Smart Cities and Sustainable Development: Global Scenario

Hillol Biswas

July 25, 2024

Smart Cities and Sustainable Development: Global Scenario

Hillol Biswas

List of Figures

List of Tables

Contents

Smart Cities and Sustainable Development: Global Scenario

Abstract

In the contemporary challenges of climate change, global warming, and carbon emission era, smart city building is a vast global approach undertaken by the respective countries. In the cyber-physical world of many dimensions, the use of data streaming out from many sources is a massive inspiration for exploring yet untapped potentials. The use of artificial intelligence, albeit ethically, has the potential to streamline the global stride for ripping the benefits. The attention to the global classification of smart cities on defined parameters is inspiring for inculcating improvements to make smart cities and sustainability a consistent and coherent approach. Innovations, new approaches, and progress in smart city-making can be achieved with the proportionate transpiring of artificial intelligence. Exploring new areas for artificial intelligence use should be a common focus for the 'democratization' of this emerging technique. Apart from discussing a few areas of smart city and sustainability, this chapter also provides a typical use case of using a few regression machine learning techniques for gaining intelligence based on open-source Birmingham, United Kingdom parking data.

Keywords: Smart City, Artificial Intelligence, Data Analytics, Cyber Security, Smart City Index

Introduction

"A smart city is where traditional networks and services are made more efficient using digital solutions to benefit its inhabitants and business. A smart city goes beyond the use of digital technologies for better resource use and less emissions." European Commission, on Smart City [1].

"Smart Cities focus on their most pressing needs and the greatest opportunities to improve lives. They tap a range of approaches - digital and information technologies, urban planning best practices, public-private partnerships, and policy change - to make a difference. They always put people first." What is a Smart City [2]

Smart cities are a way of life focused on utilizing previously unheard-of technological advancements like artificial intelligence systems, the Internet of Things, and big data. The goals are to maximize resource utilization, minimize energy consumption and waste, foster an environment that encourages creativity and innovation, and improve people's quality of life by lowering living expenses and making life simpler and safer [3].

When governments describe any aspect as "smart," it alludes to how physical space and a layer of technology interact, including breakthroughs that support system learning and the integration of ICT infrastructure using the platforms of virtual clouds. The concept of "smart growth," which first surfaced in the 1980s with the rise of the New Urbanism movement, gave rise to the term "smart city." With the communitarian principles of improving urban living through limited land usage and questioning developmental concepts influenced by the automotive, real estate, and oil sectors, New Urbanism tried to improve the thinking of the 1970s, a decade of superhighways and urban sprawl. The 1990s technological boom and New Urbanism concepts laid the groundwork for the rise of the smart city movement. The inaugural "Smart City Summit" was held in 2004 at a Toronto, Ontario, Canada conference. A smart state or city aims to provide the highest quality of life for its residents and guests. The Europe 2020 strategy, the IBM smart planet, and the Kyoto Protocol are examples of frameworks that offer an optimal quality of life. Cities in the Americas, Europe, Asia, and the African Union are implementing smart city projects to improve the quality of life for their citizens by utilizing improved ICT and Internet of Things technologies. One approach to achieving equitable distribution of public services across numerous access points—such as senior living communities, libraries, post offices, schools, and other public spaces—is using smart city infrastructure [4].

Digital technology is used in a smart city to connect, safeguard, and improve the lives of its residents. As a nervous system, IoT sensors, security cameras, social media, and other inputs give residents and the city manager continuous information to make wise judgments [5]. From the UN perspective, developing inclusive, livable, and sustainable urban regions is a top development objective, as evidenced by the Global Center's establishment of a program focused on smart cities. Utilizing innovation and technology, smart cities enhance the urban environment, resulting in a higher standard of living, increased prosperity and sustainability, and more involved and empowered residents. The Global Centre is located in Singapore, which has been repeatedly acknowledged as a top smart city. Digitalization plays a significant role in enhancing lifestyles and means of subsistence [6].

