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Artificial Intelligence and Machine Learning: Smart City Applications

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Abstract— Improving the economic and living conditions of its population, managing expanding urbanization and energy consumption effectively, maintaining a green environment, and raising people's capacities to utilize and adapt contemporary information and communication technology (ICT) are all goals of smart cities. ICT plays a crucial part in the smart cities concept's policy formulation, decision-making, implementation, and productive service outcomes. Examining how AI, ML, and DRL have contributed to the development of smart cities is the main goal of this comprehensive analysis. The aforementioned methods are effectively used to formulate ideal policies pertaining to a range of intricate issues pertaining to smart cities. Smart transportation systems (ITSs), cyber-security, smart grids (SGs) that use energy efficiently, UAVs to guarantee the best 5G and B5G communications services, smart health care systems in smart cities, and more are all covered in detail in this survey. Lastly, we outline a number of research obstacles and potential avenues for further study where the aforementioned methods might be very useful in making the smart city vision a reality.

IndexTerms— Smartcity; 5G and B5G Communication; UAVs; Intelligent Transportation System; Smart Grids; Cyber-Security; Internet of Things; mmWave communication;

I. INTRODUCTION

Reports [1] and [2] estimate that 66% and 70% of the world's population will live in urban areas by 2050, respectively. City environments, administration, and safety would be profoundly affected by this rate of urbanization boom. Smart cities are being advocated by several nations as a means to minimize energy usage, manage resources effectively, and deal with the rapid increase in urbanization. By creating and implementing low-carbon emission technology, smart city projects may effectively manage environmental sustainability. Smart city initiatives have been suggested and are being implemented by many countries (e.g., the US, EU, Japan, etc.) in an effort to effectively address potential future difficulties. Efficient utilization of information and communication technologies (ICTs) is crucial for smart city requirements, including data analysis, data communications, and the effective implementation of complex strategies to keep a smart city running smoothly and securely [3, 4, 5, 6].

Most smart city applications rely on the Internet of Things (IoT) as their primary component. to produce massive amounts of data [7], [8]. It is challenging to properly determine the most accurate and efficient actions in the midst of such large and complicated data. Advanced methods such as Artificial Intelligence (AI), Machine Learning (ML), and Deep Reinforcement Learning (DRL) may be used to analyze vast data in the best possible way, leading to an ideal decision [2, 9]. Optimal or nearly-optimal control choices may be reached using the aforementioned methods, which take the long view [10]. Raising the quantity of training data for the aforementioned methodologies improves their learning capacities and, by extension, the efficiency of automated decision-making [11]. This, in turn, improves their accuracy and precision. Smart city realization and the application of sophisticated data analysis tools for Big Data both saw surges around the same time, as shown by the authors of [12].

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More possibilities will arise in the future as the concepts of smart cities, the Internet of Things (IoT), blockchain, unmanned aerial vehicles (UAVs), and the usage of artificial intelligence (AI), machine learning (ML), and deep reinforcement learning (DRL) in diverse applications continue to evolve.

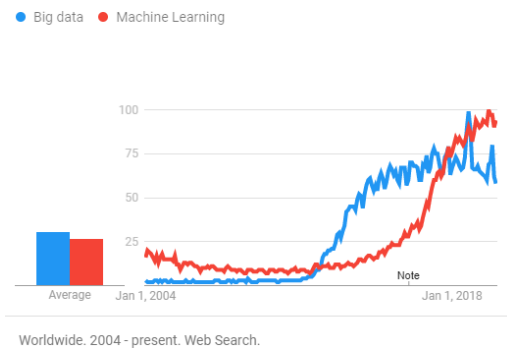


Figure 1.This figure (obtained from google trends) shows an era of Big Dataand ML from 2004 to January 2020.

Many different industries are contributing significantly to the smart city project, including cyber-security, UAVs-assisted next-generation communication (5G and B5G), smart grids (SGs), intelligent transportation, and many more. Big data analytics and the appropriate application of AI, ML, and DRL-based approaches greatly impact all the previous smart city sectors, making them more efficient and scalable in a smart city project.The contemporary

TableI:Acronymsusedinthisarticle.

Acronym	Text	Acronym	Text	Acronym	Text
ML	MachineLearning	DRL	deepreinforcementlearning	UAV	UnmannedAirVehicle
UAV	UnmannedAirVehicle	UAS	UnmannedAerialSystem	BS	BaseStation
MDP	MarkovDecisionProcess	Relay-BS	RelayBaseStation	UE	userequipment
LTE	LongTermEvolution	AI	ArtificialIntelligence	R&d	Researchanddevelopment
DS	DeliverySystem	RMS	Real-time multimedia streaming	ITS	Intelligent transportation systems
RL	ReinforcementLearning	TD	TemporalDifference	MC	MonteCarlosystems
DP	DynamicProgramming	LoS	LineofSight	ESN	echostatenetwork
ELM	ExtremeLearningMachine	QoE	quality-of-experience	CSI	ChannelStateInformation
SGs	smartgrids	ICT	informationandcommuni- cationtechnology	US	UnitedStates
EU	EuropeanUnion	IoT	InternetofThings	MEC	mobileedgecomputing
DNN	DeepNeuralNetwork	GPS	GlobalPositioningSystem	ECC	edgecognitivecomputing
ANN	ArtificialNeuralNetwork	PMUs	phasemeasurementunits	PLC	powerlinecommunication

has significantly impacted almost all the sectors of a smart city. In [15], the authors have surveyed an in-depth role ofML and DRL techniques in cyber-security of IoT devices that playsafundamentalroleinsmartcityapplications.Theenergy generation, management, and consumption is an essential featureofasmartcityandbigdataanalyticshaveanoteworthy impact on ICT-based SGs operations

