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Research Article

AI in Smart Cities: A Review of Urban Data Processing, Prediction, and Optimization Techniques

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ABSTRACT

Rapid advancement in the information and communication technologies ICs has recently provided new techniques for processing and analyzing the current data sources in smart cities. Various technologies for distributing cities to build them more livable, efficient, intelligent, sustainable and resilient. Intelligent and efficient data processing models for machine vision smart cities applications include intelligent detecting systems to monitor vehicle speeds and flow and pedestrian movements in roads and walkways. Smart and efficient storage and retrieval models for processing massive video data in the cloud for vehicle and traffic law monitoring in video surveillance and transportation systems are also discussed. Imaging and recognition-based models for analyzing the currently prevalent image data in cities are also reviewed, including deep learning-based fire recognition systems for smart fire prevention and manhole cover detection systems in the roadway and street monitoring. There is also a noteworthy review of prediction models for flow data in smart cities to anticipate traffic congestion and pedestrian movement trends. In addition, there are optimization models applied in smart cities, including intelligent routing models and path planning for vehicle navigation in logistics/distribution and delivery systems [1].

The above family of models are mainly adapted to smart mobility and pedestrian application domains. However, there are also various researchers working on data processing models in other urban domains, either independently or in an integrated manner with transportation. Numerous smart city platforms in the markets for data management and integration with diverse applications have also been reviewed. It is promising to deliver a relatively comprehensive review of urban data processing models with various techniques for different application domains. Smart cities have been subjected to rapid growth and therefore have become a major trend in the development of smart environments. Smart cities aim to improve the livability of urban settlements, enhance sustainability, and reduce operational costs. The smart city concept is expected to be of enormous benefit and it has been embraced by major cities around the world. However, the vision value of smart cities can only be fully realized through the successful integration of cutting-edge technologies and promising urban management models.

1. INTRODUCTION

The rise of vast collections of sensing devices together with the advances of wireless technologies and low-cost sensors enabled the development of Smart City projects around the world. Smart Cities is a collection of technologies and urban data processing tools that transform the innovative data from the embedded sensors, citizens, and IoT devices into tools for urban knowledge extraction, monitoring, and support for sustainable development [2]. There are significant advances in types and numbers of collected data from cities, which create demands to extract information from these data collections, predict future conditions, and optimize or control the cities based on this information and these predictions [1]. However, in Smart Cities, some collected data today may contain great value for the future, and some prediction tools may need to consider a great amount of historical data to build precise models, which occur challenges in the early time of Big Data era such as Volatility and High-dimensionality.

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Smart Cities also provide many high-dimensional photo-like images and videos captured at a high frame rate from more than one cameras which create VAST and VAR data that these data vary in interval and resoluteness besides their great size. Therefore, modelling, predicting, and controlling Smart Cities bring higher difficulties than traditional ones. The operation of prediction and optimization in Smart Cities is reviewed based on the characteristics, difficulty in Research and Development, and the necessary computational tools of the urban data [3]. Data Processing, as the first step of addressing Smart Cities issues, is introduced through detailing its Bottlenecks in Operability and Scalability and the technique of pre-processing necessary in urban data processing and controllable factors in predictability. The data being modelled and the output of modelling together shape the types of knowledge extracted from a Smart City [4].
Prediction is the processes to estimate the Veracity variable's values in the predictive time. The Veracity variable of demand prediction is the level of demand in the pre-sustainable time. The uncertainty and noises generated from measuring instruments, which limit the controllability of the database generated from sets of measurements, rarely exist in Smart Cities [5].

