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Multiscale Modeling in Smart Cities: A Survey on Applications, Current Trends, and Challenges

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Abstract

Megacities are complex systems facing the challenges of overpopulation, poor urban design and planning, poor mobility and public transport, poor governance, climate change issues, poor sewerage and water infrastructure, waste and health issues, and unemployment. Smart cities have emerged to address these challenges by making the best use of space and resources for the benefit of citizens. A smart city model views the city as a complex adaptive system consisting of services, resources, and citizens that learn through interaction and change in both the spatial and temporal domains. The characteristics of dynamic development and complexity are key issues for city planners that require a new systematic and modeling approach. Multiscale modeling (MM) is an approach that can be used to better understand complex adaptive systems. The MM aims to solve complex problems at different scales, i.e., micro, meso, and macro, to improve system efficiency and mitigate computational complexity and cost. In this paper, we present an overview of MM in smart cities. First, this study discusses megacities, their current challenges, and their emergence to smart cities. Then, we discuss the need of MM in smart cities and its emerging applications. Finally, the study highlights current challenges and future direc-

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tions related to MM in smart cities, which provide a roadmap for the optimized operation of smart city systems.

Keywords: Multiscale modeling; Multiscale Systems; Megacities; Smart Cities; Multiscale Modeling Applications;

1. Introduction

The population is increasing everyday and more than 50% of the total population is living in urban areas [1, 2, 3]. Urbanization is one of the most important phenomena in today's society and the rate of urbanization continues to increase; therefore, the 21^{st} century is often referred to as the century of cities [4, 5]. Around the globe, there are 30 megacities with populations of around 10 million or more, larger than several countries [6]. However, megacities are considered complex systems that face challenges such as overpopulation, lack of and poor urban design or planning, poor mobility and public transport, poor governance, climate change issues, poor sewerage and water infrastructure, waste and health issues, unemployment, and so on. The concept of a smart city is flourishing in developed and modern countries. The key infrastructure elements present in a smart city are affordable and smart housing, sustainable power supply, efficient public transport and urban mobility, solid waste management, sanitation, and factors that contribute to a clean environment for citizens. In addition, robust information technology and digitization, the internet of things (IoT), artificial intelligence (AI), and machine learning (ML) techniques are used to operate and execute all the functions of a smart city smoothly and efficiently [7].

The use of these components and services provided in a smart city to citizens make it a complex adaptive system [8, 9]. In a complex adaptive system, the elements, also called agents, are not fixed and they learn and adapt as they interact with other agents. A complex adaptive system is a framework for studying, learning, explaining, and understanding the agents of that system. These agents can range from groups of intelligent cars, humans, and animals to anything that can generate an emergent pattern and self-organization through correlated feedback. Therefore, a smart city model views the city as a complex adaptive system consisting of services, resources, and citizens that learn through interaction and change in spatial and temporal domains.

Motivation and Related Works: All these features of dynamic development and complexity are key issues for city planners that require a new modeling and systematic approach. A MM is an approach that can be used for better understanding of complex adaptive systems [10]. The MM is a new type of modeling that uses multiple models at different scales simultaneously to describe a complex adaptive system [11]. These models at micro, meso, and macro levels focus on different scales of resolution. Thus, MM in smart cities paves the way for many emerging intelligent applications that aim to achieve reduced computational complexity and cost, reliability, sustainability, and many more in smart city subsystems, including smart transportation, smart power system, smart healthcare, smart community, and smart industry. In the literature, there are several surveys/reviews on MM, either covering aspects of the multiscale modeling paradigm, such as architecture, classifications, principles, and frameworks, or focusing on different application domains. For example, the authors of [12, 13, 14] reviewed MM for emergent behavior, complexity, and combinatorial explosion, while Jebahi *et al.* presented a survey on MM for complex dynamic issues [15]. Welsh *et al.* focused on the applications and benefits of MM in the food drying industry [16], while the work [17] presents an overview of MM in behavioral, biomedical, and biological fields. Furthermore, the study presented in [18] reviews the application of MM in food engineering and Li *et al.* review and present challenges related to polymer dynamics [19]. As per the best of our knowledge (based on the literature survey), there is no survey/review work in the literature that focuses on MM in smart cities.

Contributions: Motivated by the above, this article attempts to review MM in smart cities. We start with the introduction of megacities and their transfor-

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mation into smart cities by discussing various challenges associated with it. We then examine the emergence of smart cities, their characteristics, and five generations 1.0 to 5.0. We also provide a detailed overview of MM, classification, and their emerging applications in smart cities, including urban expansion modeling, social systems modeling, healthcare systems modeling, and traffic control modeling. Finally, current challenges and future directions in the field of MM and smart cities are presented, including smart mobility, monitoring of urban infrastructure growth, integration of ML and MM, uncertainty quantification, and growing and pruning multiscale models.

Outline: In Section 2, megacities, their challenges, and its transformation towards smart cities are unfolded. The next Section introduces MM in smart cities along with its classifications, i.e., sequential and concurrent MM. Section 4 presents some emerging applications of MM in smart cities and Section 5 discloses current challenges and future directions related to MM. At the end, Section 6 concludes this study.

2. Megacities and its Challenges: Towards Smart Cities

In this section, we uncover the background of megacities along with their key challenges, and then the introduction of smart cities has been unfolded.

2.1. Background of Megacities

The city has significant importance for growth as it carries most of the human activities, i.e., cultural, economic, and social. In other words, it is the engine and crystallization point of cultural and social change. Today, urbanization is accepted as an important phenomenon of society and economy around the globe [20]. Urbanization's trends continue to increase worldwide so that the current era (21st century) is often referred to as the century of the city [21, 22]. Fig. 1 presents the trends of urban, rural, and total population around the globe. In addition, this figure also shows the urbanization trend (red curve),

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which is continuously growing. It can also be seen from the figure that in 1950, the population in rural areas was more than twice the size of the urban population; however, due to the increasing pace of urbanization, the urban population has been increasing since 2005 and will be more than twice the size of the rural population in 2050. The high pace of urbanization is the emergence of megacities, where more than 10 million people live in a single megacity [23]. According to [6], there are 30 megacities in the world with combined residents of more than 300 million, and they are greater in size than many countries. Therefore, in this study, we use the definition of megacities as presented in [24, 25, 26].