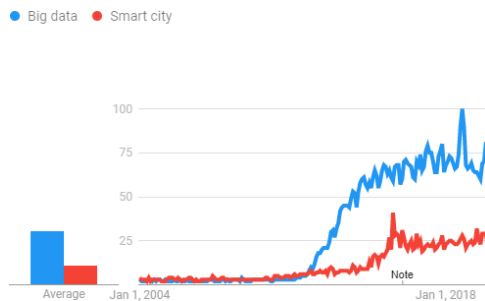


Figure 2. The popularity of smart city concept and big data over the given period particularly after 2012 (source: google trends).

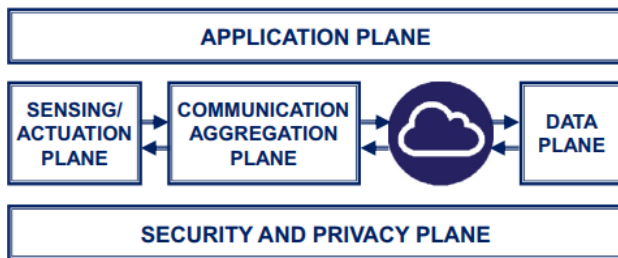


Figure 3. A generalized architecture of smart city applications, composed of environment sensing, communication protocols, data transmission, and security and privacy. The significance of the security plane in smart city applications is clearly shown [13].

The goals of ML and DRL-based approaches in the intelligent transportation system (ITS) include the following: the standardization of self-driving cars; the protection of linked vehicles; the optimization of passenger searches; and the assurance of safe trips. In their study, the authors examined the influence of DRL-based procedures on ITS ([14]). It is impossible to fulfill the dream of a smart city without first ensuring its cyber-security. Figure [13] depicts the security plane that has to be created and connected to all the elements of the suggested architecture in order to make it a reality. This plane needs to be vast, dynamic, and forceful. What an incredible role cyber-security approaches based on AI, ML, and DRL play! and Artificial intelligence is becoming more pervasive in our everyday lives. The advent of AI is having far-reaching consequences for our everyday lives, altering the way we think and how we interact with the world around us. To what extent should new rules be crafted to mitigate AI's potential harms while maximizing its potential benefits to society? Also, how to design rules and policies that use AI to promote economic and social growth [16], [17]. In order to effectively detect and evaluate any illegal behavior, the authors of [18] presented a smart city crime detection system that relies on DRL and neural networks. The authors of [19] also presented an ML-based architecture for incident prediction and pre-action reaction generation.

In this paper, we have presented the latest advancements in smart city applications based on AI, ML, and DRL. Focusing on the most crucial areas of smart cities—ITS, cyber-security, SGs, UAV-assisted 5G and B5G connectivity, and smart health

care—we have reviewed the function and effect of the previous approaches. Part II contains the results of the literature review of the different ML and DRL procedures. The third portion delves into the specifics of intelligent transportation systems (ITS), the fourth section examines new developments in cyber-security, and the fifth section summarizes the latest breakthroughs in smart city energy production and management. The sixth section provides an up-to-date overview of UAV applications based on ML and DRL in 5G and B5G communication. Similarly, Section (VII) delves into the latest advancements in the smart healthcare industry, Section (VIII) lays out the obstacles, trends, and potential solutions for future study, and lastly, Section (IX) brings the review to a close.

II. A Brief Overview of Machine Learning

Supervised, unsupervised, and RL are the three main types of machine learning techniques. Figure 4 shows the many cases in which the RL utilizes algorithms from all branches [20]. With several examples, we will quickly go over supervised and unsupervised learning. Following this, we shall introduce RL and its primary algorithms.

Supervised learning involves training an Artificial Intelligence (AI) network to develop a mapping function that converts input data into output using a dataset that contains both the input and target values. Regression and classification are two subsets of supervised learning. A few well-known applications of supervised learning include random forest, support vector

machine, and linear regression.

In unsupervised learning, the AI network is trained to discover hidden patterns, answers, and distributions using just a non-labeled and non-classified input dataset, without any assistance. Clustering and association are two examples of unsupervised learning tasks. The k-means and auto-encoder algorithms are two examples.

