the IoT-based healthcare industry. In [111], the authors proposed a novel architecture called HealthFog to efficiently and autonomously analyze heart diseases. The proposed framework is composed of edge computing devices supported by DRL protocols to precisely classify and manage the incoming patient's data. The authors in [112] proposed an innovative security mechanism called HealthGuard. The proposed technique is based on ML protocols to identify suspicious and skeptical activities in Smart Healthcare System (SHS). The HealthGuard continuously monitors the fundamental operations of various SHS devices and compares the vitals to the changes happening in the patient body to differentiate between the tranquil and alarming activities. In [113], the author has proposed a telemonitoring system using remote body sensors and ontology regulations supported by communication protocols and REST API. In [114], the authors have proposed an idea to use ML and DRL techniques to assess satellite imagery and map far-off communities for better healthcare and planning assistance. The authors in [115], have developed a review to study the impacts of DRL protocols in medical image analysis and classify various syndrome types related to stomach and spleen issues. The authors in [116] developed an ML-based technique to assess patients' chances of survival after percutaneous coronary intervention (PCI) (see Table 4).

Table 4
Use of AI, ML, and DRL techniques in smart healthcare applications.

References	Year	Approach	Summary
[109]	2019	AI	Using AI for drug discovery applications.
[111]	2019	DRL	HealthFog platform to analyze heart diseases.
[112]	2019	ML	HealthGuard platform to continuously monitors and compare the connected devices operations and body conditions.
[113]	2019	REST API	Remote patients care using telemonitoring and ontology regulations.
[114]	2019	DRL	Communities mapping for better healthcare using satellite imagery and DRL techniques.
[116]	2019	ML	Estimating patient chances of survival after PCI .
[117]	2020	AI System and three DRL Techniques	An AI system that surpasses human expertise in breast cancer detection.
[118]	2019	Genetic Programming	To differentiate between benign and fatal breast cancer.
[119]	2020	DRL	Breast cancer detection through mammograms screening.
[120]	2020	DRL	Categorization of invasive ductal carcinoma breast cancer.
[121]	2020	Logistic dependent model	Breast Cancer detection through Biomarker using innovative generalized logistic dependent model.

8. Challenges and future research directions

The AI, ML, and DRL-based applications have shown promising results, as evident from the existing literature of smart cities. However, the academia and industry-based expert can focus on the following open research issues that can effectively use the AI, ML, and DRL approach to further enhance the efficiency of smart cities :

- For more accurate and precise decision-making processes, a large set of training data (e.g., vehicle speed, position, the spacing between vehicles, the behavior of drivers, UAVs altitude, relay BS, etc.) is required to better train the ML and DRL protocols.
- Joint optimization of UAV onboard capabilities (e.g., caching, computing, processing, sensing and communication resources) and its trajectory using ML-techniques can significantly improve ITS efficiency during UAVs–vehicle communication.
- Measurement campaign in modeling the vehicle–vehicle, vehicle–UAV, UAV–UAV, UAV–GBS channel, etc. with various UAVs and vehicle velocities in different directions in the presence of regular and irregular shaped infrastructure.
- Standardization of big data development in SGs, communication protocols used during interoperability of various SGs devices, and selection of the most efficient AI, ML, DRL techniques that can improve SGs performance to near-optimal level.
- In 2020, the 5G technology is expected to be standardized that raises the need for the standardization of SGs communication infrastructure for the effective interoperability of the existing SGs and new 5G technology.
- The optimization of power-down circumstances is the main concern of any SGs and electric companies. The communication delay assessment analysis is highly required to develop an efficient network. The ML and DRL based techniques can play a crucial role to devise strategies that enable switching between 5G communication technologies while assuring the seamless power supply.

- In smart cities, security issues are applications-oriented. For example, the security breach at smart meters can lead to energy manipulations and SGs inefficiency. Therefor more advanced and big data analytics based innovative techniques are needed to ensure the cyber safety and security of smart city applications.