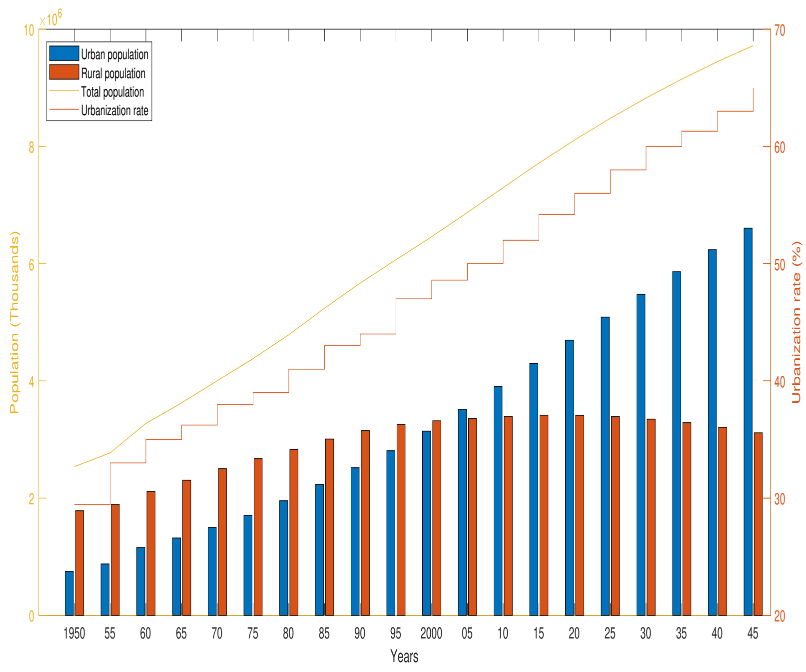

Figure 1: Evolving urban and rural populations along with the growth of urbanization around the globe [27, 20]

Definition 1. *Megacities are dense centers of population, economic activities, and pollutant emissions, and at the same time areas where effective pollution*

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control strategies could maximize benefits.

Basically, the megacities act as magnets that attract residents from rural areas to work, seek job opportunities, and improve their standard of living. They can earn more in cities than in rural and remote areas. Although people move to cities because of a better standard of living and many other opportunities, there are many problems raised by rapid urbanization, such as deterioration of the ecological environment, health problems, traffic congestion, unusually fragile infrastructure, the increased crime rate in cities, environmental problems, fierce competition due to low resources, living conditions of migrant workers, etc. [28, 29]. Some of the major challenges of megacities are discussed below.

2.1.1. Mobility Issue

Megacities face severe mobility problems due to poor transportation systems [30]. Especially in Asia, where the population is high relative to other contents, congestion is common in the megacities. Due to lack of planning and inefficient control of transportation systems, it has become a Herculean task for ordinary citizens to drive a few miles. In [31], the authors demonstrated a 14.3-30.4% increase in carbon emissions during peak hours using an open-access congestion index in the road network of Shenzhen, China. Lee *et al.*, in a case study of Seoul, focused on development around transportation hubs through the provision of improved public facilities, pedestrian improvements, and proper implementation of multi-level planning to achieve desired outcomes between metropolitan and stakeholders [32]

2.1.2. Health Issue

Chaotic traffic and environmental problems cause air, noise, and other pollution that can lead to mass health challenges. These challenges include respiratory problems, high blood pressure, heart disease, etc. Mapar *et al.* [33] had given a composite index based on three community aspects: health, safety, and environment. The result showed that the health-environment had the highest score for the municipality of Tehran, Iran. According to Kelly and Fussell,

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air pollutants in megacities have a significant negative impact on public health and are not only difficult but also expensive to control. The four main sources contributing to human health problems are biomass emissions from urban households, air pollution from megacities, desert storms, and wildfires, which need to be managed by promoting smart cities [34].

2.1.3. Housing Issue

The housing projects that are being carried out in the megacities are not able to meet the growing needs of the population demands. Moreover, the illegal construction of shopping malls and hospitals in busy areas in most developing countries violates urban planning rules and building codes. Tian *et al.* focused on the housing problems in China's megacities and gave a theoretical framework for rental housing and land supply [35]. Housing problems are not limited to land supply, but also include water issues [36], energy shortages [37], and sanitation [38].

2.1.4. Environmental Issue

Lack of planning and uncontrolled urbanization and settlement of megacities have led to severe environmental problems. Megacities have become the most polluted cities with piles of garbage piling up in every nook and corner. In developing countries, due to the lack of a sewage system, a light downpour causes sewage to erupt from everywhere and the streets become the sight of a flood. Li et al. noted in their review article that air pollution is one of the biggest problems of megacities in China. [20]. Khan and Javaid in [39], focused on environmental crimes related to carbon and other emissions in the use of energy from renewable and non-renewable energy sources.

2.1.5. Security Issue

The law and order situation is also a major problem in megacities. Incidents of cell phone robbery and robbery with the use of firearms are rapidly increasing in the outskirts of cities in developing countries. Peng et al. [40] applied a population-based ant colony algorithm to identify ecological security

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patterns based on corridors and restoration of 34 key points during a case study of Beijing city. In addition to physical security, as mentioned in [41], there are other challenges, including water security [42], food security [43], and natural disasters such as flooding [44].

It is pertinent to mention here that the problems of megacities are inherently neglected, interconnected, and complex. Therefore, the vision of the multiscaling approach can play an important role in the transformation towards smart cities, which uses a more efficient approach to culminate all these problems.