Martindale-Douglas procedure Markov Decision Process (MDP) is the foundation of most RL challenges. The goal of a Markov decision process (MDP) is to find the best answer to a sequential decision problem (SDP). Even though an MDP can't provide absolute solutions for stochastic SDPs, it can help find the best answers out of all the ones that are conceivable. State space, action space, transition model, and reward function are the four main components of a Markov decision process (MDP) model. The present state, the action taken, and the subsequent state are all factors that determine the reward and the transition.

Learning by Reinforcement (RL) Based on its many interactions with the environment, the purpose of RL agents is to increase their long-term aggregated reward. An agent is the portion of RL algorithm that learns and interacts with the world. An ideal policy allowed an agent to accomplish this goal. A policy is a plan of action for a certain set of states, and an ideal policy would be one that maximizes the total benefit in the long run. The most important thing for an agent to accomplish is to take advantage of the activities that are currently known to work, while also researching new actions that may be even better. A fundamental difficulty in the RL setting is the balance between exploration and exploitation, or the trade-off between seeking out new horizons that may provide a better result and maximizing reward from existing movements. Model-based and model-free RL algorithms are the two main categories into which they fall. Algorithms for model-based RL that use function approximators are thought to be very efficient with samples. But generalization is a big problem in the RL framework, and model-based algorithms aren't great at it when it comes to probabilistic, complicated, and high-dimensional models. A variety of methods, such as value functions, policy searches, return functions, and transition models, are available for addressing model-based RL issues. Two RL algorithms that do not require models are Monte Carlo (MC) and Temporal Difference (TD). Some examples of TD methods include the SARSA and Q-Learning approaches that will be discussed later.

Programming in real time functional programming, de-is a mathematical and computer-based approach to optimization issues that Richard Bellman developed in the mid-twentieth century. DP is a recursive strategy that, in order to solve a large issue, first simplifies it into smaller ones. Because it is model-based, the DP method requires complete, observable

environmental information. Policy iteration or value iteration is used to discover the best policy in various RL issues when the provided environment model is an MDP model.

The MC approach [1] The Monte Carlo (MC) approach solves issues using a random number generator. You can distinguish between first-visit MC and every-visit MC. The First-Visit MC takes into account only the returns that occur after a state's initial visit within a given set of episodes, whereas the Every-Visit MC accounts for all of a state's visits within that same set of episodes. The key benefits of MC over DP are as follows: (i) It is compatible with sample models. (ii) MC algorithms are efficient and easy to implement. (iii) MC learns optimum solutions via direct engagement.

Temporal difference approaches A issue with MC techniques is that for an update one has to wait till the end of an episode and this problem may be overcome by Temporal difference (TD) approaches, a type of model-free RL algorithm. As an estimate of the current value function, the TD technique learns via bootstrapping. The usual use of TD is the forecasting of a quantity dependent on the future values of the provided signal. Nonetheless, it is used in the RL framework to forecast future rewards in the long run. It is among the most popular ways to assess the policy. The following are descriptions of two prominent TD-based algorithms: Q-learning and SARSA.

SARSA is an active RL-TD control case approach that was first proposed by [21] as "modified Q-learning" because of its similarities to Q-learning. Subsequently, Sutton [21] referred to it as SARSA. Although SARSA is an on-policy learning algorithm, it is otherwise comparable to Q-learning. The update is based on 'State-Action-Reward-State-Action,' as is evident from its name. Following the current strategy instead of the greedy ones allows it to learn the optimum Q-value from the consequences of action.

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 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

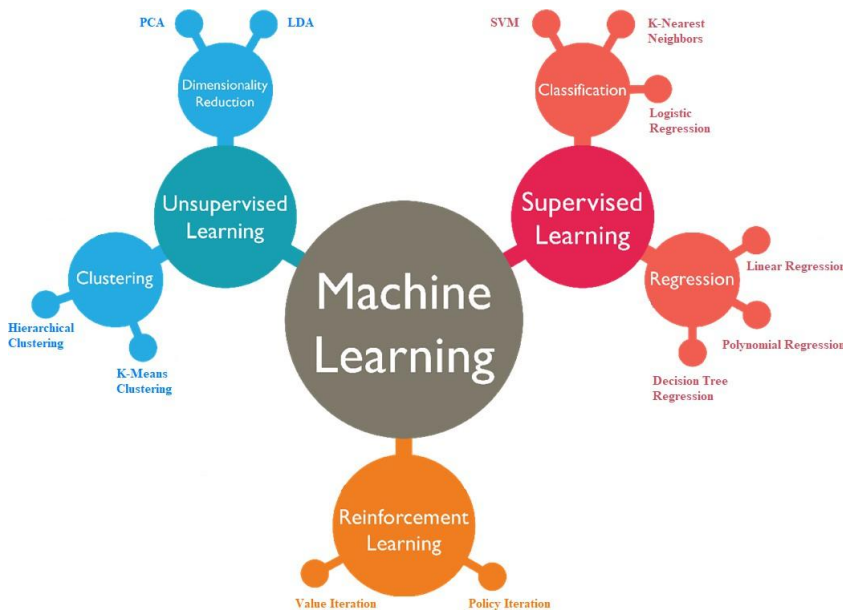


Figure4.Classificationofmachinelearningtechniques.

fills in the value function, while the actor revises the policy based on criticism. Because it estimates the policy and value functions, this sort of technique is intermediate between value-based and policy-based approaches. It works for both big action-state spaces and tiny state-action spaces. Associating the actor-only and critic-only procedures is the goal of the prior technique. The critic approach is a framework for learning value functions that makes use of simulation. By using the value function, the actor's policy values may be updated to improve efficiency [22].