National Institute of Standards and Technology (NIST), USA frameworks of Smart City, 2018 stipulates interoperability, composability, and harmonization, among other things. The term "interoperability" describes the capacity of several systems and parts to function together, even when parts are integrated and substituted from various sources. Different stakeholders have different "concerns," which specific technologies must address. Every one of these issues—such as communications, cybersecurity, or precise timing—represents an additional aspect of interoperability. "composability" describes the capacity to include new features while preserving ongoing system integration and advancement. It would be preferable to acquire these functional additions gradually rather than completely replacing or re-engineering the system. Achieving interoperability between technologies and systems—even when they initially seem incompatible—is called "harmonization." These technologies could, for instance, originate from various industries (such as energy, public safety, or transportation), or they might be created with adherence to different standards from various standards development bodies. Interoperable and complementary solutions can be produced by harmonizing the various requirements. Composability and interoperability, the other two objectives of the framework, cannot be achieved without harmonization [7].

Components of smart city

Anthopoulos, 2015 [8] cited different prevalent architectures and a generic multi-tier ICT architecture meeting, among other things, UN-Habitat key-performance indicators, containing five layers viz. natural environment, hard-infrastructure (ICT and non-ICT based), services, and soft infrastructures as corresponding layers. The elements of a smart city are environment, mobility, economy, people, living, and governance as ascribed by various scholars [9] and sub-areas of the smart city concept, with each having 4 clusters viz. smart technology, socio-economic aspects, environmental aspects, and urban logistics. Moreover, their literature study revealed a deficiency in research, indicating that integrating the smart city concept needs to be more adequately incorporated into a comprehensive and diverse vision of the future. Adopting the smart city concept can enhance the quality of life for individuals by offering innovative solutions to long-standing issues, such as pollution, traffic congestion, and energy wastage [3]. Scholarly categorization of smart cities as smart infrastructure, smart economy and policy, smart technology, smart sustainability, and smart health as depicted by Stubinger et al. [10]. The social dimension encompasses principles of fairness, self-governance, individual welfare, and fulfillment of basic human requirements.

In contrast, the economic dimension pertains to the economic strength and variety of metropolitan regions. In the context of this research, an urban environment can be considered sustainable when it successfully achieves social fairness, conservation of the natural environment and its resources, economic vitality, and a high quality of life. The concept of urban sustainability is often discussed in smart city literature. However, it is essential to determine how much this concept is integrated into understanding smart cities and how thoroughly it is addressed [11]. Smart city Barcelona, which gained success and acknowledgment, boasts of components of smart districts, living lab initiatives, infrastructures, newly introduced services for the citizens, open data, and smart city initiative management [12].

Global Smart Cities Ecosystem

IMD Smart City Index (SCI) classifies the global smart city based on some defined criteria. It uses the rankings, rating, structure, and ranking for the previous year, which depicts any change in ranking with respect to the current one for comparison purposes. The SCI 2024 Results for the top 5 ranked cities are provided in Table 1 [13]. The results IMD published have been used to produce a few quick tabular form representations to gain a brief overview. They are presented in Table 2 and Figures 1 to 4, respectively.

Table 1: In 2024 City Ranking Order and 2023 Ranking Comparison for the first five global cities

City	Smart City Rank 2024	Smart City Rating 2024	Structure 2024	Technology 2024	Smart City Rank 2023	Change
Zurich	1	AAA	AAA	AA	1	▬
Oslo	2	AA	AA	A	2	▬
Canberra	3	AA	AA	A	3	▬
Geneva	4	AAA	AAA	AA	9	+5▲
Singapore	5	A	A	A	7	+2▲

Zurich and Geneva in Switzerland, Oslo in Norway, Canberra in Australia, and Singapore City in Singapore surface in the top five list among 142 cities worldwide.

Table 2 provides a smart city rankings group list with the city names. The ranking A, AA, AAA, B, BB, BBB, and CCC categories are based on the SCI 2024 results for quick comparison purposes.