9. Conclusion

We reviewed recent smart cities' research trends and development regarding different complex issues and applications accomplished by academia and industry. A brief study of the fundamental concepts of AI, ML, and DRL techniques have been developed. We explored the effective role of the aforementioned protocols to design near-optimal strategies regarding various applications that are considered vital to smart city efficiency. We presented the most recent AI, ML and DRL applications in designing smart governance and the need for AI-assisted and AI-compatible new regulations, energy-efficient ITS, SGs, cybersecurity, and UAVs-assisted 5G and B5G communications in smart cities. We briefly presented the growing role of the aforementioned techniques in smart health care from efficient diagnosis, health recovery, the security of health-oriented IoT devices, and possible role in the discoveries of the most convenient drug. Finally, we presented smart cities oriented recent research challenges and future research trends where the prior techniques can play a significant role.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] E. O'Dwyer, I. Pan, S. Acha, N. Shah, Smart energy systems for sustainable smart cities: current developments, trends and future directions, Appl. Energy 237 (2019) 581–597.

[2] Y. Liu, C. Yang, L. Jiang, S. Xie, Y. Zhang, Intelligent edge computing for IoT-based energy management in smart cities, IEEE Netw. 33 (2) (2019) 111–117.

[3] R. Petrolo, V. Loscri, N. Mitton, Towards a smart city based on cloud of things, a survey on the smart city vision and paradigms, Trans. Emerg. Telecommun. Technol. 28 (1) (2017) e2931.

[4] U. Aguilera, O. Peña, O. Belmonte, D. López-de Ipiña, Citizen-centric data services for smarter cities, Future Gener. Comput. Syst. 76 (2017) 234–247.

[5] P. Neirotti, A. De Marco, A.C. Cagliano, G. Mangano, F. Scorrano, Current trends in smart city initiatives: some stylised facts, Cities 38 (2014) 25–36.

[6] F. Al-Turjman, I. Baali, Machine learning for wearable iot-based applications: a survey, Trans. Emerg. Telecommun. Technol. (2019) e3635.

[7] F.M. Al-Turjman, Information-centric sensor networks for cognitive IoT: an overview, Ann. Telecommun. 72 (1–2) (2017) 3–18.

[8] F. Al-Turjman, Information-centric framework for the Internet of Things (IoT): Traffic modeling & optimization, Future Gener. Comput. Syst. 80 (2018) 63–75.

[9] Z. Allam, Z.A. Dhunny, On big data, artificial intelligence and smart cities, Cities 89 (2019) 80–91.

[10] H. Li, T. Wei, A. Ren, Q. Zhu, Y. Wang, Deep reinforcement learning: framework, applications, and embedded implementations, in: 2017 IEEE/ACM International Conference on Computer-Aided Design, ICCAD, IEEE, 2017, pp. 847–854.

[11] S. Ramchurn, P. Vytelingum, A. Rogers, N.R. Jennings, Putting the "smarts" into the smart grid: a grand challenge for artificial intelligence, Commun. ACM 55 (4) (2012) 86–97.

[12] Z. Allam, P. Newman, Redefining the smart city: culture, metabolism and governance, Smart Cities 1 (1) (2018) 4–25.

[13] H. Habibzadeh, T. Soyata, B. Kantarci, A. Boukerche, C. Kaptan, Sensing, communication and security planes: a new challenge for a smart city system design, Comput. Netw. 144 (2018) 163–200.

[14] A. Ferdowsi, U. Challita, W. Saad, Deep learning for reliable mobile edge analytics in intelligent transportation systems: an overview, IEEE Veh. Technol. Mag. 14 (1) (2019) 62–70.

[15] M.A. Al-Garadi, A. Mohamed, A. Al-Ali, X. Du, M. Guizani, A survey of machine and deep learning methods for internet of things (IoT) security, 2018, arXiv preprint arXiv:1807.11023.

[16] W. Wang, K. Siau, Artificial intelligence: a study on governance, policies, and regulations, in: Thirteenth Annual Midwest Association for Information Systems Conference, MWAIS, 2018.