Bayesian approaches In dynamic reinforcement learning (DRL), an agent may get rewards from multiple states, and those rewards will only become better with time. The agent learns to avoid states that are reward-based and instead focus on those that provide higher rewards. A key factor in maximizing reward is the uncertainty information of the environment. To assess and investigate model uncertainty at a suitable computing cost, Bayesian models provide an analytical framework [23]. Because they may prevent over-fitting and incorporate uncertainty in learning parameters, Bayesian approaches can be a solution to the exploitation-exploration conundrum. Notable Bayesian approximation techniques include Myopic and Thompson Sampling. The exploration-exploitation dilemma may be solved with Thompson sampling.

One of the most popular RL algorithms, Deep Q Network TD (and Q-learning in particular) suffers from a lack of generalizability when dealing with huge state spaces. Previously, we would use a look-up table or matrix to hold the value function. The Q table, for instance, is kept as a two-dimensional array in Q-learning. It is challenging to visit and

estimate the value function for all states in situations with a vast state space and numerous related activities. Overcoming the problem of generalization is achievable with the advent of RL based on neural networks for function approximation. In order to estimate the value function in a vast state space, The Deep Q-Network (DQN) [21] use a Neural Network. The Q-learning update rule is used for training the network.

chapter two: the intelligent transportation system Smart cities and intelligent transportation systems (ITS) are both shaped by the massive data produced by the integration of various sensors, control systems, and information and communication technologies (ICT) [24]. A crucial component of sustainable ITS, artificial intelligence (AI), machine learning (ML), and deep learning (DRL) methods are actively contributing to the accurate monitoring and estimation of real-time traffic flow data in urban environments [25], [26]. We provide a high-level summary of the latest innovations in ITS below, which would be crucial to the construction of a smart city. To better understand how ML and DRL can be applied to ITS in smart cities, Veres et al. [27] conducted an extensive study to investigate a range of topics, including traffic flow assessment, fleet management, passenger hunt, channel estimation in MEC, accident probability estimation, and more. Issues such as trajectory design, fleet management, cyber-physical security, etc., may play a crucial role in the development of smart cities; a research based on DRL approaches and edge analytics in ITS was produced by the authors of [14]. An improved driving behavior decision-making approach in a heterogeneous traffic environment based on DRL is suggested in this work [28]. To achieve an optimum policy, this method employs a data compressor that transforms data into a hyper-grid matrix, a two-stream deep neural network (DNN) for feature extraction, and a

decision-relational learning (DRL) technique. The results of Simulation findings employing several traffic situations for linked cars have verified the suggested scenario. Emerging security concerns with mobile edge computing (MEC) are the primary emphasis of the writers in [29]. In order to effectively deal with potential security risks, a technique based on DRL is suggested to learn different ways to attack via unsupervised learning. The suggested model has been compared with state-of-the-art ML-based methods. A six percent improvement in accuracy is shown by the results of the suggested method. To forecast highway traffic in the near future, the authors in [30] used a DRL-based method. Researchers in South Korea analyzed data from the Gyeongbu Expressway and developed a model for congestion prediction using the Deep Long-Short-Term Memory Recurrent Neural Network (LSTM-RNN). When it came to forecasting the short-term traffic flow in highway networks, the experimental findings produced a notable reaction. The authors of the research on effective use of GP trajectories data from taxis in a region for passenger searching published their findings in [31]. Based on the architecture of DNN, the suggested recommendation system (TRec) is both efficient and effective. In TRec, the passenger's quest is carried out by the taxi drivers, who serve as learning objects. Their tasks include predicting the road conditions and evaluating their net earnings. Using a real-world dataset, we test the suggested recommendation system (TRec) and find that it works as advertised. The authors of [32] suggested a novel LSTM (long short-term memory) network-based prediction method for optimising system performance by forecasting a number of wireless communication channel characteristics. When it comes to studying the spatio-temporal correlation among various communication channel characteristics, the LSTM network can organize the available data in an array that makes it easy to do so. The results of the simulation confirm that the suggested model is effective in this particular situation. The authors of [33] created a smart offloading system for vehicle edge computing by using a DRL approach. In order to improve the Quality of Experience (QoE) for users, the authors designed a combined optimization problem based on task and resource management and used a finite Markov chain to simulate the communication and computation states. In order to handle it effectively, the suggested NP-hard problem is further separated into two sub-problems, and numerical results have proven its efficacy. Both unicast and broadcast situations may benefit from the novel decentralized resource allocation approach for V2V communication that Ye et al. [34] developed based on DRL. If the suggested method is to be implemented, autonomous vehicles or V2V links will be able to seek for the ideal power level for data transmission and sub-band without necessarily waiting for global information. All users and agents learn to optimize interference in vehicle-to-infrastructure (V2I) connections and meet with strict latency requirements on v2v lines, according to the simulation findings. The author of [35] found a way to simulate the traffic flow using approaches based on DRL. The stacked auto-encoder model is trained greedily layer-wise to understand the many features of traffic flow. When compared to current methods, the suggested method