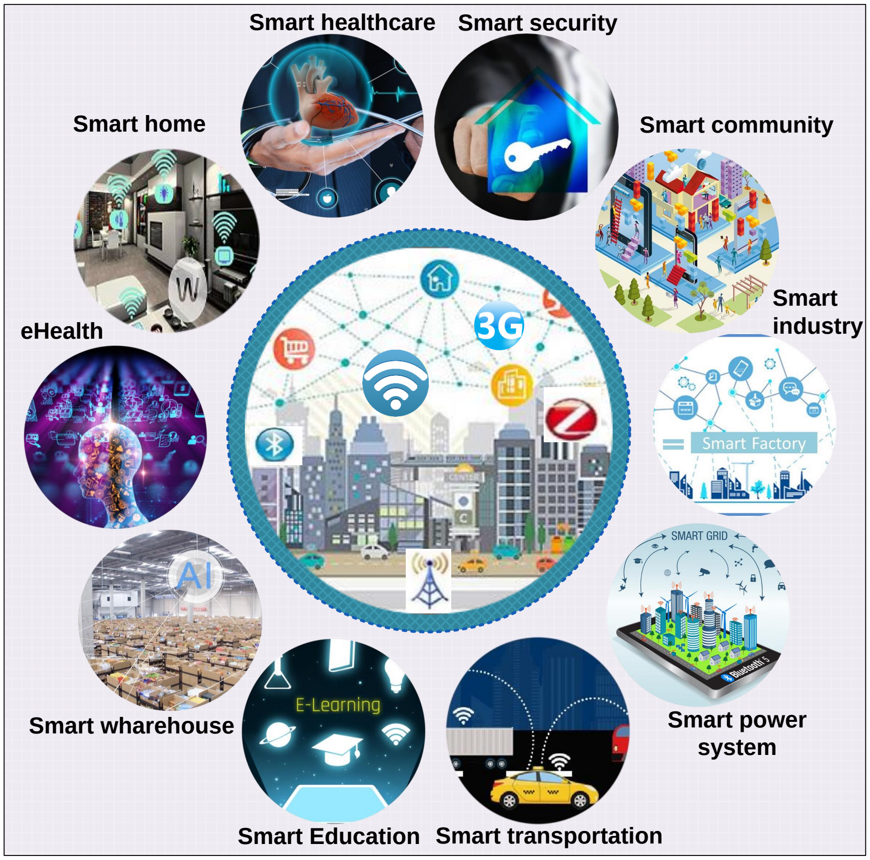

Figure 2: A generic composition of smart city architecture

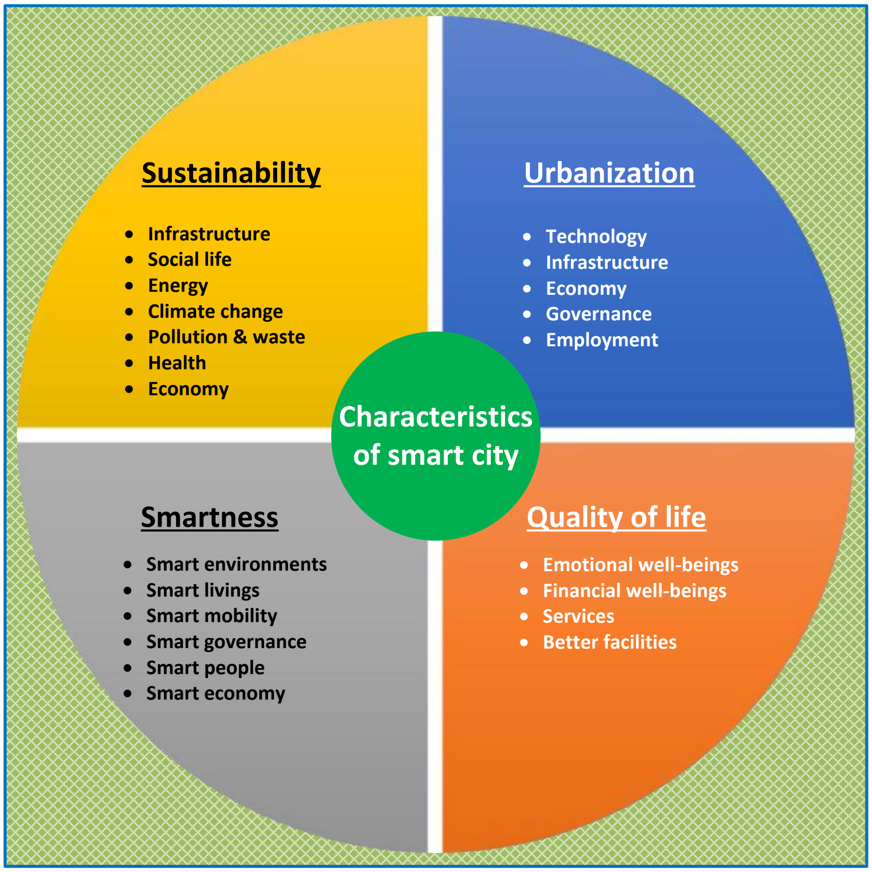

Figure 3: Characteristics of smart city

2.2. Introduction to Smart City

The concept of connecting several devices through state-of-the-art network became very praising with the advent and advancements of smart devices. The IoT emerged from the development of traditional networks connecting millions of smart objects. Thanks to the great attention of various stakeholders, the IoT has spawned impressive applications as it spreads, such as smart healthcare, smart warehouses, smart cities, smart homes, and so on [45, 46, 47]. Smart cities have come into focus in recent decades due to drastic urbanization around the globe. The implementation of city operations with the help of information and communication technologies (ICTs) has made cities effective in several ways, i.e., smart transportation, smart healthcare, smart energy, and smart shopping. But the inclusion of ICT to carry out urban operations does not yet imply the full interpretation of smart cities [48]. The smart cities were favored among the other city models, i.e. digital city, information city, and telicity, as it represents the abstraction of all the other models [49]. Since smart cities is an application domain of the IoT [50], therefore the operating mechanism of smart cities is the same as that of IoT.

The smart city concept integrates information and communication technology (ICT) and various physical devices connected to the IoT network to optimize the efficiency of city operations and services provided to citizens. Broadly speaking, a smart city is an urban area that uses ICTs and various types of IoT-based sensors to collect data and then use the insights gained from that data to efficiently manage assets, resources, and services with the goals of improving city operations performance and quality of service (QoS). This includes data collected from citizens, devices, and assets that are processed and analyzed to monitor and manage traffic and transportation systems, power plants, utilities, water supply networks, waste management, crime detection, information systems, schools, libraries, hospitals, and other municipal services. A comprehensive definition of a smart city is given by [51, 52] as:

Definition 2. *A smart city is an advanced modern city that utilizes information and communication technologies and other technologies to improve the quality of life, competitiveness, operational efficacy of urban services while ensuring resource availability for present and future generations in terms of social, economic, and environmental aspects.*

There are several components that build smart city architecture, i.e., smart healthcare, smart homes, smart security, smart community, smart industry, smart energy, smart transportation, and smart education system, as presented in Fig. 2.

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2.2.1. Characteristics of Smart City

There are four major attributes of smart city, including sustainability, smartness, urbanization, and QoL [49], as depicted in Fig. 3.

Sustainability: The sustainability of a smart city relates to urban infrastructure and governance, energy and climate change, pollution and waste, and social issues, economy, and health.

Urbanization: The urbanization aspects of a smart city include several aspects and indicators, such as technology, infrastructure, governance, and economy.

QoL: QoL can be measured in terms of the emotional and financial well-being of citizens.