Table 2: Groupby column of Smart City 2024 ranking, corresponding ranks, and city name of the SCI 2024 data

Smart City Rating 2024	Smart City Rank 2024	City
A	5	Singapore
	8	London
	11	Stockholm
	15	Prague
	16	Taipei City
	18	Amsterdam
	20	Hong Kong
	21	Munich
	22	Sydney
	30	Brisbane
	33	Melbourne
	39	Gothenburg
	41	Rotterdam
	42	The Hague
AA	2	Oslo
	3	Canberra
	6	Copenhagen
	7	Lausanne
	9	Helsinki
	17	Seoul
	23	Vienna
AAA	1	Zurich
	4	Geneva
B	25	Riyadh
	48	Doha
	52	Mecca
	55	Jeddah
BB	10	Abu Dhabi
	12	Dubai
	13	Beijing
	19	Shanghai
	34	New York
	35	Madrid
	44	Dusseldorf
	45	Busan
	50	Washington D.C.
	53	Hanover
	54	Tianjin
	59	Riga
	61	Lyon
	63	Seattle

BBB	14	Hamburg
	24	Tallinn
	26	Reykjavik
	27	Luxembourg
	28	Wellington
	29	Bilbao
	31	Auckland
	32	Ljubljana
	36	Boston
	37	Berlin
	38	Warsaw
	40	Brussels
	43	Vancouver
	46	Ottawa
	47	Vilnius
	49	Paris
	51	Toronto
	56	Bratislava
	66	Denver
CCC	57	Zaragoza
	58	Zhuhai
	60	Shenzhen
	62	Nanjing
	64	Hangzhou
	65	Guangzhou

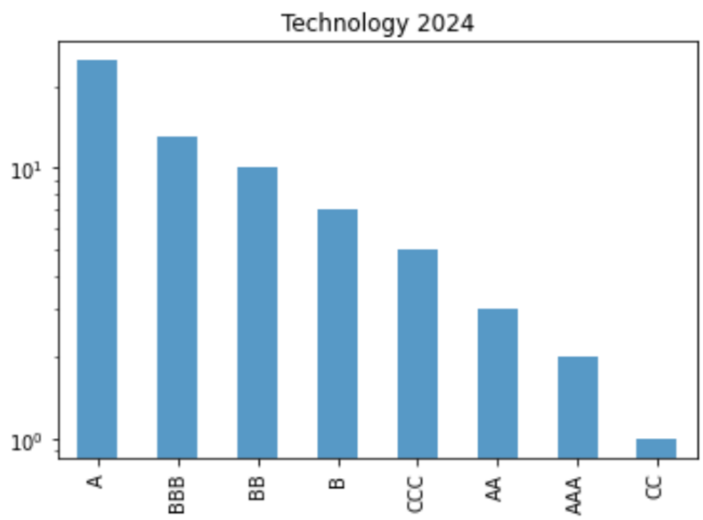

Figure 1: The ratings based on Technology 2024 as per SCI data

Fig 1 depicts the ratings counts based on Technology 2024 on the different types viz. A, B, AA, BB, AAA, BBB, and CC, respectively, fig 2 provides the ratings count based on Structure 2024 criteria.

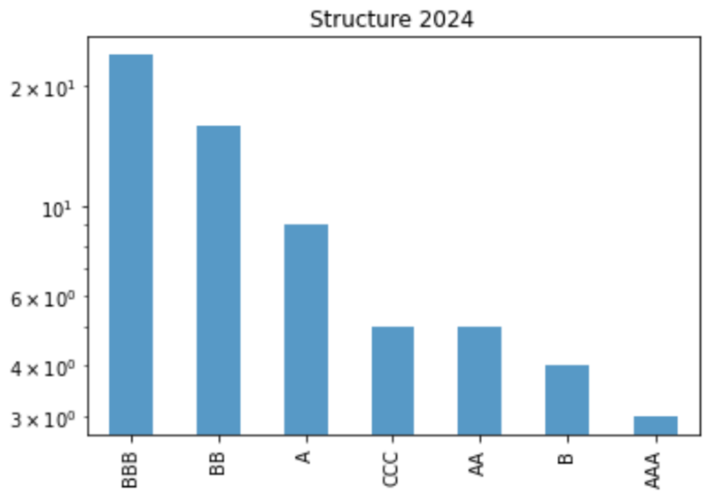

Figure 2: The ratings based on Structure 2024 as per SCI data

Fig 3 depicts the bar chart of city raking counts in each category. A, B, AA, BB, AAA, BBB, and CCC