[17] S. Feldstein, The global expansion of AI surveillance, 2019, Carnegie Endowment. https://carnegieendowment.org/2019/09/17/global-expansion-of-ai-surveillance-pub-79847.

[18] S. Chackravarthy, S. Schmitt, L. Yang, Intelligent crime anomaly detection in smart cities using deep learning, in: 2018 IEEE 4th International Conference on Collaboration and Internet Computing, CIC, IEEE, 2018, pp. 399–404.

[19] A.K. Baughman, C. Eggenberger, A.I. Martin, D.S. Stoessel, C.M. Trim, Incident prediction and response using deep learning techniques and multimodal data, Google Patents, US Patent 10,289,949, 2019.

[20] https://www.datasciencecentral.com/profiles/blogs/machine-learning-can-we-please-just-agree-what-this-means (4 December 2017).

[21] R. Sutton, A. Barto, Reinforcement Learning: An Introduction, vol. 2, second ed., The MIT Press Cambridge, Massachusetts London, England, 2014, 2015.

[22] V.R. Konda, J.N. Tsitsiklis, Actor-critic algorithms, in: Advances in Neural Information Processing Systems, 2000, pp. 1008–1014.

[23] Y. Gal, Z. Ghahramani, Dropout as a bayesian approximation: Representing model uncertainty in deep learning, in: International Conference on Machine Learning, 2016, pp. 1050–1059.

[24] L. Zhu, F.R. Yu, Y. Wang, B. Ning, T. Tang, Big data analytics in intelligent transportation systems: a survey, IEEE Trans. Intell. Transp. Syst. 20 (1) (2018) 383–398.

[25] J. Zhang, Y. Zheng, D. Qi, Deep spatio-temporal residual networks for city-wide crowd flows prediction, in: Thirty-First AAAI Conference on Artificial Intelligence, 2017.

[26] Z. Zhao, W. Chen, X. Wu, P.C. Chen, J. Liu, LSTM network: a deep learning approach for short-term traffic forecast, IET Intell. Transp. Syst. 11 (2) (2017) 68–75.

[27] M. Veres, M. Moussa, Deep learning for intelligent transportation systems: a survey of emerging trends, IEEE Trans. Intell. Transp. Syst. (2019).

[28] Z. Bai, W. Shangguan, B. Cai, L. Chai, Deep reinforcement learning based high-level driving behavior decision-making model in heterogeneous traffic, in: 2019 Chinese Control Conference, CCC, IEEE, 2019, pp. 8600–8605.

[29] Y. Chen, Y. Zhang, S. Maharjan, M. Alam, T. Wu, Deep learning for secure mobile edge computing in cyber-physical transportation systems, IEEE Netw. 33 (4) (2019) 36–41.

[30] H. Yi, K.-H.N. Bui, H. Jung, Implementing a deep learning framework for short term traffic flow prediction, in: WIMS, 2019, pp. 7–1.

[31] Z. Huang, G. Shan, J. Cheng, J. Sun, Trec: an efficient recommendation system for hunting passengers with deep neural networks, Neural Comput. Appl. 31 (1) (2019) 209–222.

[32] G. Liu, Y. Xu, Z. He, Y. Rao, J. Xia, L. Fan, Deep learning-based channel prediction for edge computing networks toward intelligent connected vehicles, IEEE Access 7 (2019) 114487–114495.

[33] Z. Ning, P. Dong, X. Wang, J.J. Rodrigues, F. Xia, Deep reinforcement learning for vehicular edge computing: an intelligent offloading system, ACM Trans. Intell. Syst. Technol. (TIST) 10 (6) (2019) 60.

[34] H. Ye, G.Y. Li, B.-H.F. Juang, Deep reinforcement learning based resource allocation for V2V communications, IEEE Trans. Veh. Technol. 68 (4) (2019) 3163–3173.

[35] Y. Lv, Y. Duan, W. Kang, Z. Li, F.-Y. Wang, Traffic flow prediction with big data: a deep learning approach, IEEE Trans. Intell. Transp. Syst. 16 (2) (2014) 865–873.