Smartness: The smartness of a smart city is conceptualized as the effort to improve the social, economic, and environmental standards of the city and its inhabitants. The various aspects of smartness of a city that are frequently cited include smart environments, smart living, smart mobility, smart governance, smart people, and smart economy [49, 53]. A *smart environment* represents an attractive and clean natural state with the least pollution and sustainable management of resources. Health conditions, the standard of living, safety, cultural and educational facilities are the key indicators contributing to *smart living*. The key factors for *smart mobility* are safe, sustainable, and innovative transport systems, and the availability of ICT infrastructure availability. *Smart governance* is concerned with a transparent government that involves its citizens in decision-making and provides easy access to public and social services. *Smart people* are characterized by creativity, skill level, open-mindedness, an affinity for learning, and participation in public life. The elements that contribute to creating a city with a *smart economy* are entrepreneurship, labor flexibility, productivity, and international embeddedness.

2.2.2. Smart City Generations

This section discusses the five generations of smart cities range from 1.0 to 5.0, as depicted in Fig. 4.

Smart City 1.0: Smart city 1.0 is characterized by technology vendors driving

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the adoption of their solutions in cities. These cities are often criticized for their technology push and the influential role of large companies, such as IBM and CISCO. The smart city 2.0, unlike the technology providers in smart city 1.0, is led by a government agency, mayors, and city councils.

Smart City 2.0: Smart city 2.0 is appropriate when technological tools are explicitly developed to address problems such as pollution, sanitation, health, and transportation in consultation with citizens. Unfortunately, citizen participation in informal decision-making structures and assemblies is poor and appeals only to a small minority [54]. While smart city 1.0 and 2.0 are driven by technology and government decisions respectively, smart city 3.0 is driven by citizen/user expectations.

Smart City 3.0: In Smart city 3.0, the public should be able to express their opinions, with the government acting as a facilitator and definer of government-specific user needs [55]. Thus, a smart city represents the entire connected ecosystem that brings together the technologies, solutions, actors, and audiences in the smart city, including IoT, 5G connectivity, transportation and smart automotive, energy and utilities, health and public safety, artificial intelligence, and data analytics [56].

Smart City 4.0: By adopting industrial revolution 4.0, the benefits of smart cities are appreciated to overcome the cost of the city with the platformization of the city [57]. smart city 4.0 represents the best of the past, for instance, the technological disruption of generation 1.0, the individualization of 2.0, and the engagement of 3.0; however, it adds two critical success factors: a holistic approach and the challenge of integrating solutions [58]. The holistic approach aims to integrate not only new technologies with old, but also new technologies with technologies that may not have been developed yet. Moreover, successful city leaders understand the opportunities and limitations of new technologies and appreciate the impact that smart cities technologies can have on their communities, while also recognizing that these positive impacts may not be felt equally by all members of the community.

Smart City 5.0: Smart city 5.0 is characterized by the cooperation between humans and Artificial Intelligence system [59, 9], and can harmoniously balance all aspects of life and conflicting interests of different city stakeholders. The city 5.0 provides the approach that can help to find a "consensus" between different services and, more importantly, with citizens. As it reflects real-life, it should not only take into account past or current information, but constantly changing interests, preferences, and constraints of all actors in real-time, which should be continuously identified, analyzed, transformed into plans, implemented, and controlled.

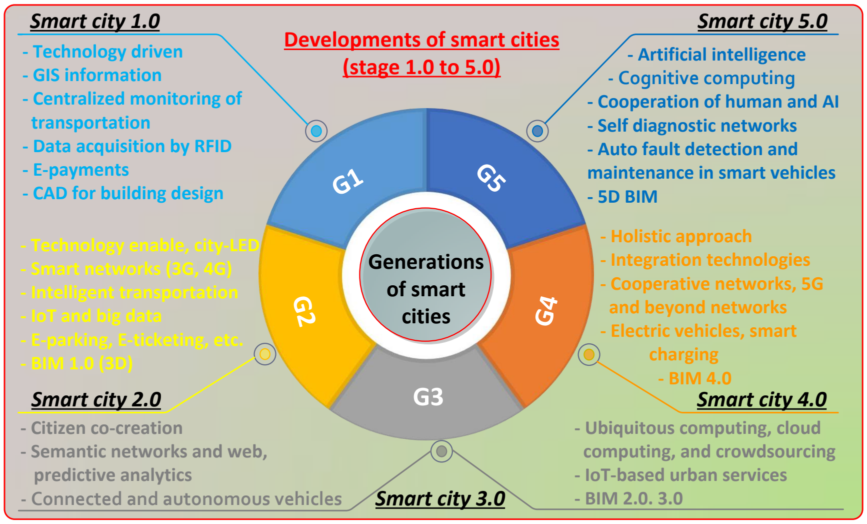

Figure 4: Five generations of smart city

3. Preliminary on Multiscale Modeling

Multiscale phenomena have become a part of our daily lives, for instance, we have divided our time into years, months, and days based on the multiscale dynamics of the solar system. Similarly, our hierarchical structure of society into continents, countries, states, and cities is also based on the multiscale geographic earth structure [12]. The term "multiscale modeling (MM)" was coined in the early 1980s and it can be defined as: a modeling approach in which multiple

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models are used simultaneously at different scales to describe a complex system. The term MM was coined in the early 1970s and the number of articles has grown tremendously over time, as shown in Table 1.
The authors of [60] define multiscale modeling (MM) as:

Definition 3. *MM is an approach that deals with several different scales in a single framework.*

In a complex system, objects consist of several interrelated parts. Complexity is classified into two different types: complex physical system (CPS) and complex adaptive system (CAS). CPS has fixed properties like atoms and is expressed by differential equations. In CPS laws, the elements change with time; the only element that changes is the positions of the objects. In CAS, however, elements, also called agents, are not fixed and they learn and adapt as they interact with other agents [61]. Complex systems focus on different scales of resolution. These models are eventually combined to produce more accurate results than if only one scale approach is taken. Both accuracy and efficiency can be achieved when using MM in complex systems. In addition, the topic of multiscaling covers three different areas, including multiscale analysis, multiscale models, and multiscale algorithms. A multiscale analysis is a fundamental component of MM that allows us to understand the relationship between different models at different scales. Multiscale models help us to build a model that consists of different models at different scales. Finally, multiscale algorithms are developed by employing multiscale ideas. Numerical simulations of MM are typically divided into four different scales, including nanoscopic (10^{-9}), microscopic (10^{-6}), mesoscopic (10^{-4}), and macroscopic (10^{-2}) [15].