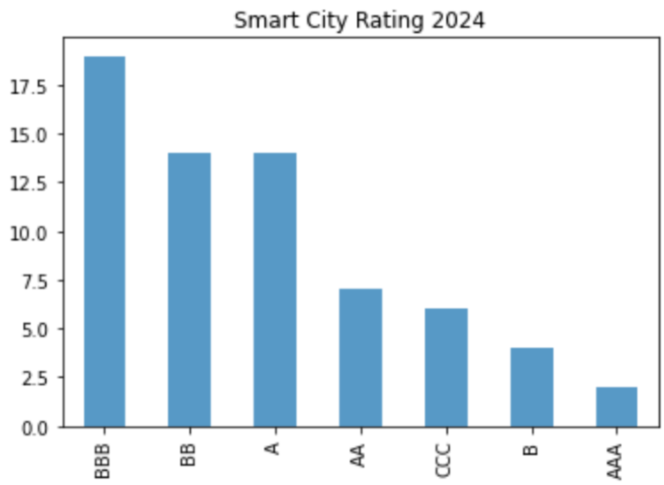

Figure 3: The smart city rating 2024 bar chart based on SCI data

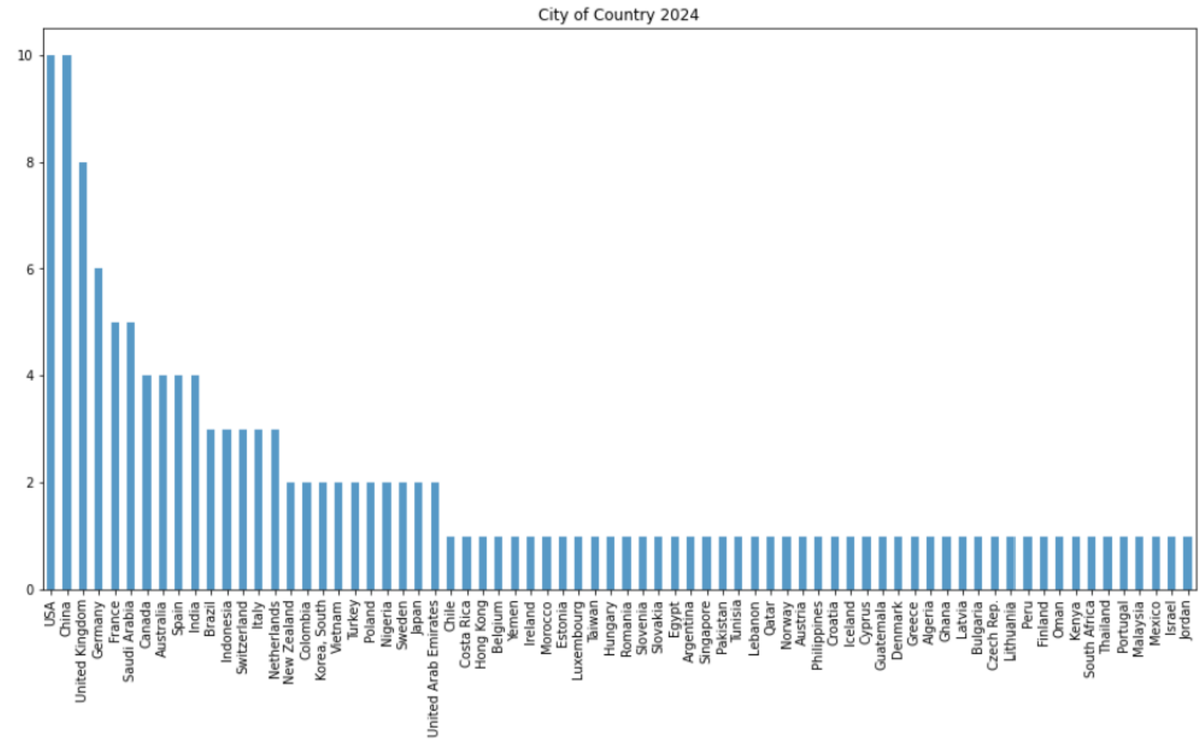

Figure 4: The bar chart of the number of cities in the respective countries in the SCI data

Fig 4 depicts the SCI 2024 country list, which contains a number of the cities belonging to the list. The USA and China are at the top jointly, with ten cities in each country. The United Kingdom appears second with eight cities, and Germany has six cities on the global list.