2. OVERVIEW OF SMART CITIES

Due to rapid urbanization and population growth, cities are increasingly facing challenges regarding infrastructure, traffic congestion, economic performance, and access to health services. In addition to these substantial challenges, large cities suffer from climate change and environmental pollution. Emerging advancements in the fields of artificial intelligence, smart sensors, and wireless communication technologies have developed ubiquitous sensing and computational layers to enhance technical and managerial skills. Smart systems of cities cooperate and connect with each other in the shape of networks to construct an integrated city. Smart cities with complex air/water transportation/mobility, energy, health/sustainability/data networks rely heavily on data analytics for smart decision-making [6]. This revolutionary technology leads to enormous challenges in data acquisition, prediction, and optimization which intelligent decision-making in smart cities cannot be addressed directly by existing machine learning and operational research. Improving mobility and sustainability, making efficient delivery, pleasant living, and timeliness of services have always been an issue for the city administrators. On the other side, trillions of sensors, user, and societal data generated every day in the city hand in opportunity and collaborative works for researchers to innovate decision-making technologies. In the past few years and with the dramatic increase in communication capacity, computer, and processing capacity, this line of research showed compelling advances and movement models, mobility prediction models/classifiers, real-time optimal solutions, and frameworks for decision-making. However, making smart mobility services is one of the utmost challenges due to the wider environmental, transportation, and behavior aspects as well as multipoint-of-views, multi-factors and complex uncertainties affecting the decisions [7]. The survey focuses on the vast advancements on technologies and methodologies around big data, machine learning, and operational research and their applications in decision-making for smart mobility. Decision-making in smart cities often involves exploring various aspects simultaneously. Various aspects include diverse forms of urban data - such as transportation modes, images, ambient noises, geo-locations, satellite and aerial photographs, etc. - collected through mobile telecommunication, sensory and satellite technologies and comprised of diverse features such as quantity, scale, quality, and representation forms. It includes prediction spaces, time windows, and noise level for user/urban information. It also includes various forms of data estimations with the diversity and incompleteness of predictive outputs. Meanwhile, decision-making involves the connections among various aspects, which can be dynamic across cities/regions, periods, and data sources [8]. As shown in figure 1

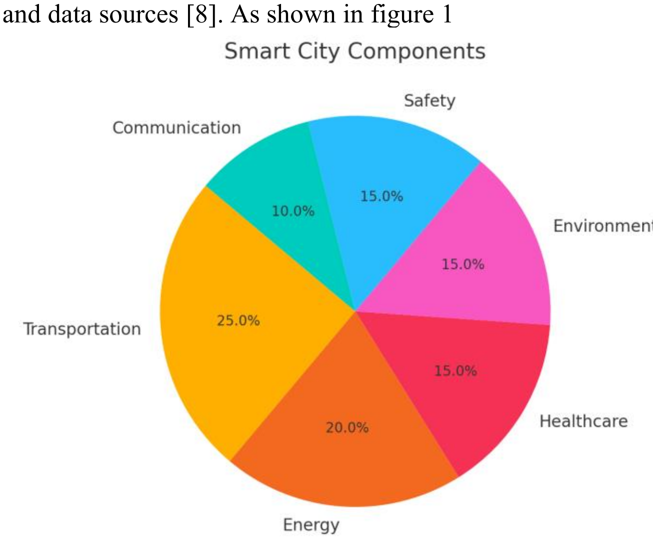

Fig. 1. Smart City Components

2.1 Role of AI in Urban Development

Artificial Intelligence (AI) plays a critical role in the urban development of smart cities; where AI systems are used to support decision-making in design and planning processes to meet complex interrelated challenges, this is referred to as the AI-urbanism relationship. AI can significantly enhance the data processing, prediction, and optimization capabilities of smart cities, enabling the explicit understanding of complexity, dynamics, and trends in urban environments. AI-driven insights related to data-driven urban modeling, forecasting, protocol recommendation, knowledge discovery, and sensor network optimization are discussed [9]. A taxonomy is also introduced that groups the reviewed studies in terms of the AI technology adopted and the high-level task proposed. Some critical challenges and future research directions in the development of AI-based urban data processing, prediction, and optimization systems, are highlighted in the context of smart cities [10].

The increasing level of complexity experienced in today's urban environments has augmented the significance of using data-driven approaches in urban modeling to help regulators and decision-makers better understand spatial-physical, societal, and environmental complexities and dynamics. The integration of advanced computational techniques with large and heterogeneous datasets has opened new avenues to explore urban environments and their human-environment interactions and impact. By leveraging the strengths of AI and IoT, the Artificial Intelligent Internet-of-Things (AIoT) framework is expected to reshape urban landscapes and make it possible to design and offered more sustainable and inclusively intelligent smart city services tailored to individual needs, behaviors, and characteristics [11].

Using AI empowers non-expert users to participate actively in AI-enabled services and interact with the AI systems, knowledge, and processes used in a particular context. This can accelerate human understanding of the complexity of challenges in need of AI solutions and the interpretation of the insights and deliverables generated by AI systems, as well as the analysis of human-AI interactions in the course of the process and outcome of service provisioning for model improvement. The design of human-centric AI technologies for urban decision support should accommodate higher order thinking and reasoning mechanisms beyond the cognitive approach and consider both potential opportunities and risks [12][13].