Piro et al. in [62] stated that the use of ICT has enabled an era of advanced services to improve living standards. The research community has identified information services that include starting new businesses in a country, making reservations for medical examinations, a system for remote patient monitoring, and waste disposal by the city administration. The authors of [63] analyzed

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Table 1: Number of published articles on “MM” on sciencedirect.com

Years	**Number of articles**
1976-1980	65
1976-1980	93
1981-1985	120
1986-1990	198
1991-1995	638
1996-2000	1227
2001-2005	2494
2006-2010	5862
2011-2015	10315
2016-2020	20237

the case of Barcelona, the second-largest city in Spain, in terms of becoming a smart city. The aim of the research was to find out the necessary infrastructures/assets requirements for the transformation of Barcelona into a smart city and to identify the challenges during the transformation. The methodology adopted was a case study approach using interviews, observations, site analysis, and the use of other various sources. The Barcelona model of the smart city consists of four main components, including 1) Smart People, 2) Smart Economy, 3) Smart Living, and 4) Smart Governance. Smart Governance includes better and free access to government information through the Open Data project. Smart Economy consists of providing an interactive platform for individuals, companies, and enterprises to interact, collaborate and boost their businesses. Smart living involves smart public transportation. Smart People involves digital literacy. The three cornerstones of the Barcelona smart city model are ubiquitous infrastructures, human capital, and information. Infrastructures include buildings, roads, and fiber connections. Information includes data that comes from sensors, Open Data, or social media. Human capital are agents that help

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make the city smarter. Components of Barcelona smart city Strategy include smart labs for living, smart infrastructures, neighborhoods, new and fast services for citizens, data that is open and accessible to all, and the management of the smart city.

3.1. Categories of Multiscale Modeling

This section unfolds two main categories of MM, i.e., sequential and concurrent.

3.1.1. Sequential Multiscale Modeling

In the sequential MM, the microscale models are used first to precompute and generate the data inputs that can then be further used for the macro model. In this way, the information is communicated from lower to upper scales and operations/activities at the upper levels wait until operations at a lower level are completed. Based on the above fact, sequential multiscale models are also called "parameter passing" because some parameters are passed between the macro and micro scale models [11]. Fig. 5 presents a typical example of sequential MM, where it can be seen that vehicle speed, weather forecasting, traffic control, and navigation control operations are performed at the micro level; subsequently, based on data given by micro scale, traffic flow prediction, travel time prediction, and routs are optimized at meso scale. Eventually, based on input from meso scale, whole traffic is managed and new policies and rules are developed.

3.1.2. Concurrent Multiscale Modeling

In the concurrent MM, both micro and macro models operate simultaneously and the data required by the macro model is generated on-the-fly from the micro models. The concurrent model is further divided into two subcategories called "partitioned-domain" and "hierarchical" methods. The partitioned-domain concurrent approach deals with the physical problem that is partitioned into two or more contiguous regions, where a different model scale is used in each region. On

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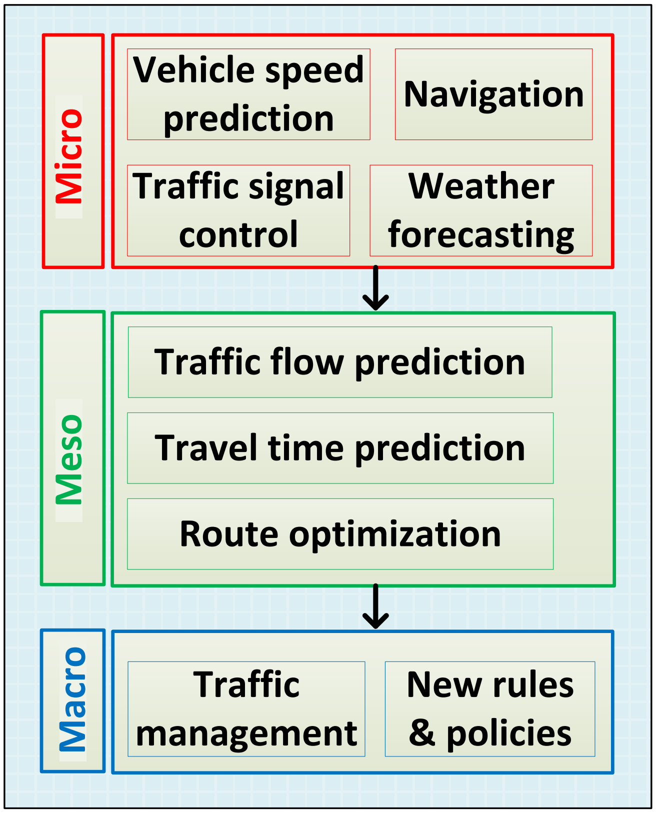

Figure 5: A typical example of sequential multiscale modeling for smart transportation systems in smart city environment

the other hand, hierarchical methods, use both scales micro and macro everywhere [64]. Fig. 6 shows a typical example of the concurrent multiscale model that was developed for social systems [65], where three scales are considered, i.e., micro, meso, and macro. It can be seen from the figure, there are three modeling scales along with decision-makers at a particular scale.

4. Emerging Applications of Multiscale Modeling in Smart Cities

smart cities and MM have emerged due to the rapid progress in ICTs and the need to develop methods that address large problems at different scales to

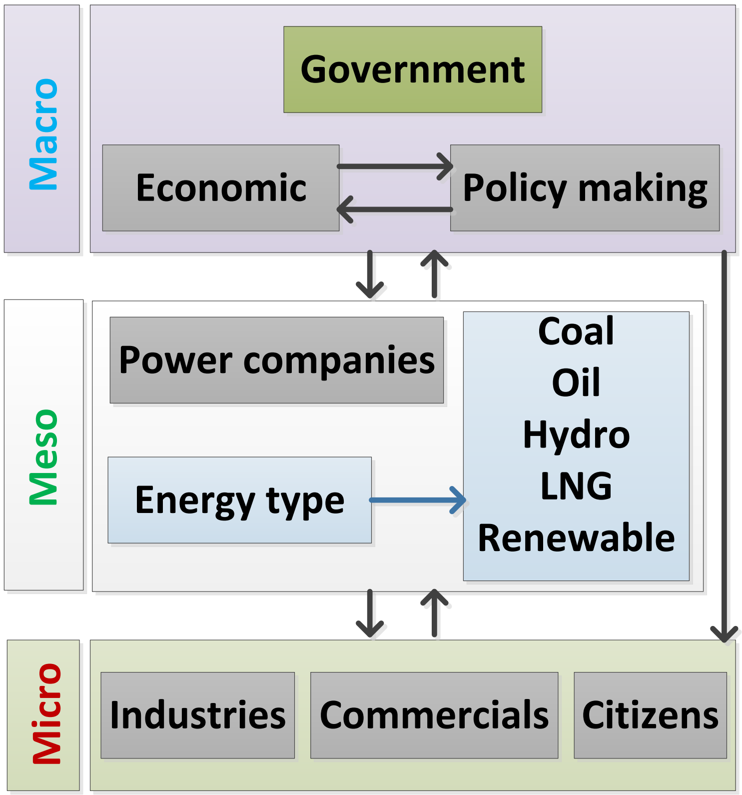

Figure 6: A typical example of concurrent multiscale modeling developed for social systems in smart cities (taken from [65])