Barcelona ranks 81 in SCI 2024 and is known for the use of its integrative frameworks [14]. Five axes served as the framework for the city project: The Barcelona City Council (2014) outlined five initiatives related to sustainable city growth: 1) open data; 2) smart lighting; 3) social innovation; 4) alliance-building between research centers, universities, private and public partners; and 5) offering "smart services" based on ICT [15]. Barcelona has implemented substantial measures to transition into a smart city. Moreover, the Barcelona case holds particular importance because of its evident inclination in municipal policies and reforms to emerge as a prominent Smart City among European cities. Therefore, evaluating the Smart City program will provide insight into the present urban policies of Barcelona and their future trajectory [12].

Costa Rica, a nation in Central America, is proud to have its own "blue zone," one of the world's healthiest and longest-living places [16]. San Jose, the capital, ranks 125 in the SCI 2024. Costa Rica is the 9th Healthiest [17] country ranked in the 2017 UK news site, The Independent. Avenue Escazú, fig 5, a Living Avenue, is Costa Rica's first urban mixed-use development as part of the Real Estate Portfolio. At Avenida Escazú, they build a residential neighborhood that promotes well-being via unique urban experiences [18]. Nonetheless, an innovative approach to the smart city aim of the global community is being reflected in their works. As their website proclaims, they build living communities for the benefit of both people and the environment.

While electric vehicles, including buses, are a reality in China to ensure low carbon emissions, the introduction of buses with electric overhead lines (Fig 6) has also occurred in some cities. According to BBC news sites, China has a long history of electric buses dating back to the

1920s [19]. Modern buses run on a dedicated track with an overhead electric line in Hangzhou, the capital of Zhejiang province, which ranks 64 in the 2024 SCI ranking.

Figure 5: Avenida Escazu is a smart building in San Zose, Costa Rica's capital, one of the healthiest countries in the global ranking.

Figure 6: Smart Electric Bus connected with Overhead lines for smart mobility and sustainable development in Hangzhou, capital of Zhejiang province, China

Sustainability

The ability of public organizations and public servants to plan, carry out, and evaluate a strategy and involve citizens and other stakeholders in its development makes a city smart, regardless of its technological sophistication. This means creating a city model that is co-conceived and co-implemented with regular people and other stakeholders [14]. United Nations (UN) 2030 Agenda for Sustainable Development, unanimously endorsed by all United Nations Member States in 2015, serves as a collective strategy for achieving peace and prosperity for humanity

and the environment, both presently and in the future. The initiative's core consists of the 17 Sustainable Development Goals (SDGs), which serve as a pressing demand for action from all developed and developing nations in a worldwide collaboration. They acknowledge the necessity of simultaneously addressing poverty and other forms of deprivation while implementing policies to enhance health and education, diminish inequality, stimulate economic growth, combat climate change, and safeguard our oceans and forests [20].
Building upon previous research conducted by The World in 2050 program, Sachs et al. proposed six SDG Transformations as fundamental components for achieving the Sustainable Development Goals (SDGs). The six areas of focus for sustainable development are (1) education, gender, and inequality; (2) health, well-being, and demography; (3) energy decarbonization and sustainable industry; (4) sustainable food, land, water, and seas; (5) sustainable cities and communities; and (6) the digital revolution for sustainable development [21]. Notably, the flourishing success of smart cities is a direct outcome of the implementation of these areas. Knowledge and capacity building is one of the critical drivers of SDG, wherein a data-driven approach and big data are becoming key enablers for the years and in the coming future [22].