[36] H. El-Sayed, M. Chaqfa, S. Zeadally, D. Puthal, A traffic-aware approach for enabling unmanned aerial vehicles (UAVs) in smart city scenarios, IEEE Access 7 (2019) 86297–86305.

[37] C.H. Liu, X. Ma, X. Gao, J. Tang, Distributed energy-efficient multi-UAV navigation for long-term communication coverage by deep reinforcement learning, IEEE Trans. Mob. Comput. (2019).

[38] M. Zhu, X.-Y. Liu, X. Wang, Deep reinforcement learning for unmanned aerial vehicle-assisted vehicular networks, 2019, arXiv preprint arXiv:1906.05015.

[39] D.B. Rawat, K.Z. Ghafoor, Smart Cities Cybersecurity and Privacy, Elsevier, 2018.

[40] N. Sengupta, Designing cyber security system for smart cities, 2018.

[41] T. Braun, B.C. Fung, F. Iqbal, B. Shah, Security and privacy challenges in smart cities, Sustain. Cities Soc. 39 (2018) 499–507.

[42] R. Miotto, F. Wang, S. Wang, X. Jiang, J.T. Dudley, Deep learning for healthcare: review, opportunities and challenges, Brief. Bioinform. 19 (6) (2017) 1236–1246.

[43] A.A. Diro, N. Chilamkurti, Distributed attack detection scheme using deep learning approach for internet of things, Future Gener. Comput. Syst. 82 (2018) 761–768.

[44] I. Alrashdi, A. Alqazzaz, E. Aloufi, R. Alharthi, M. Zohdy, H. Ming, AD-IoT: anomaly detection of IoT cyberattacks in smart city using machine learning, in: 2019 IEEE 9th Annual Computing and Communication Workshop and Conference, CCWC, IEEE, 2019, pp. 0305–0310.