achieve efficient outcomes. Currently, MM in smart cities is gradually moving from the conceptual phase to the implementation phase. As the demand for smart cities is increasing everyday, academia and industry are trying to explore various technologies to develop sustainable smart cities. The MM is one of the most important approaches that is widely used in smart cities. In smart cities, MM is adopted in various fields, such as urban expansion modeling, pollution management, disease modeling, crowd modeling, and vehicle fleet modeling.

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4.1. Urban Expansion Modeling

For the growth of urban extensions, there are various factors such as infrastructure, housing, industry, hospitals, population, etc., which need to be monitored from the administrative point of view. Zeng *et al.* used a multiscaling approach to model and monitor the urban expansion of Wuhan city in Central China [66]. Three approaches, including a geographic information system, remote sensing, and spatial analysis, were combined to monitor urban expansion from 1995 to 2010. For the purpose of exploring the driving mechanisms underlying urban expansion, twenty variables were categorized into different groups, i.e., proximity, density, and characteristics. The simulation results showed the supremacy of the spatial regression models, and with the increase in scales, a better fit is obtained. Another study also uses MM to examine the relative importance of policy factors and socioeconomic at different administrative levels on urban expansion and the associated conversion of cultivated land in China [67]. They conduct the analysis for urban hot-spot counties across the country and use multilevel modeling approaches to inspect how policy factors and socioeconomic at different administrative levels affect the conversion of cultivated land over three-time intervals (1989-to-1995, 1995-to-2000, and 2000-to-2005).

4.2. Atmospheric Dispersion Modeling

Measuring air quality by running atmospheric dispersion models is time-consuming. Integrated assessment modeling is a new development for measuring air pollutants, greenhouse gases for a smart environment. Oxley et al. in [68] used a multiscale UK integrated assessment model (IAM) for the UK to measure emissions of sulphur, nitrogen (SO2, NH3, NOx, etc.) in air quality for better health and ecosystem protection. The proposed multiscale IAM is applied in various scenarios, including agriculture [69], road transport [70], and energy projections [71], and compared with other UK models. The experimental results demonstrate the higher performance of their proposed multiscale-based model against its counterparts. Another study [72] also uses MM for the atmospheric environment and it is proved from the results that the proposed approach better solves the diurnal variations in temperature, humidity, and wind speed over complex urban areas.

4.3. Social Systems Modeling

The Super Smart Society is a novel concept that has attracted a lot of attention in Japan. It consists of almost 12 interconnected systems and all systems contain multiple subsystems simultaneously [65]. Furthermore, there are citizens or society at the end of each system. So, it is quite a difficult task to model these kinds of systems. The authors of [65] have developed a multiscale approach for modeling social systems where three steps are proposed, i.e., 1) scale separation, 2) identification of decision-makers, and scale bridging. The first step further contains two phases, the selection of scale separation characteristic and the setting of scale granularity. The scale separation characteristic is selected as the amount of energy. Moreover, the developed model consists of three scales, i.e., macro, meso, and micro.
In the second step (identification of decision-makers), there are three decision-makers in a micro scale, such as citizens, commercials, and industries. In this stage, various decisions are made such as the amount of energy to be consumed, which utility company will supply energy, whether the electricity is safe or not, etc. At the meso scale, decisions are made regarding energy companies and decisions at this scale affect both scales, i.e., upper and lower (macro and micro). The macro scale is responsible for the decisions made by the government.
Finally, the last step deals with the scale bridging, which shows the type of MM (information flow), i.e., sequential and concurrent models (see figures 5 and 6). This study adopts both models for information flow and decisions. Several experiments were also conducted to show the effectiveness of the proposed model, which is confirmed by the results.

4.4. Diseases and Viruses Modeling

The multiscaling approach is widely applied in various fields of biology, i.e., public health management [73, 74], cell to organ modeling [75], MM in medicine

[76]. One of the powerful tools is microrheology, which is used to find out the mechanical properties of living cells. Microrheology deals with the study of cells at different length scales and over different time spans. Biological functions can span a variety of elements, including cell migration, cellular adhesion, and division. Viruses and bacterial cells use the actin polymerization machinery for their growth and propulsion. Cancer is caused by cell migration and eventually leads to metastasis, which results in the death of living organisms. Therefore, cell motility and migration are important areas of biology that cause tumor growth in which MM is applied [77].

Cancer Cell Growth Modeling: Cancer is a disease in which a cell deviates from its normal pathway into adjacent tissue and forms a tumor. Cancer is a complex biological phenomenon that requires a multiscale approach to monitor all activities in which cancer cells communicate with their microenvironment to grow and survive. Masoudi-Nejad et al. in [78] studied cancer cells using a multiscale approach including (micro, meso, and macroscopic scales) in continuation of using various biological modeling techniques including Boolean networks, differential equations, stochastic methods, agent-based systems, etc. Since cancer follows and uses a common progression schedule, it is possible to use an appropriate modeling approach for better clinical outcomes and better understanding of cancer treatment approaches.

MM approaches that incorporate biological and physical modeling are commonly used to study the tumor microenvironment. F. Kunz et al. focused their work [79] on a multiscale approach to melanoma metastasis in which tumor cells interact with polymorphonuclear neutrophils. Finally, the latest technological biochemistry and structural models related to the tumor environment at the micro level and cell growth and population at the macro level have been summarized.

Influenza A virus (IAV) infection has increased rapidly in recent years, and most studies have addressed on one scale modeling either tissue-level or population-scale infection. Murillo et al. [80] reviewed IAV infection and emphasized the use of a MM approach that includes spatial intrahost models and links viral

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load to transmission.