3. DATA PROCESSING TECHNIQUES

The smart city data analytics platform is an intelligent cloud-based solution that provides a universal smart city data analytics framework. This framework consists of three main sections: (1) Data Capturing: which aims to collect data from various data capturing equipment placed throughout the city on the edge. (2) Data Analysis: In which errors, extreme values, normal and abnormal data are detected, and the descriptive statistics of each analytic method is gathered and transformed into the pre-defined standard format for further processing. (3) Decision Making: which uses the analysis results to consider the quality of the city's atmosphere, suggest solutions, and longer-term considerations for city managers [1]. Smart cities suffer from excessive data because of the presence of various smart equipment. This excess data is an issue for city managers and smart cities' systems, requiring prior management for data efficiency and great results from big data analysis. Regarding efficiency, the data is automatically grouped into seven domains of activity and is specific to each big data analysis slot. The data gathering process is challenged by the presence of data capturing equipment. Types of data vary from video to strings or timestamps and must be captured by IOT devices. Data must be converted into numerical unit of measurement in a defined format for conformance with machine learning (ML) algorithms, while video also needs special procedures to convert the pixels format either into strings or vectors form. Pre-processing of captured data is crucial for handling a wide variety of missing information and missing values in datasets. Various approaches and tools are described in this section for managing the mentioned issues. The input data is managed in the data engineering section. The input data is labeled by the dataset and unlabeled data for further usage in supervised or semi-supervised ML models. The data engineering section requires the expertise of domain specialists and is a time-consuming process for pre-processors [14]. As such in Table I

TABLE. I. AI TECHNIQUES FOR URBAN DATA PROCESSING IN SMART CITIES

Technique	Description	Applications
Image Recognition	Detects objects, patterns, or events from visual data	Pedestrian detection, vehicle tracking, fire recognition
Video Analytics	Processes high-frame-rate video streams	Traffic monitoring, law enforcement
Cloud-Based Storage & Retrieval	Stores and manages large volumes of urban data	Surveillance systems, real-time traffic control

Technique	Description	Applications
Data Preprocessing Tools	Handles missing values, noise, and format conversion	Machine learning input preparation

4. PREDICTIVE ANALYTICS IN URBAN PLANNING

Predictive analytics leverages historical data to generate understandable and actionable data-driven predictions about potential future events. In the context of cities, predicting and efficiently distributing available resources to meet residents' needs can be achieved by analyzing historical information. With the aid of data from the physical world, machine learning models can make data-driven predictions of social dynamics, enabling municipalities and businesses to address specific needs in a timely manner according to the predicted future. Prioritizing urban data enables access to a finer granularity of information about a city, predicting the demand of one taxi in a few minutes, predicting the density of passengers at a given time in a subway station, etc. The scale and potential benefits of these techniques are such that they are termed Smart City Services, which may improve the organization, efficiency, and smoothness of city services. To complement urban data processing, two additional dimensions of predictive analytics have emerged: Predictive Modeling and Predictive Optimization [15].

By using historical data, Predictive Modeling transforms the parameters of a machine learning model into algorithms that encode the knowledge of a specific underlying process, enabling decision-making or analysis. It compresses the understanding of a slow-to-evaluate process into a small, swift-to-evaluate model and has been applied to enhance any dispatching response of Transportation Systems, such as taxi requests assignment, bus rapid transit on-time performance, and subway passenger service management. The understanding of physical processes governing the dynamics of the city may also be expressed with Predictive Modeling. Understanding the urban data and dynamics via Predictive Modeling empowers the development of a more efficient and effective city, as a rigged system can be operated quicker and more smoothly with a better understanding of urban data and dynamics [16].

In the fields of domain-specific AI optimization, optimally possible strategies that reach the best planning target and policy at an assigned period can be synthesized, such that both the target and time constraint are satisfied. There are two sources of information that will impact the choice of actions over events: a predictable behavior of individuals and a geographic and physical world in which the events exist. AI optimization schemes allow for planning and strategy generation by synthesizing an event-action-space scenario that achieves the target. AI optimization schemes have also been incorporated with Predictive Models, which result in a better understanding of the planning domain, shorter planning time, and more effective planning quality. Under this combination, Predictive Modeling narrows the planning random domain by limiting which aspect of the world of a city has an effect on the planning quality, and AI optimization traverses through possible planning in a wide space, sampling best strategies under the narrowed state [17]. As shown in Table II

TABLE. II. PREDICTIVE MODELS IN SMART CITY PLANNING

Model Type	Description	Use Cases
Time Series Forecasting	Uses historical data to predict future trends	Taxi demand prediction, subway passenger flow
Deep Learning Models	Learns complex patterns from large datasets	Urban growth modeling, environmental impact forecasting
Regression Models	Estimates relationships between variables	Energy consumption prediction, traffic congestion estimation
Hybrid Models (AI + OR)	Combines AI with optimization techniques	Efficient dispatching, route planning