[45] A. Elsaeidy, I. Elgendi, K.S. Munasinghe, D. Sharma, A. Jamalipour, A smart city cyber security platform for narrowband networks, in: 2017 27th International Telecommunication Networks and Applications Conference, ITNAC, IEEE, 2017, pp. 1–6.
[46] A.A. Alli, M.M. Alam, SecOFF-FCIoT: Machine learning based secure offloading in Fog-Cloud of things for smart city applications, Internet of Things 7 (2019) 100070.
[47] M. Chen, W. Li, G. Fortino, Y. Hao, L. Hu, I. Humar, A dynamic service migration mechanism in edge cognitive computing, ACM Trans. Internet Technol. 19 (2) (2019) 30.
[48] H. Huang, S. Guo, G. Gui, Z. Yang, J. Zhang, H. Sari, F. Adachi, Deep learning for physical-layer 5G wireless techniques: opportunities, challenges and solutions, IEEE Wirel. Commun. (2019).
[49] M. Aloqaily, S. Otoum, I. Al Ridhawi, Y. Jararweh, An intrusion detection system for connected vehicles in smart cities, Ad Hoc Netw. 90 (2019) 101842.
[50] U. Challita, A. Ferdowsi, M. Chen, W. Saad, Artificial intelligence for wireless connectivity and security of cellular-connected UAVs, 2018, arXiv preprint arXiv:1804.05348.
[51] M.R. Manesh, J. Kenney, W.C. Hu, V.K. Devabhaktuni, N. Kaabouch, Detection of GPS spoofing attacks on unmanned aerial systems, in: 2019 16th IEEE Annual Consumer Communications & Networking Conference, CCNC, IEEE, 2019, pp. 1–6.
[52] Z. Lin, X. Lu, C. Dai, G. Sheng, L. Xiao, Reinforcement learning based UAV trajectory and power control against jamming, in: International Conference on Machine Learning for Cyber Security, Springer, 2019, pp. 336–347.
[53] B.P. Bhattarai, S. Paudyal, Y. Luo, M. Mohanpurkar, K. Cheung, R. Tonkoski, R. Hovsapian, K.S. Myers, R. Zhang, P. Zhao, et al., Big data analytics in smart grids: state-of-the-art, challenges, opportunities, and future directions, IET Smart Grid 2 (2) (2019) 141–154.
[54] H. Shahinzadeh, J. Moradi, G.B. Gharehpetian, H. Nafisi, M. Abedi, Iot architecture for smart grids, in: 2019 International Conference on Protection and Automation of Power System, IPAPS, IEEE, 2019, pp. 22–30.
[55] H. Karimipour, S. Geris, A. Dehghantanha, H. Leung, Intelligent anomaly detection for large-scale smart grids, in: 2019 IEEE Canadian Conference of Electrical and Computer Engineering, CCECE, IEEE, 2019, pp. 1–4.
[56] D. Du, R. Chen, X. Li, L. Wu, P. Zhou, M. Fei, Malicious data deception attacks against power systems: a new case and its detection method, Trans. Inst. Meas. Control 41 (6) (2019) 1590–1599.
[57] Y. Wang, Q. Chen, T. Hong, C. Kang, Review of smart meter data analytics: applications, methodologies, and challenges, IEEE Trans. Smart Grid 10 (3) (2018) 3125–3148.
[58] S.N. Fallah, R.C. Deo, M. Shojafar, M. Conti, S. Shamshirband, Computational intelligence approaches for energy load forecasting in smart energy management grids: state of the art, future challenges, and research directions, Energies 11 (3) (2018) 596.
[59] A. Tureczek, P. Nielsen, H. Madsen, Electricity consumption clustering using smart meter data, Energies 11 (4) (2018) 859.
[60] M. Ghorbanian, S.H. Dolatabadi, P. Siano, Big data issues in smart grids: a survey, IEEE Syst. J. 13 (4) (2019) 4158–4168.
[61] T. Dragičević, P. Siano, S. Prabaharan, et al., Future generation 5G wireless networks for smart grid: a comprehensive review, Energies 12 (11) (2019) 2140.
[62] E. Hossain, I. Khan, F. Un-Noor, S.S. Sikander, M.S.H. Sunny, Application of big data and machine learning in smart grid, and associated security concerns: a review, IEEE Access 7 (2019) 13960–13988.