Cardiac Contraction Modeling: Sophisticated and complex cardiac models provide the opportunity to combine biophysical-clinical data using multi-physics and multiscale techniques to better understand the functionalities of the heart. However, coupling different models representing different aspects of cardiac contraction into a single model is one of the most challenging tasks. In [81], Bhattacharya-Ghosh et al. presented a multi-physics and multi-scale parameter model for a cardiac contraction of the left ventricle from the micro (protein level) to the macro (organ level) based on calcium dynamics.

4.5. Energy Forecasting

To cope with the problems of carbon emission and costly power generation in smart cities, the world is moving towards renewable energy sources, solar panel, wind turbine, etc [82]. In particular, electricity generation from solar panels is considered more attractive because there is no cost to operate solar panels other than the initial installation cost [83, 84]. However, since solar energy is significantly affected by weather conditions, accurate and efficient solar energy prediction methods are crucial for managing energy supply with power demand in a smart city. There are many research works that provide various deep learning and machine learning models for predicting solar or wind energy for proper energy supply management [85, 86, 87]. However, the structure of most predictive models is not based on MM. Since it is observed that irregular factors have a negative impact on the prediction results of a very short-term energy prediction, the overall prediction performance is degraded. To solve this problem, multiscale forecasting models are needed. For example, the authors of [84] have developed a deep learning model based on LSTM (Long-short-term-memory (LSTM) with multiple scales, which is able to perform very short-term energy forecasting for efficient power supply management. The developed multiscale LSTM method concatenates two different scaled LSTM modules to overcome the degradation caused by the irregular factors.

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4.6. Traffic Control Modeling

Modern transportation technology in smart cities is witnessing the emergence of a new era of transportation systems commonly known as cooperative systems. Recent advances in autonomous vehicles (AVs) and connected vehicles (CVs) are expected to completely change the way people use and perceive modern transportation. Therefore, in order to improve the efficiency, throughput, and safety of traffic flow, researchers are becoming increasingly interested in exploring V2V and V2I communication technologies. In the last decade, the research community has been exploiting the AVs and CVs for efficient control, proper management, improved safety, and efficient throughput in the smart city traffic flows [88, 89]. The main motive for using MM in smart city traffic control is to properly understand and analyze CVs and AVs in a traffic flow. For instance, Kachroo *et al.* [89] developed a multiscale control architecture for V2X traffic control and analysis in a smart city environment. Whereby in the newly developed framework, CVs are treated as discrete objects that can be controlled microscopically, and in this way, they can macroscopically influence and control the overall traffic flows.

4.7. Multiscaling Approach in Behavioral Sciences

In behavioral science, animal and human behavior is studied through a systematic approach. This behavior is studied through controlled and disciplined scientific experiments. The following are some areas of behavioral science in which a multiscaling approach is used.

Crowd's Modeling: Modeling and analyzing crowd dynamics at the micro and macro levels is one of the motivating research areas that are studied separately. A multiscale approach based on microscopic and macroscopic levels has never been studied in crowd dynamics, leading to new consequences of properties such as self-organization and emergent behavior. Cristiani et al. in [90] in their study modeled and coupled micro and macro scales of crowd dynamics together in a rigorous mathematical framework to interact and obtain more accurate results. The study and analysis of crowds is an important concern in today's world. It is a difficult task to use multiscale texture analysis for inferring unsupervised crowds without having contextual knowledge. Fagette et al. presented a novel algorithm to find out crowds and backgrounds in still images without any prior knowledge [91]. Dense crowds are successfully inferred using the following three steps: i) extracting the crowd features from the image in pixels and storing them in a vector ii) using the binary classification approach to distinguish the crowd from its background iii) optimizing the time and data volume for computation.

A smart and intelligent environment requires visual crowd detection for various applications such as security, surveillance, etc. Zitouni et al. in their review paper studied 83 papers and showed the progress and trends in crowd analysis and modeling for the seven years from 2007 to 2014 [92]. The conclusion drawn shows inadequacies and challenges in datasets, assumptions, modeling, and methods for crowds, including density dependence, and the focus was directed to the study of crowd behavior at both macro and micro-levels understandings of crowds.

Surveillance through Micro Aerial Vehicles: Micro aerial vehicles, also called micro air vehicles, are used to monitor an object for surveillance. Khan et al. developed an algorithm that can effectively observe multiple scenes [93]. The methodology used the centralized quad-tree strategy of MAVs for monitoring two or more moving targets. Mobility options were also considered, which achieved a common goal of maximizing the observation of interactivity of multiple moving targets.

5. Current Challenges and Future Directions in Multiscale Modeling

The great problem of the world now is to manage the population with improving quality of life. Planning is more efficient for well infrastructure and connectivity of the city by using modern ICT tools. Cities with a large population can only rely on better connectivity of transport inside and outside the city. As cities are a focal point of all facilities for the people, there is tremen-

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dous pressure on the management and maintenance of various services in the cities. The cities are overcrowded and overburdened due to the influx of people from rural areas. This has put tremendous pressure on the city authorities to deal with the situation and apply modern and innovative ways to improve the standard of living. Smart city enables such platforms to deal with problems like waste management, smart traffic, surveillance and security, better health facilities, crime management, mobility, environment, and smart living. Multi-scale simulation and modeling approaches are adopted for analyzing complex problems such as urbanization, pedestrian and traffic flows, study of oceans, and various biological domains such as cancer growth, tumor growth, etc. The MM and simulation are essential for the design, monitoring, and analysis of smart cities that are considered as complex systems. The progress of cities lies in the accurate monitoring of resources, including the growth of urban infrastructure, traffic, and pedestrian flows, mobile monitoring of user locations, etc., which could be successfully carried out by using MM and simulation. Micro and macro scales are suitable for modeling smart cities, e.g., the micro scale can be used to monitor the individual aspects of factors related to smart cities, e.g., a single pedestrian or vehicle flow, the growth of a small urban area, etc. The macro scale can then be chosen to monitor the overall behavior of subjects and objects, e.g., studying groups of pedestrians, the flow of the vehicle fleet, and the growth of the entire city.

Up to this point, this paper has focused on understanding and reviewing the current literature on MM in smart cities, including recent advances in developments and the latest trends. Although this area has received a lot of attention from the research community in the last decade, there are still many topics/gaps in this field that need to be explored as future research. In this section, this study presents a list of current challenges along with future directions for using MM to improve the performance of smart cities.

5.1. People and Communities

One of the main challenges of MM is to model different systems at different scales having different complexities. It is quite a difficult task to deal with different systems simultaneously when each system has a particular complexity. However, modeling and analyzing crowd dynamics at the micro and macro scales is one of the motivating research areas that are being studied separately. A multiscale approach based on microscopic and macroscopic levels has never been investigated in crowd dynamics, leading to new consequences of properties such as self-organization and emergent behavior. Cristiani *et al.* [90] modeled and coupled micro and macro scales of crowd dynamics to obtain accurate results.