outperformed them in terms of traffic flow prediction. A key component of smart city ITs, UAVS is characterized by its quick and easy mobility, cheap production cost, long durability, rising payload capacities, and simplicity of deployment. The positive features of UAVs mentioned earlier have made their contribution to ITS, which ranges from blood transport to package delivery, a reality. The use of ML and DRL algorithms has been essential in improving the efficiency, trajectory, and energy consumption of UAVs in ITS. The authors of [36] suggested a traffic-aware method to ease the deployment of UAVs in a vehicular setting with the goal of improving service quality. In a traffic-congested environment, the deployed UAVs function as MEC nodes. The results of the simulation have proven the performance of the suggested protocol. Coverage services for mobile users in a specified area were suggested by the authors in [37] as being achievable using a decentralized architecture of airborne UAVs based on DRL. Aiming to minimize energy consumption, maintain inter-connectivity of UAVs, restrict airborne UAVs within the area of interest, and maximize coverage of regions of interest are the aims of the suggested model. Simulation findings confirm the suggested model's higher performance. In their study, the authors investigated the possibility of using UAVs for downlink transmission in order to maximize throughput for automobiles. The suggested model investigates several UAV and vehicle transition stages by drawing on the MDP issue. In order to examine the energy consumption of flying UAVs effectively, DDPG algorithms based on three distinct DRL approaches were proposed. The suggested model's efficacy is tested in a more authentic setting and confirmed by means of simulation outcomes.

II. Section Three: Cyber-Seva

Interconnected sensors, actuators, and relays that collect, analyze, and transfer data to guarantee trustworthy and efficient digital services are expected to make up a smart city. The proliferation of interconnected gadgets has given rise to new cyber security concerns that must be addressed [39]. Many smart city applications rely on data collected by Internet of Things (IoT) devices housed in the cloud [40]. Several important and crucial components of a smart city are examined in a short survey that the authors have created in [41]. Data privacy and security, network defense against cyberattacks, fostering an ethical data sharing culture, and making AI, ML, and DRL tools easily accessible are all important issues that have been addressed. Hadi et al. [13] surveyed extensively to examine many research issues and solutions related to the idea of smart city design from the viewpoints of communication, privacy, and security. The integration of current communication protocols, sensors, actuators, and infrastructure presents a variety of hard challenges, which they mainly sought to explore. Mohammad et al. conducted a comprehensive investigation and investigated the function of ML and DRL in [15].

methods using a cutting-edge security stance on the Internet of Things (IoT) and the newly-minted security risks. Concerning probable Internet of Things (IoT) security, the authors examined

ML and DRL protocols, outlining their benefits, drawbacks, and suggested future research routes. In order to explore the potential benefits and roles of using ML and DRL techniques in Bioinformatics and the healthcare industry, Riccardo et al. [42] conducted a literature study. In order to make the most of cutting-edge healthcare technology, they investigated several obstacles and offered solutions based on ML and DRL. In order to distinguish between normal and abnormal traffic, the authors of [43] explored the latent pattern in the training dataset using the self-taught potential and capabilities of DRL approaches. For the purpose of detecting and identifying cyber assaults in smart city IoT applications, they suggested a distributed deep learning-based strategy. The suggested method outperforms the shallow models-based approach in terms of efficiency. Concerned with the safety of smart city Internet of Things (IoT) devices, the authors of [44] suggested an Anomaly Detection-IoT (AD-IoT) solution based on Random Forest ML. By analyzing data sets using machine learning, the suggested method may quickly detect any suspicious behavior occurring at remote fog nodes. The authors of [45] presented a novel DRL-based architecture to protect a smart city's digital infrastructure against cyberattacks. By analyzing the invaders' data activity, the suggested model may detect them early on, allowing for proactive network security. A variety of safe and confidential apps may be developed to bring the smart city idea to life using the previous paradigm. The authors of [46] introduced a system for safe computational offloading in the Fog-Cloud-IoT context that uses machine learning to improve latency and energy usage. The suggested system relies on a Neuro-Fuzzy model that makes sure data is secure at the gateway and that Internet of Things devices choose the best fog nodes to offload computing to using Particle Swarm Optimization (PSO). When it comes to minimizing latency, the suggested framework performs better. The construction of an edge cognitive computing (ECC) network and an examination of its primary issues are detailed in [47]. The ECC architecture was also designed to facilitate active and dynamic service transfer. Cognitive mobile user practice and customary behaviors form the basis of the prior ECC design. According to the results of the performance investigation, the ECC framework is more efficient than the conventional computer architecture. To learn how to offload binary decisions based on experience, the authors of [48] suggested a DRL-based Online Offloading method. Binary offloading systems divide tasks into two categories: those that are handled locally at the node level and those that are handled wholly by a MEC device. The computational complexity is greatly reduced, especially in large-scale networks, and significant optimization issues are eliminated by the suggested paradigm. While drastically cutting down on computing time, the suggested methodology still manages to reach near-optimal performance. The authors of [49] envisioned a secure cloud service for connected automobiles that can identify cyberattacks and meet the user's quality of service and quality of experience needs. The three-pronged approach to intrusion detection involves analyzing traffic data, compressing it, and then using classification algorithms to distinguish between legitimate and malicious service requests. The simulation results verify the