[63] N. Zhou, J. Liao, Q. Wang, C. LI, J. LI, Analysis and prospect of deep learning application in smart grid, Autom. Electr. Power Syst. 43 (4) (2019) 180–191.
[64] F. Liang, W.G. Hatcher, G. Xu, J. Nguyen, W. Liao, W. Yu, Towards online deep learning-based energy forecasting, in: 2019 28th International Conference on Computer Communication and Networks, ICCCN, IEEE, 2019, pp. 1–9.
[65] S. Mujeeb, N. Javaid, M. Ilahi, Z. Wadud, F. Ishmanov, M.K. Afzal, Deep long short-term memory: a new price and load forecasting scheme for big data in smart cities, Sustainability 11 (4) (2019) 987.
[66] F. Pallonetto, M. De Rosa, F. Milano, D.P. Finn, Demand response algorithms for smart-grid ready residential buildings using machine learning models, Appl. Energy 239 (2019) 1265–1282.
[67] K.M. Lee, J. Yoo, S.-W. Kim, J.-H. Lee, J. Hong, Autonomic machine learning platform, Int. J. Inf. Manage. 49 (2019) 491–501.
[68] G. Prasad, Y. Huo, L. Lampe, V.C. Leung, Machine learning based physical-layer intrusion detection and location for the smart grid, in: 2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), IEEE, 2019, pp. 1–6.
[69] I.A. Oyewumi, A.A. Jillepalli, P. Richardson, M. Ashrafuzzaman, B.K. Johnson, Y. Chakhchoukh, M.A. Haney, F.T. Sheldon, D.C. de Leon, Isaac: the idaho cps smart grid cybersecurity testbed, in: 2019 IEEE Texas Power and Energy Conference (TPEC), IEEE, 2019, pp. 1–6.
[70] M. Wu, Z. Song, Y.B. Moon, Detecting cyber-physical attacks in cybermanufacturing systems with machine learning methods, J. Intell. Manuf. 30 (3) (2019) 1111–1123.
[71] A. Kuznetsov, O. Shapoval, K. Chernov, Y. Yeromin, M. Popova, O. Syniavska, Automated software vulnerability testing using in-depth training methods, in: CMIS, 2019, pp. 227–240.
[72] M.A. Ferrag, L. Maglaras, Deepcoin: a novel deep learning and blockchain-based energy exchange framework for smart grids, IEEE Trans. Eng. Manage. (2019).
[73] H. Karimipour, A. Dehghantanha, R. Parizi, K. Choo, H. Leung, A deep and scalable unsupervised machine learning system for cyber-attack detection in large-scale smart grids, IEEE Access (2019).
[74] F.A. Asuhaimi, S. Bu, P.V. Klaine, M.A. Imran, Channel access and power control for energy-efficient delay-aware heterogeneous cellular networks for smart grid communications using deep reinforcement learning, IEEE Access 7 (2019) 133474–133484.
[75] H. Kumar, Explainable AI: deep reinforcement learning agents for residential demand side cost savings in smart grids, 2019, arXiv preprint arXiv:1910.08719.
[76] R. Lu, S.H. Hong, Incentive-based demand response for smart grid with reinforcement learning and deep neural network, Appl. Energy 236 (2019) 937–949.
[77] D.I. Dogaru, I. Dumitrache, Cyber security of smart grids in the context of big data and machine learning, in: 2019 22nd International Conference on Control Systems and Computer Science, CSCS, IEEE, 2019, pp. 61–67.
[78] D. An, Q. Yang, W. Liu, Y. Zhang, Defending against data integrity attacks in smart grid: a deep reinforcement learning-based approach, IEEE Access 7 (2019) 110835–110845.
[79] V.N. Nguyen, R. Jenssen, D. Roverso, Intelligent monitoring and inspection of power line components powered by uavs and deep learning, IEEE Power Energy Technol. Syst. J. 6 (1) (2019) 11–21.
[80] S. Paramanik, P.S. Sarkar, K.K. Mondol, A. Chakraborty, S. Chakraborty, K. Sarker, Survey of smart grid network using drone & PTZ camera, in: 2019 Devices for Integrated Circuit, DevIC, IEEE, 2019, pp. 361–364.