4.1 Forecasting Urban Growth

Urban regions are the centers of economic growth in the modern world. These regions are growing entities that maintain socioeconomic networks. Due to the sprawl of urban regions, however, several research works show that uncontrolled expansion of urban areas and cities has potentially adverse effects in terms of biodiversity, loss of habitat and fragmented landscape. Growth of urban region also drives the construction and improvement of infrastructure, which sometimes threatens the sustainability of the environment. Monitoring and controlling urban growth has thus eminently been the focus of interest for government and environmentalist agencies for finding an appropriate balance between the environment and urban planning.

With the rapid expansion of cities, it has become very important to monitor and control changes in urban land use. A fundamental difficulty in monitoring urban areas has been found to be the huge spread of these regions, making manual tracking intractable from geospatial and temporal scales. Current-day remote sensing satellites globally capture images of the earth's surface frequently and periodically. Satellite borne passive sensors provide images of big chunks of the planet covered with different types of land use classes [18].
Satellite imagery has been considered an effective component for real time monitoring of urban growth. Urban growth monitoring using satellite-derived products has been addressed by a number of researchers in the past with respect to advance warning mechanism and for planning assistance. The primary idea has been to relate the change vector generated in the image time series by considering the temporal increment of land use with urban sprawl. Advanced urban growth models using cellular automaton, agent-based methods, artificial neural networks, logistic regression, fractals and support vector machines have been developed for robust and accurate prediction of urban growth. Cellular automata is one of the most widely preferred model for urban growth prediction due to their simplicity and comparatively straightforward applicability. On the basis of precepts of cellular automata, a number of CA models and corresponding case studies have been done on various major cities of the world for detecting urban change. On the other hand, artificial neural networks have also been quite popular in recent years handling high dimensions of input data and being able to learn from the data through nonlinear functions [19].

4.2 Traffic Prediction Models

Traffic prediction plays a crucial role in alleviating traffic congestion which represents a critical problem globally, resulting in negative consequences such as lost hours of additional travel time and increased fuel consumption. Integrating emerging technologies into transportation systems provides opportunities for improving traffic prediction significantly. This survey aims to provide a comprehensive overview of traffic prediction methodologies. Specifically, they focus on the recent advances and emerging research opportunities in Artificial Intelligence (AI)-based traffic prediction methods, due to their recent success and potential in traffic prediction, with an emphasis on multivariate traffic time series modeling. They first provide a list and explanation of the various data types and resources used in the literature. Next, the essential data preprocessing methods within the traffic prediction context are categorized, and the prediction methods and applications are subsequently summarized. Lastly, they present primary research challenges in traffic prediction and discuss some directions for future research.
Given the dynamic and uncertain nature of road traffic, traffic prediction is essential for smart city development. Recently, the utilizing of emerging technologies, including the concept of smart cities, has advanced the process of traffic prediction significantly. This research work presents a comprehensive overview of traffic prediction methodologies. Aiming at identifying the gaps and future opportunities of research efforts in AI-based traffic prediction, they organize this survey into four categories, including data preprocessing, prediction methods, and applications. Candidate data types, resources, and sources, as well as essential preprocessing methods, are identified, presented, and explained. A comprehensive categorization within three groups regarding the application of each prediction method is constructed; this review presents 14 traffic prediction methods categorized as classical, statistical and AI-based methods, with the number of works developed for each method mentioned. As shown in figure 2