system's performance. The authors of [50] discussed the many security issues that ITS-using airborne UAVs confront and offered an ANN-based solution to these problems. While performing various tasks, such as information technology (IT), real-time data streaming, and UAVs-assisted freight delivery, the suggested model allows the UAVs to make frequent use of the system resources while guaranteeing the real-time safety of flying UAVs. The performance of the previous approach has been confirmed by the results of the simulation. emphasis [51], the authors zeroed emphasis on the GPS spoofing assault, in which fake signals may fool both the UAVs and the people controlling them from the ground. Their solution to the problem of GPS spoofing assaults was an ANN based on machine learning. Using metrics such as signal-to-noise ratio (SNR), Doppler shift, and signal pseudo-range, the suggested method characterizes GPS signals. With a low false alarm rate and a high likelihood, the suggested methodology finds GPS spoofing attempts. A DRL-based method to counter jamming assaults on UAVs in the air was created by the authors in [52]. The jammer's geographic position, channel model, and UAV channel model are not considered while modelling the suggested method. This method evaluates the quality of the UAV's transmission and uses that information to determine the UAV's trajectory and power transmission level. The aforementioned method enhances the QoS of the deployed mission-specific UAVs, according to the simulation findings.

III. SMARTGRIDS

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 communications 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], [56], [57], [58], [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 retrained 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 security test bed for SGs systems. It's 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

Table II: 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 cyberattacks on SGs, the proposed model utilizes the generation of blocks using short signatures and hash functions.
[73]	2019	ML	Designing an 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.

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 contribute 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.

IV. DRL BASED UAVS APPLICATIONS IN 5G AND B5G COMMUNICATION

5G and B5G communications are the future of mobile wireless communication due to the rising need for low latency, high dependability, and huge data speeds. Artificial intelligence (AI), machine learning (ML), and deep reinforcement learning (DRL)-based approaches are the best tools for solving the many complicated communication problems caused by massive amounts of network data [48], [82], [83], [84]. While the aforementioned methods have been useful in 5G communication, the focus here will be on unmanned aerial vehicles (UAVs) and their contributions to 5G and B5G networks, which are essential to the development and maintenance of smart cities.

Effective analysis and detection of cyber-attacks in 5G and B5G communication networks was suggested by the authors in [85]. By examining several facets of network flows, DRL methods are used to evaluate network traffic. The authors provide a new method to detect cyberattacks in 5G and Internet of Things networks in [86]. The suggested method effectively identifies multiple cyber intrusions and is built upon a deep auto-encoded dense neural network protocol. UAVs still confront several unresolved issues, while having promising uses. For instance, LTE cellular service is not everywhere, especially in the sky. In long-term evolution (LTE), base station antennas are mainly meant to serve users on the ground and are angled downwards. Due to architectural constraints, interference and loss of signal (LOS) concerns, and cost hurdles, it is still difficult to provide ubiquitous sky coverage in 5G and B5G communication. Furthermore, there are some restrictions on UAV-supported communications. For example, a realistic end-to-end communication, path loss, channel/antennas, terrain/environment, etc. model is required to formulate an ideal model. Above all else, optimizing complex communication networks isn't always an easy task.

Avoiding aerial UAV collisions through learning UAV flying dynamics, UAVs landing on mobile platforms, UAV identification based on rotor number, data acquisition and image processing techniques for soil moisture content estimation and plant identification in precision agriculture, joint optimization problem based on UAV flight trajectory and schedule of getting updated data from GTs, etc., are all examples of the kinds of complex challenges that ML-based approaches like DRL can effectively handle. Below, we provide a concise overview of a handful of research initiatives that aim to address several issues related to UAVs. For the purpose of optimizing the trajectories of several airborne UAVs, Challita et al. [87] presented a deep RL