[81] A. Shihavuddin, X. Chen, V. Fedorov, A. Nymark Christensen, N. Andre Brogaard Riis, K. Branner, A. Bjorholm Dahl, R. Reinhold Paulsen, Wind turbine surface damage detection by deep learning aided drone inspection analysis, Energies 12 (4) (2019) 676.
[82] T. Wang, S. Wang, Z.-H. Zhou, Machine learning for 5G and beyond: from model-based to data-driven mobile wireless networks, China Commun. 16 (1) (2019) 165–175.
[83] R. Kulandaivel, M. Balasubramaniam, F. Al-Turjman, L. Mostarda, M. Ramachandran, R. Patan, Intelligent data delivery approach for smart cities using road side units, IEEE Access 7 (2019) 139462–139474.
[84] F. Al-Turjman, Intelligence and security in big 5G-oriented IoNT: an overview, Future Gener. Comput. Syst. 102 (2020) 357–368.
[85] L.F. Maimó, Á.L.P. Gómez, F.J.G. Clemente, M.G. Pérez, G.M. Pérez, A self-adaptive deep learning-based system for anomaly detection in 5G networks, IEEE Access 6 (2018) 7700–7712.
[86] S. Rezvy, Y. Luo, M. Petridis, A. Lasebae, T. Zebin, An efficient deep learning model for intrusion classification and prediction in 5g and iot networks, in: 2019 53rd Annual Conference on Information Sciences and Systems, CISS, IEEE, 2019, pp. 1–6.
[87] U. Challita, W. Saad, C. Bettstetter, Deep reinforcement learning for interference-aware path planning of cellular-connected uavs, in: 2018 IEEE International Conference on Communications, ICC, IEEE, 2018, pp. 1–7.
[88] H. Bayerlein, P. De Kerret, D. Gesbert, Trajectory optimization for autonomous flying base station via reinforcement learning, in: 2018 IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications, SPAWC, IEEE, 2018, pp. 1–5.
[89] U. Challita, W. Saad, C. Bettstetter, Cellular-connected UAVs over 5G: deep reinforcement learning for interference management, 2018, arXiv preprint arXiv:1801.05500.
[90] U. Challita, A. Ferdowsi, M. Chen, W. Saad, Machine learning for wireless connectivity and security of cellular-connected UAVs, IEEE Wirel. Commun. 26 (1) (2019) 28–35.
[91] F. Al-Turjman, J.P. Lemayian, S. Alturjman, L. Mostarda, Enhanced deployment strategy for the 5G drone-BS using artificial intelligence, IEEE Access 7 (2019) 75999–76008.
[92] S. Meng, X. Dai, B. Xiao, Y. Zhou, Y. Li, C. Gao, Deep learning–based fifth-generation millimeter-wave communication channel tracking for unmanned aerial vehicle internet of things networks, Int. J. Distrib. Sens. Netw. 15 (8) (2019) 1550147719865882.
[93] M. Chen, M. Mozaffari, W. Saad, C. Yin, M. Debbah, C.S. Hong, Caching in the sky: proactive deployment of cache-enabled unmanned aerial vehicles for optimized quality-of-experience, IEEE J. Sel. Areas Commun. 35 (5) (2017) 1046–1061.
[94] Q. Zhang, W. Saad, M. Bennis, X. Lu, M. Debbah, W. Zuo, Predictive deployment of UAV base stations in wireless networks: machine learning meets contract theory, 2018, arXiv preprint arXiv:1811.01149.
[95] Y. Yayeh Munaye, H.-P. Lin, A.B. Adege, G.B. Tarekegn, UAV Positioning for throughput maximization using deep learning approaches, Sensors 19 (12) (2019) 2775.
[96] K. Li, W. Ni, E. Tovar, On-board deep Q-network for UAV-assisted online power transfer and data collection, 2019, arXiv preprint arXiv:1906.07064.
[97] X. Liu, Y. Liu, Y. Chen, L. Hanzo, Trajectory design and power control for multi-UAV assisted wireless networks: a machine learning approach, IEEE Trans. Veh. Technol. (2019).