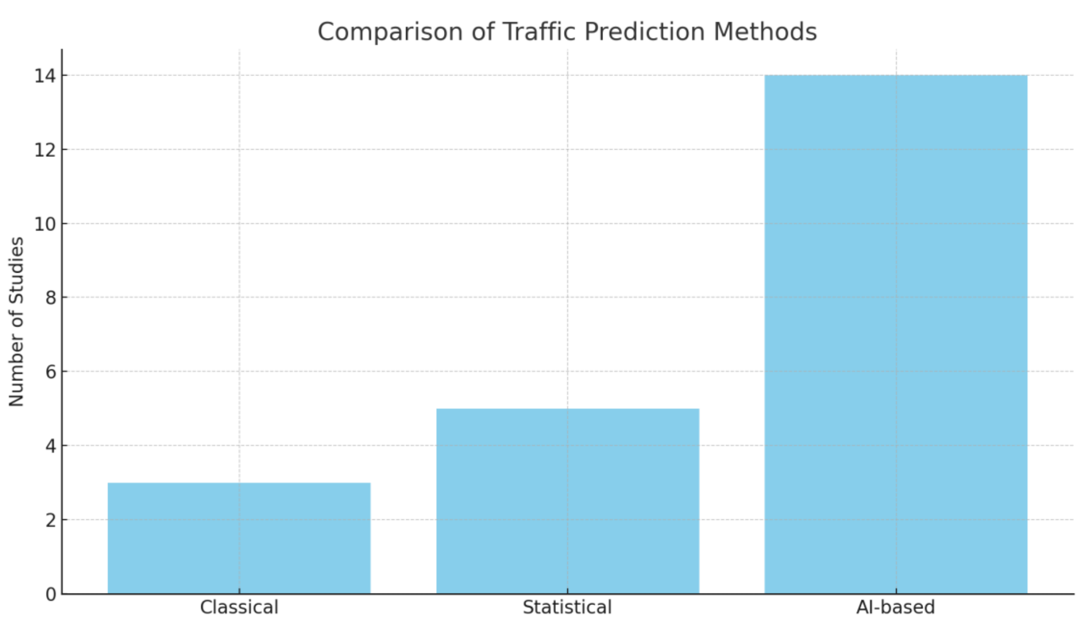

Fig. 2. Comparison of Traffic Prediction Methods

By accurately determining the intensity of traffic in the near future, ATCS can optimize the traffic light control program to minimize congestion. When applied at multiple intersections, a forecasted traffic congestion can be distributed over multiple intersections to lower the overall impact. Accurate predictions can be used as an indication to swap the current plan with a more appropriate plan. The most effective way to pre-process data is to use a simple moving average without timestamp as an input. This means that the machine can generate a prediction with only the traffic flow of past few minutes without any knowledge of the time. Moreover, to establish the robustness of this approach, architecture with different datasets are cross-examined [20].

4.3 Environmental Impact Predictions

Environmental impact predictions address the environmental impact of transportation systems and municipal solid waste management. These predictions can be modeled using AI techniques, including deep learning, machine learning, and reinforcement learning. AI techniques are employed to model the time-series air pollutants, which are fed to XGBoost for transportation system predictions and pollution modeling. Deep learning-based seq2seq models successfully predict the time-series environmental impacts of municipal solid waste management systems. Random forest and SVR are employed to forecast the environmental impact of multi-city transportation systems. Reinforcement learning with graph neural networks models the environmental impact from a spatio-temporal perspective. AI in smart cities primarily addresses the urban environmental impact from the temporal aspect.

Environmental impact refers to the positive and negative effects of a service or process on the environment. A positive environmental impact, such as the improvement of ecological quality, is the environmental benefit. Environmental aspects refer to environmental attributes that affect a service or process and can be characterized by the type of source, region, and impact area of the environmental aspect. The transportation system and municipal solid waste management system are the main mass flow services in smart cities. AI-based systems monitor urban transportation and municipal solid waste management from various aspects. AI techniques are employed for the prediction of the environmental impact of these systems due to the quantitative and time-sensitive characteristics of the environmental impacts of the transportation system and the municipal solid waste management system. Time-series prediction has received increasing attention, and AI techniques, including learning methods and deep learning methods, are employed to model the time-series air pollutants because of their superior interpretability and efficiency [9]. It has been shown that the time-series prediction task is modeled with long short-term memory to predict the time-series environmental impacts of transportation systems, while the predictions of CO, NO_2, O_3, PM10, and PM2.5 are used to further model the occupancy of taxi drivers and thus implicitly prevent rise users through reinforcement learning.

An AI-based modeling approach using random forest and support vector regression to forecast the environmental impact of multi-city transportation systems on land occupancy on-edge accounting, energy consumption, and CO_2 emission is proposed. Reinforcement learning with graph neural networks is employed to model the environmental impact of the metro transportation systems from a spatio-temporal perspective by the topology structure of transportation modes and land-use distribution [21]. The smart city service, data type, and AI technique type are reviewed in detail. AI in smart cities mainly addresses the urban environmental impact from the temporal aspect [22].

5. OPTIMIZATION TECHNIQUES

Optimizing various operations is essential for the effective and sustainable functioning of smart cities. Large amounts of data are generated from the various sensors and Internet of Things (IoT) devices deployed throughout the city and optimization algorithms take advantage of these data to improve quality of life within these cities. A Smart City is thoroughly investigated from an optimization perspective, with detail on relevant and widely used algorithms and models. A comprehensive review of the discipline is also provided, reporting on current research, open problems, as well as a number of avenues for future work [23].