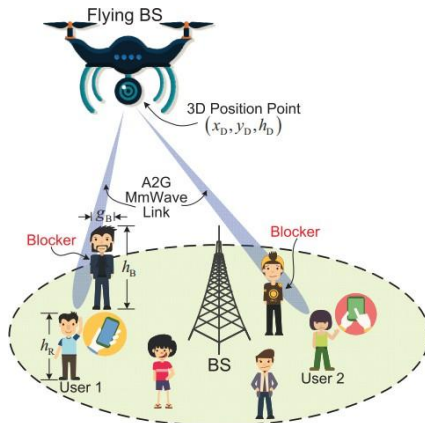
framework that makes use of an echo state network (ESN). Optimizing data connection latency and reducing interference at GBSSs are both made easier with the suggested system, which UAVs may use. In the proposed framework, each UAV operates autonomously and learns its own path, transmission power level, and association vector, both separately and in tandem. An ESN-based DRL method was suggested to guarantee the best possible routes for UAVs and associated resources. To improve the improvement between energy economy, latency, and interference caused at GBSSs, the author claims this is the first-ever effort to use an ESN-based DRL technique for UAVs communication. Herald et al. [88] presented a model in which UAVs carry BS and function as network users. While in the air, the sum rate is improved using the reinforcement Q-learning technique. To control the UAV and maximize interference at terrestrial BSs, Challita et al. [89] used an ESN-based DR algorithm. When it comes to UAV identification and classification utilizing radar technology, machine learning and deep learning are kings in pattern recognition and may provide acceptable study direction.

5G and B5G communications are the future of mobile wireless communication due to the rising need for low latency, high dependability, and huge data speeds. Artificial intelligence (AI), machine learning (ML), and deep reinforcement learning (DRL)-based approaches are the best tools for solving the many complicated communication problems caused by massive amounts of network data [48], [82], [83], [84]. While the aforementioned methods have been useful in 5G communication, the focus here will be on unmanned aerial vehicles (UAVs) and their contributions to 5G and B5G networks, which are essential to the development and maintenance of smart cities.

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Avoiding aerial UAV collisions through learning UAV flying

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A. 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 help 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 helps in reducing interference and enhance data security [99]. Figure (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 modelled 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.

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

B. 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

TableIII:UseofDRLalgorithmsinUAVsorientedapplications.

References	Year	Approach	Summary
[90]	2019	ANN	UAVsconnectivity,security,andsecureoperations.
[87]	2018	ESN-basedDRLframework	Trajectory,latency,&interferenceoptimization.
[88]	2019	Q-learning	UAVsasBStoimprovesum-rate.
[89]	2018	DRLalgorithm	UAVsutilizationforinterferenceoptimization.
[91]	2019	GeneticandSimulatedannealing(SA)algorithms	OptimalnumberofUAVstoensure5Gcommunication
[92]	2019	AttitudeestimationmechanismusingaDNN	Improvementinnetworkcoverage.
[93]	2017	ESNtechniquetomodelusersbehaviors	ImprovementinQualityofExperience(QoE).
[94]	2018	MLtechniques	AssistingcellularBSsinhighcongestionzones.
[95]	2019	MLPandLSTMtechniques	UAVsoptimalpositionstomaximizedatathroughput.
[96]	2019	Q-learningandMDP	Optimaldecisiontochargensornodes,datacollection,and UAVshoveringspeed.
[97]	2019	Q-learningandESNtechnique	Jointoptimizationofpowercontrolandsun-rate.
[98]	2018	DRL	UAVshandoverissueandimprovementindatarate.

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 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 derivedtheUAVsoptimalpositionandcontenttobecachedat UAVs. In [94] Zhang et. al, proposed a framework to predict UAVsdeploymentasrelay-BStoassistcellularBSincaseofa 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 pro- posed to assign an optimal number of UAVs to the predicted data demanding zones. Simulation results confirm that the proposed UAVs predictive deployment significantly improve the overall performance of ground BSs in hot spot regions. In [95],Yirgaet.al,proposedutilizationofmulti-layerperceptron (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 accurate UAV position and enhances user throughput.

V. SMART CITY HEALTH CARE AND MACHINELEARNING

Health intelligence, which makes use of AI, ML, and DRL methodologies, has become more popular in modern healthcare systems due to the proliferation of high-performance Internet of Things (IoT) devices, cloud computing, and sophisticated sensors. Citations [100], [101], and [102]. When it comes to medical imaging, social media analytics for particularailment, cure prognosis, and illness diagnosis, the aforementioned

methods are indispensable[104], [105]. What follows is a synopsis of current initiatives and trends in smart city health care research.

Studying the role of 5G communication in the healthcare system, the necessary methods, hardware, and architecture, and analyzing the important goals are all part of the research that the authors have created in [106]. They have mainly contributed to a taxonomy of communication protocols and technologies, a 5G-based health care architecture and core technologies, and a list of upcoming concerns at the network layer that will affect IoT-based health care systems, such as scheduling, congestion management, routing, and more.In[107], the authors conducted a comprehensive research on healthcare systems' use of Big Data analysis using AI, ML, and DRL.The authors investigate the many benefits of the aforementioned methods in areas such as complicated data analysis, categorization, diagnosis, illness risk, optimal therapy, and anticipated patient survival. Nevertheless, there are several obstacles that must be overcome in order for the aforementioned methods to be effectively used. These include, but are not limited to, accurate model training, dealing with actual clinical situations, ensuring that physicians comprehend the data analysis tools and research data, and attending to clearly stated ethical concerns.The authors rule out the implications in [108]. that in healthcare systems of the future, AI will completely replace human physicians and focus on four areas where the aforementioned methods may have a big impact: patient monitoring, administration, health care mediation, and clinicians' decisions.Realistic data from the aforementioned field would provide the basis for the construction of an efficient AI-enabled system [108]. The authors of [109] talk about how the current pharmaceutical industry's research and drug development procedures will be changed by the use of AI for drug discovery. The authors of [110] have described a number of possible AI, ML, and DRL protocols that might improve healthcare based on the Internet of Things.