[98] Y. Cao, L. Zhang, Y.-C. Liang, Deep reinforcement learning for user access control in uav networks, in: 2018 IEEE International Conference on Communication Systems, ICCS, IEEE, 2018, pp. 297–302.
[99] L. Zhang, H. Zhao, S. Hou, Z. Zhao, H. Xu, X. Wu, Q. Wu, R. Zhang, A survey on 5G millimeter wave communications for UAV-assisted wireless networks, IEEE Access 7 (2019) 117460–117504.
[100] E.J. Topol, High-performance medicine: the convergence of human and artificial intelligence, Nat. Med. 25 (1) (2019) 44–56.
[101] M.N. Boulos, G. Peng, T. VoPham, An overview of GeoAI applications in health and healthcare, 2019.
[102] F. Al-Turjman, M.H. Nawaz, U.D. Ulusar, Intelligence in the internet of medical things era: a systematic review of current and future trends, Comput. Commun. (2019).
[103] W.L. Bi, A. Hosny, M.B. Schabath, M.L. Giger, N.J. Birkbak, A. Mehrtash, T. Allison, O. Arnaout, C. Abbosh, I.F. Dunn, et al., Artificial intelligence in cancer imaging: clinical challenges and applications, CA: Cancer J. Clin. 69 (2) (2019) 127–157.
[104] A. Shaban-Nejad, M. Michalowski, D.L. Buckeridge, Health intelligence: how artificial intelligence transforms population and personalized health, 2018.
[105] F. Al-Turjman, H. Zahmatkesh, L. Mostarda, Quantifying uncertainty in internet of medical things and big-data services using intelligence and deep learning, IEEE Access 7 (2019) 115749–115759.
[106] A. Ahad, M. Tahir, K.-L.A. Yau, 5G-Based smart healthcare network: architecture, taxonomy, challenges and future research directions, IEEE Access 7 (2019) 100747–100762.
[107] K.Y. Ngiam, W. Khor, Big data and machine learning algorithms for health-care delivery, Lancet Oncol. 20 (5) (2019) e262–e273.
[108] S. Reddy, J. Fox, M.P. Purohit, Artificial intelligence-enabled healthcare delivery, J. R. Soc. Med. 112 (1) (2019) 22–28.
[109] K.-K. Mak, M.R. Pichika, Artificial intelligence in drug development: present status and future prospects, Drug Discov. Today 24 (3) (2019) 773–780.
[110] S. Durga, R. Nag, E. Daniel, Survey on machine learning and deep learning algorithms used in internet of things (IoT) healthcare, in: 2019 3rd International Conference on Computing Methodologies and Communication, ICCMC, IEEE, 2019, pp. 1018–1022.
[111] S. Tuli, N. Basumatary, S.S. Gill, M. Kahani, R.C. Arya, G.S. Wander, R. Buyya, Healthfog: an ensemble deep learning based smart healthcare system for automatic diagnosis of heart diseases in integrated IoT and fog computing environments, Future Gener. Comput. Syst. 104 (2020) 187–200.
[112] A.I. Newaz, A.K. Sikder, M.A. Rahman, A.S. Uluagac, Healthguard: a machine learning-based security framework for smart healthcare systems, in: 2019 Sixth International Conference on Social Networks Analysis, Management and Security, SNAMS, IEEE, 2019, pp. 389–396.
[113] S.K. Polu, S.K. Polu, Modeling of telemonitoring system for remote healthcare using ontology, Int. J. Innov. Res. Sci. Technol. 5 (9) (2019) 6–8.
[114] E. Bruzelius, M. Le, A. Kenny, J. Downey, M. Danieletto, A. Baum, P. Doupe, B. Silva, P.J. Landrigan, P. Singh, Satellite images and machine learning can identify remote communities to facilitate access to health services, J. Am. Med. Inform. Assoc. 26 (8–9) (2019) 806–812.
[115] Q. Zhang, C. Bai, Z. Chen, P. Li, H. Yu, S. Wang, H. Gao, Deep learning models for diagnosing spleen and stomach diseases in smart chinese medicine with cloud computing, Concurr. Comput.: Pract. Exper. (2019) e5252.
[116] C.J. Zack, C. Senecal, Y. Kinar, Y. Metzger, Y. Bar-Sinai, R.J. Widmer, R. Lennon, M. Singh, M.R. Bell, A. Lerman, et al., Leveraging machine learning techniques to forecast patient prognosis after percutaneous coronary intervention, JACC Cardiovasc. Interv. (2019).
[117] S.M. McKinney, M. Sieniek, V. Godbole, J. Godwin, N. Antropova, H. Ashrafian, T. Back, M. Chesus, G.C. Corrado, A. Darzi, et al., International evaluation of an ai system for breast cancer screening, Nature 577 (7788) (2020) 89–94.
[118] H. Dhahri, E. Al Maghayreh, A. Mahmood, W. Elkilani, M. Faisal Nagi, Automated breast cancer diagnosis based on machine learning algorithms, J. Healthc. Eng. 2019 (2019).
[119] L. Shen, L.R. Margolies, J.H. Rothstein, E. Fluder, R. McBride, W. Sieh, Deep learning to improve breast cancer detection on screening mammography, Sci. Rep. 9 (1) (2019) 1–12.
[120] M. Toğaçar, B. Ergen, Z. Cömert, Application of breast cancer diagnosis based on a combination of convolutional neural networks, ridge regression and linear discriminant analysis using invasive breast cancer images processed with autoencoders, Med. Hypotheses 135 (2020) 109503.
[121] H. Pham, D.H. Pham, A novel generalized logistic dependent model to predict the presence of breast cancer based on biomarkers, Concurr. Comput.: Pract. Exper. 32 (1) (2020) e5467.