Optimization cases within smart cities are examined. The applications within each case are reviewed, categorizing applications based on both the objectives of the optimization problems and their constraints, with a focus on the different aspects of the city and their operations. A literature survey of optimization algorithms that have been used within the discipline is also presented, including detail on commonly used proprietary and open-source solvers [24]. The work efforts of the Smart Cities Initiative are discussed, as well as open data platforms and the data they have made available for further research into population and socioeconomics of cities.

The present literature is covered, discussing the modeling and solution approaches of both academic and industry sourced works. Optimizing the routing of city buses is discussed, including a robust and adaptive algorithm for planning multi-horizon bus and driver schedules. The design and location of an eco-bicycle system is covered, detailing a novel mixed integer quadratic programming model to optimize the location of public bike stations. Finally, human mobility analysis and prediction is discussed, including a multi-modal graph deep learning approach for spatiotemporal prediction of human mobility based on heterogeneous data sources. As shown in Table III.

TABLE. III. OPTIMIZATION TECHNIQUES AND THEIR APPLICATIONS IN SMART CITIES

Technique	Description	Application Area
Genetic Algorithm	Mimics natural selection to find optimal solutions	Resource allocation, traffic signal timing
Linear Programming	Solves optimization problems with linear constraints	Energy distribution, waste collection routing
Reinforcement Learning	Learns by trial-and-error interaction	Autonomous vehicles, smart grids
Graph Neural Networks	Models relationships between entities	Spatio-temporal mobility prediction

5.1 Resource Allocation Models

The section on ”Resource Allocation Models” discusses one of the major application areas of optimization in smart cities. Resource allocation problems arise in many domains including public transport, resource distribution in power networks and drones, etc. In smart cities, shrinking budgets with increased urbanization have necessitated more efficient monitoring of the usage of their resources. The objective here is to provide an overview of optimization approaches that are used for resource allocation in the IoT enabled smart city development domain. This overview consists of resource allocation problems in several application areas including smart energy, intelligent traffic, waste collection, smart taxis, the allocation of drones, food distribution, etc. The city’s resources can be physical infrastructures or even services, it is more common to optimize the fleet size and the allocation of the resources. The algorithms used to solve these optimization problems range from combinatorial algorithms to event-simulation based algorithms [24]. As shown in figure 3