5.2. Smart Mobility

Situational awareness is an important aspect of intelligent mobility that spans multiple scales, including time and space. In [94], the authors addressed the challenge of multiscale spatio-temporal tracking using active cameras, real-time video surveillance, and analysis, pattern analysis along with multiple object models to create non-intrusive, and comprehensive situational awareness. A multiscale approach was adopted for traffic flow. Traffic could be monitored and controlled using discrete-event simulation tools. Picone et al. used the DEUS software tool to simulate smart cities [95]. DEUS provides discrete event simulation to monitor key city business processes. The authors used online Google Map Application Programming Interfaces to monitor and visualize peer-to-peer traffic information systems. Monitoring a view and scene at different spatial scales from MAVs is complex. Khan et al. developed an algorithm that can effectively observe multiple scenes [93]. All the above examples have used the MM approach to focus on a specific problem domain of smart cities. In short, it can be concluded that applying the MM approach towards smart mobility could help the planners to better understand the problems at micro and macro levels.

5.3. Monitoring of Urban Infrastructure Growth

Urbanization is a complex phenomenon that requires spatio-temporal characteristics and changes in land use/land cover (LULC) are due to available choices such as individual preferences, policies, sustainability of sites. Unplanned growth with respect to urban areas is a very serious problem and the authors have studied the characteristics of peri-urban and urban growth in the paper [96]. By applying predictive models, the authors determined the impact at different stages, in the city of Lahore in Pakistan. The results were compiled after examining LULC maps from 1999 to 2011 at different scales and it was accumulated that there is a major land transition in the metropolitan region from peri-urban and urban zones. The monitoring of infrastructure growth, such as ports, buildings, roads, airports, and markets, encompasses a complex environment that has fragmentation and functional gaps between different institutions/government agencies. All these infrastructures are managed by multiple scale-dependent institutions. The challenge of interplay between institutions for better governance has been presented in [97] to improve monitoring and cost efficiency while reducing fragmentation.

5.4. Smart Energy Management

Energy management can be done at a micro level, taking into account the cycles of individual appliances. The peak consumption cycles of the appliances are shifted to off-peak hours to reduce the electricity bill of the consumers [98, 99]. At an aggregate level, different appliances are considered simultaneously and their peak load is shifted to off-peak hours [100, 101]. At a higher level, energy is shifted from surplus areas in a smart city to deficit areas according to certain criteria and tariffs agreed upon among users.

5.5. Integration of Machine Learning with Multiscale Modeling

Due to the varying complexity of systems at different scales, the parameters of the developed models are insufficient to provide a basic set for generating the dynamics of systems at higher scales. According to [17], MM and machine

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learning models can be set up to work in parallel to provide independent confirmation of parameters' sensitivity. For instance, smart home or smart health care systems in a smart city environment generate relatively simple dynamics; however, they depend on several complex underlying parameters that can be handled by MM. There is an opportunity to integrate machine learning with MM to identify both the underlying high dimensionality and low dimensionality dynamics [102].

5.6. Uncertainty Quantification

Quantifying uncertainty helps in making several important decisions in the smart city environment. Usually, most of the houses in a smart city are equipped with green energy such as solar and wind turbines. Prediction of energy is also necessary for efficient energy planning, and prediction results are used at the micro-scale in a multiscale energy management system. Furthermore, prediction results without uncertainty quantification are unreliable and untrustworthy [103]. To understand the multiscale systems (related to energy management or any other prediction domain, i.e., weather forecast, traffic forecast, accident forecast, and more in the smart city environment), it is necessary to first understand the quantification of uncertainty. For example, machine/deep learning models start with collecting appropriate datasets, selecting an appropriate forecasting model based on the performance goals, training the model by using a labeled dataset, and optimizing various learning parameters that help in achieving satisfactory performance. There are several uncertainties involved in the machine learning steps that need to be quantified. These include, for example, the selection/collection of training data, the accuracy and completeness of the training data, the understanding of the DL models along with their performance limitations and constraints, and uncertainties due to operational data [103, 104]. The primary goal of uncertainty quantification is to reveal reliable confidence values for forecasting results generated by machine learning methods and what the developed methods have not learned properly. Because several decision on the next step (meso or macro level) are made based on these results. In the field of energy management and forecasting area, uncertainty quantification has attracted noticeable attention of the research community in recent years. Current studies show its applications and advantages, for example, the application of energy management in smart grid [105] and uncertainty quantification in wind power forecasting [106, 107]. However, the uncertainty quantification of multiscale systems in the smart city environment remains open for future work to improve the performance, reliability, and accuracy of multiscale systems.

5.7. Growing and Pruning Multiscale Models

Growing and pruning are novel techniques that can be adapted to improve the performance and reduce the computational complexity of multiscale models. Since multiscale systems are more complex compared to single scale models, it is important to use such approaches that can help in reducing the complexity. In this technique (Growing and Pruning), an architecture of the multiscale system is first designed with the fewest necessary parameters. Then, new parameters are incorporated into the architecture by applying the growing approach. In contrast, when the pruning approach is applied, a number of parameters are removed from the architecture. Both the growing and pruning approach based architectures repeat three key operations until acceptable performance (low complexity) is achieved [108]: i) training the model, ii) changing the weights (parameters) based on the growing or pruning criteria, and iii) re-training the model. In recent years, the field of growing and pruning has received considerable attention from the research community and several studies have discussed its effectiveness in various research domains, including health service improvement [109], self-care activities [108], and speech emotion recognition [110]. Therefore, the implementation of growing and pruning approaches for multiscale models in a smart city environment is still an open direction for researchers and industry.

6. Conclusion

In this study, we have conducted a comprehensive review of the application of multiscale modeling in smart cities. Due to the increasing population and trend of urbanization, we first start with the introduction of megacities and their transformation into smart cities. Then, we discuss the various challenges associated with the transformation of megacities into smart cities, including mobility, health, housing, and security. In addition, this study presents the needs of MM in smart cities and also aims to identify application areas of MM to help planners and government authorities for a better understanding of complex problems associated with the transformation of smart cities. Finally, various challenges and future directions in MM and smart cities are highlighted, including smart community, smart mobility, monitoring of urban infrastructure growth, smart energy management, uncertainty quantification, and growing and pruning MMs.

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