In order to diagnose cardiac diseases effectively and autonomously, the authors of [111] suggested a new architecture they termed HealthFog. In order to accurately

categorize and handle the incoming patient data, the suggested architecture makes use of edge computing devices that are backed by DRL protocols. Health-Guard is a novel security method that the authors suggested in [112]. The suggested method for detecting suspicious and doubtful actions in Smart Healthcare Systems (SHS) relies on ML protocols. In order to distinguish between normal and dangerous activities, the HealthGuard constantly checks the core functions of different SHS devices and compares the vitals to the patient's actual physiological changes. In [113], the author suggests a system for remote body sensor telemonitoring that is backed by REST APIs, communication protocols, and ontology restrictions. In order to improve healthcare and planning support, the authors of [114] suggest using ML and DRL algorithms to evaluate satellite images and map far-off populations. In order to categorize different kinds of syndromes associated with problems with the stomach and spleen, the authors of [115] conducted a review of the effects of DRL protocols in medical image processing. For the purpose of determining patients' prognoses after percutaneous coronary intervention (PCI), the authors of [116] devised a method based on ML.

Table IV: 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	HealthFogplatformtoanalyzeheartdiseases.
[112]	2019	ML	HealthGuardplatformto continuously monitors and compare the connected devices operations and body conditions.
[113]	2019	REST API	Remotepatientcareusing telemonitoringandontology regulations.
[114]	2019	DRL	Communitiesmappingfor better healthcare using satellite imagery and DRL techniques.
[116]	2019	ML	Estimatingpatientchances ofsurvivalafterPCI.
[117]	2020	AI System andthree DRL Techniques	AnAISystemthat surpasses humanexpertiseinbreast cancer detection.
[118]	2019	Genetic Programming	Todifferentiatebetween benignandfatalbreast cancer.
[119]	2020	DRL	Breast cancer detection through mammograms screening.
[120]	2020	DRL	Categorizationofinvasive ductal carcinoma breast cancer.
[121]	2020	Logistic dependent model	BreastCancerdetection through Biomarker using innovative generalized logistic dependent model.

VI. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

It is clear from the current smartcity literature that the applications based on AI, ML, and DRL have shown promising outcomes. Still, the expert from both academia and industry can zero in on these unanswered questions to find the best ways to use AI, ML, and DRL to make smart cities even more efficient:

- If we want to make decisions that are more exact and accurate, we need a lot of data to train the ML and DRL protocols with. This data should include things like vehicle speed, location, distance between vehicles, driver behavior, UAV height, relay BS, and so on.

By using ML-techniques to optimize the UAV's trajectory and onboard capabilities (such as computation, sensing, communication, and caching), ITS efficiency during UAV-vehicle communication may be greatly enhanced.

- Data collection for a model of the vehicle-vehicle, vehicle-UAV, UAV-UAV, UAV-GBS, etc., channel in the presence of regular, non-regular shaped infrastructure using a variety of UAVs and vehicles traveling in different directions.

- Identifying the most effective AI, ML, and DRL approaches that can bring SGs performance up to a near-optimal level; standardizing big data development in SGs; and establishing communication protocols for interoperability of different SGs devices.

- The necessity to standardize SGs communication infrastructure for optimal interoperability between current SGs and future 5G technology is heightened by the expectation of 5G technology standardization in 2020.

- Any SGs and electric companies' primary focus should be on optimizing power-down scenarios. Building a reliable network relies heavily on the results of the communication delay evaluation. When it comes to developing strategies for smooth power supply and 5G communication technology switching, ML and DRL based approaches may be invaluable.

When it comes to smart cities, security is all about the apps. Energy manipulations and inefficient SGs might result, for instance, from the security compromise of smart meters. Therefore, to guarantee the cyber safety and security of smart city applications, more sophisticated and creative solutions based on big data analytics are required.

VII. CONCLUSION

Academia and business have made great strides in the field of smart cities, and we took a look back at the latest research trends and developments in this area. An overview of deep learning (DRL), artificial intelligence (AI), and machine learning (ML) has been crafted. We investigated the usefulness of the aforementioned protocols in developing near-optimal approaches to a number of applications thought

to be critical to smart city efficacy. The need for new laws that are both AI-assisted and AI-compatible, energy-efficient intelligent transportation systems (ITS), smart grids (SGs), cyber-security, and 5G and B5G communications in smart cities, as well as the most current AI, ML, and DRL applications in smart governance design, were discussed. From effective diagnosis and health recovery to the safety of health-oriented Internet of Things (IoT) devices and, maybe, the discovery of the most convenient medicine, we quickly covered the expanding importance of the aforementioned methods in smart health care. Prior approaches may play a vital part in smart city-oriented current research issues and future research trends.

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