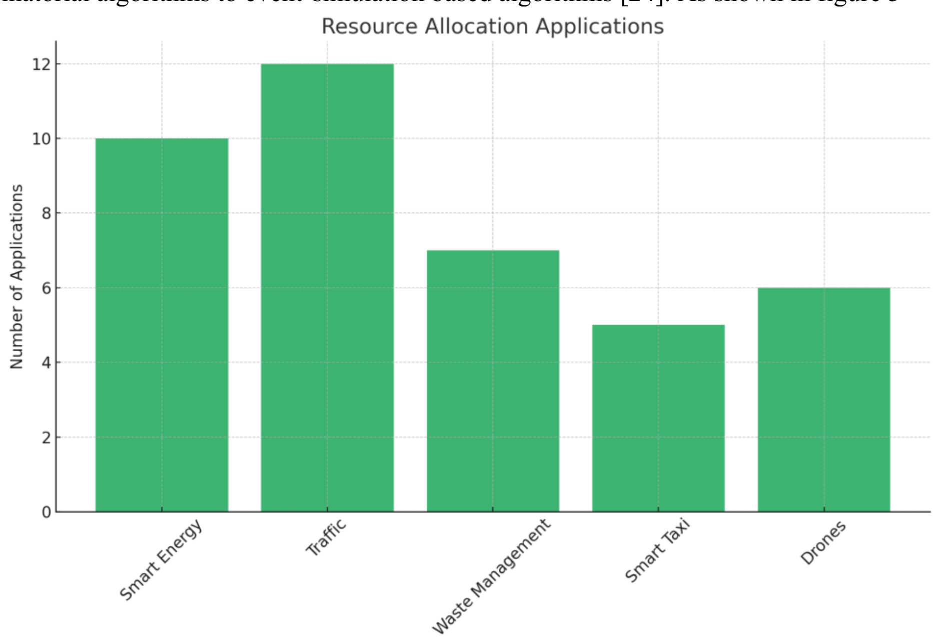

Fig. 3. Resource Allocation Applications in Smart Cities

The major ’IoT-enabled Smart City Resource Allocation Optimization Applications,’ on resource allocation in smart cities were classified into five major subcategories including ”Smart Energy,” ”Traffic,” ”Waste Management,” ”Smart Taxi,” and ”Drones,” ”Drone Delivery,” and ”Food Delivery.” Subcategories and numbers of included applications, objectives, and constraints, are shown in Fig 15. The Mathematics of Resource allocation optimization problems, are highly diverse in form, and computationally ”intractable.” How combinatorial resource allocation optimization problems are solved mathematically varies, from ”exact methods” to ”approximate methods.” Since the majority of resource allocation optimization problems make the ”myopic” (Greedy) assumption, it is more optimal to use the ”planning horizon” for considering methods that are (near) optimal for the relaxation problem, after evaluating the physical, rational or complexity constraints for pre-reserved resource allocation.

5.2 Energy Management Systems

Cities consume more than 70% of the world’s energy and account for 75% of global CO2 emissions. Therefore, to reduce energy costs, environmental and economic sustainability in cities, and increase the quality of life for citizens, energy management in cities is becoming a crucial issue [25]. It should be addressed the energy management and optimization in a smart city context. Smart cities are expected to address the data privacy concerns and apply AI techniques to processes like transactive energy management, prediction of the system, early warning systems for waste management, traffic forecasting and developing urban cooperation planning strategies, smart posters, and smart tourist tools [26].

Energy management and optimization in cities consider a system where energy flows from the Distribution System Operator (DSO) to consumers, e.g., a commercial multi-floor building complex, campuses, etc. These consumers manage their energy forecasting, pricing, and consumption by price forecasting, load consumption, and limit transparency. AI hosts a crucial role here in these intelligent processes. Techniques based upon un-supervised learning, such as clustering, can be used for finding neighborhoods. Enclaves of energy demand with comparable load profiles can also be considered when anticipating pricing policies. There is therefore a need to tackle the batteries and energy storage management. The placement of such devices and energy storage devices is crucial and must take into account other aspects besides the mere economical ones. For example, profitability for the installation should also take into consideration limits in the maximum required power of the consumption nodes.

Energy management in residences can be divided into two categories: demand control and supply optimization. The demand control identifies the critical periods during which the energy load is excessive and seeks to move the major energy loads to periods of lower loads. Common approaches for this process use optimization techniques with heuristics or exhaustive search, which are computationally expensive. There are also approaches that consider a model of the energy mesh and energy status of the supply. They point out that in the past ten years there has been a remarkable increased interest in techniques based purely on AI for the operation of energy management services in the context of a transactive system.

5.3 Transportation Optimization

Transportation optimization problems in the smart city domain can vary in terms of input, output, constraints and objectives. Urban traffic control systems are employed to estimate the traffic flows at different intersections and adjust the signals accordingly in order to optimize citywide travel times. These systems can work in both a closed-loop and open-loop manner where a closed-loop system adjusts the signal timings of the intersections based on the current travel time estimation and a real-time data stream [24]. An open loop system optimizes a zero-initial traffic flow model which is validated with a static dataset. Optimization of the closed-loop control is NP-hard but an approximate solution is found with a bio-inspired heuristic known as reactive island algorithm on various topologies including realistic city layouts. Measuring the impact of any transportation intervention on traffic before implementation is inherently an optimization problem and can be modeled as a simulation-based Markov Decision Process. It involves discretizing types of possible interventions in a computationally expensive manner. It employs a fixed-point free incremental approach to model and balance the proliferation of the interventions and their exposure to the agents.

Congestion pricing at high-rise buildings is another transportation optimization problem where, agents are users of IT systems in high-rise buildings of a business district. The users of these systems have a choice to travel using the service elevators offered by the building owners or using their own personal transportation systems which are subject to street-level traffic. In order to encourage users to prefer the building owner's services, pricing is resorted. Non-linear and non-separable pricing consumer strategies of the building owners are employed to encourage the change. Considerations include satisfaction levels of both agents and owners, traffic density and capacities of different elevators and streets. A hybrid optimization algorithm is used which combines Genetic Algorithm's search abilities and Simulated Annealing's local improvement capabilities to find the consumer strategies that approximate competitive equilibria.

6. CHALLENGES AND LIMITATIONS

Despite the high expectations of Smart Cities, several barriers and challenges remain to be solved. As its name suggests, Smart Cities inherently depend on the proper use of data, which leads to the importance of urban data resolution. In terms of input, not only historical urban data but also real-time data such as detection data and feedback data are necessary. In terms of output, prediction data is necessary to address the limitations of conventional analysis methods not considering future scenarios. Furthermore, some expectations about Smart Cities are just wishes or quasi-promises that are hard to achieve in practice. For example, sensing data collection is only a consequence of the number of mobile sensors and data custodians. Thus, that data volume would not guarantee better and richer data. Analyzing huge city data can be time-consuming and memory-intensive. Moreover, a decision-making process considering too many scenarios may be inefficient and unreasonable. Focusing only on a few topics, models, or regions might be more efficient [27].

The social nature of cities brings other challenges. For a long time, city data has been stored in silos. Each organization has its own data managed in its own way following its own privacy policy. Data sharing is basically limited in speed, completeness, granularity, comprehensibility, and usability. Each level (daily, monthly, yearly, etc.) of data collected by one organization is often inappropriate for another organization where a different level of data is required for that. The organizational barrier still remains despite the clear expectation of data transparency. Policies or regulations to enforce effective data sharing among those organizations are necessary. In addition, from a user perspective, the question of who would govern Smart Residences, which are automated cities, still remains.

Urban data in smart cities is huge and dynamic, and data contamination such as outliers, missing, or duplicate data often occurs. Data cleansing and pre-processing is critical to address these contamination problems. Such operations are tedious and cumbersome and need to be automated or semi-automated. Hardware and software barriers also pose serious issues. Past efforts for supervision level monitoring and control of complex city systems were fragmented and dependent on dedicated tools, leading to weak interoperability. Such discrete systems have caused compatibility and interactability issues for cities as a whole. To this end, a unified framework to integrate the existing monitor and control tools with open APIs is necessary.

7. FUTURE TRENDS IN AI FOR SMART CITIES

Currently, cities are the focal point of receiving huge amounts of diverse data. Homogeneous and heterogeneous data are produced and generated by the execution of day-to-day activities in cities. This data comes from various sensors, cameras, temperature recorders, utility telemetry loggers, RFID tags, etc. Using advanced computing technologies, the enormous data generated is being rapidly processed in near real-time either in the cloud or at the edge being deployed. Such processing results in improving the regular utilities of cities such as transportation, traffic management, etc. On top of that, AI-assisted technologies are being established to process this data and the potential of such technologies is just beginning to be realized. The varied types of data generated in cities, and the processing and analysis technologies have been surveyed along with various smart city techniques. AI-assisted technologies and their use in cities are being identified including such technologies and while an extensive review is being provided to distinguished patterns of care-use in order to detect possible gaps or necessary research areas, emerging business potential, local specificities, city characteristics, privacy-preserving techniques, etc. The bottom line is the possible transferability of state-of-the-art technologies to address everyday problems which are not only local but common in majority of the cities.
Considering the fact, papers have been analyzed and filtered upon six aspects: (i) Use-Mission-Objective (ii) Technological Domain (iii) Considered AI technology (iv) Technological Maturity (v) Decision making perspective and (vi) Considered Area of Application. All aspects as a holistic understanding and successful integration is required by a city or its authorities for implementing such AI technologies. While there may be confusion or judgment difficulty considering them all or few, in the research, emphasis was placed on providing effective tools to easily filter papers/models upon the above six aspects and the need output as a useful starting point to select one or more efforts of this work.

8. CONCLUSION

With the application of various techniques and technologies in smart cities, there is a need for evaluating, implementing, and developing technologies and algorithms for data gathering, pre-processing, processing, analysis, visualization, prediction, and automation of domain-wide smart city data. The vast amount of data produced in the smart city enhances its operational efficiency and reduces costs, enhances citizens' quality of life, and minimizes impacts on the environment. To realize this goal, systems and tools for gathering, collecting, pre-processing, processing, analyzing, visualizing, monitoring, predicting, and optimizing smart city data need to be developed. In summary, massive quantity and variety of data from smart city domains can be processed by data-driven algorithms and systems, and the smart city can be made smarter by such processing. This review systematically grouped the techniques and technologies for urban data processing and prediction into four categories: intersection data processing and analysis, data sharing and fusion, mobility data prediction, and urban data monitoring and optimization techniques. For each category, a full review of state-of-the-art techniques and systems was provided, and the relevant datasets were listed. It is anticipated that this review will provide useful insights into smart city data processing, prediction, and optimization techniques. On the other hand, there are shortcomings in the current techniques and systems related to urban data processing, prediction, and optimization. Challenges in urban data processing and optimization techniques include domain relevance transferability, variational factors in optimizing tasks, data quality, heterogeneous data fusion, and massive data processing. The above challenges need to be further investigated in order to make smart cities more intelligent [1].

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Conflicts of Interest:

The authors declare no competing interests.

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