Seoul, which ranks 17 in the SCI 2024, is an industrial country. The South Korean capital exhibits modern problems by adopting the idea of ancient solutions; Figure 7 depicts a multi-purpose electric boat on the Great Canal for passengers and goods transportation, avoiding traffic jams, a tiny part of the smart mobility program implementation.

Figure 7: Seoul, the South Korean capital, is one of the significant Smart City

Figure 8: Wifi equipped roads and Green corridor for Ambulance in the city of Seoul

Artificial intelligence and machine learning

History

Arthur Samuel's work in the last few decades has sparked significant interest and research because of the abundance of real-world data. Machine learning is primarily concerned with two interrelated problems: What are the methods for developing computer systems that exhibit automatic improvement through usage? What are the core principles of statistics, computation, information theory, and learning that are universally applicable to all learning systems, including those found in computers, humans, and organizations? It progresses rapidly in various fields as it is still considered relatively young.

While artificial intelligence defines the broader term, machine learning is usually considered a subset, and deep learning is a further subset, as depicted in Figure 9.

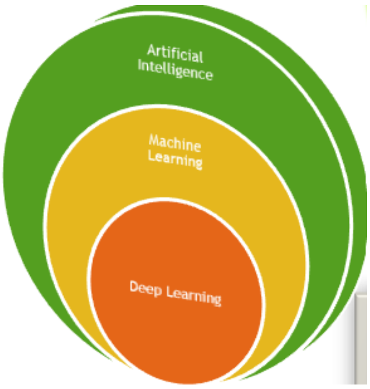

Figure 9: Artificial intelligence-machine learning and deep learning Venn diagram

Types of machine learning

An algorithm generates a function in supervised learning that maps inputs to desired outputs. The classification problem is a frequently used term to describe the difficulties of supervised learning. The learner is expected to comprehend the behavior of a function that translates a vector to one of several classes by analyzing different input-output examples of the function.

Unsupervised learning is employed when labeled examples are unavailable and involves simulating a set of inputs.

Semi-supervised learning involves utilizing labeled and unlabelled samples to construct an appropriate function or classifier.

Reinforcement learning is an algorithmic approach to training an algorithm to make decisions by seeing and interacting with the external world. Each action elicits a response from the environment, subsequently providing feedback to the learning process.

Supervised Learning types

Supervised classifications are of regression and classification types.

i) Regression

Linear, polynomial, and advanced techniques such as Lasso and Ridge regression are used to forecast continuous target variables in numerical predictions.

ii) Classification

Decision tree [23], Random Forest [24], k-nearest neighbor (kNN) [25], [26], Support vector machine (SVM) [27], Navies Bayes, Logistic Regression, etc

Unsupervised Learning types

Clustering – k-means, k-mode, k-median, Hierarchical, Principal Component Analysis (PCA), and Independent Component Analysis (ICA).

Reinforcement Learning

Reinforcement learning originated from the early stages of cybernetics and has been influenced by computer science, psychology, neurology, and statistics research. Over the past few decades, the artificial intelligence and machine learning communities have shown significant and rapid interest in this topic [28]. The approach of alluring promise involves training agents using a system of rewards and penalties without explicit instructions on executing the task. Robotics and driverless cars are applications of this type of learning.

Deep learning

Deep learning enables computational models with multiple processing layers to acquire data representations at different degrees of abstraction. These techniques have greatly improved the current level of advancement in various other domains, such as drug discovery and genomics, object identification, visual object recognition, and speech recognition. Deep learning utilizes the backpropagation technique to propose modifications to a machine's internal parameters, which are responsible for calculating each layer's representation based on the preceding layer's representation. This enables deep learning to reveal intricate structures inside extensive datasets. Recurrent neural networks have provided insights into analyzing sequential data such as text and voice. In contrast, deep convolutional neural networks have made significant progress in processing images, videos, speech, and audio [29].

A few popular deep learning algorithms are Convolutional Neural Networks (CNN) [30], Long Short-Term Memory (LSTM) [31], Stacked LSTM [32], Gated Recurrent Unit (GRU) [33], and Bidirectional LSTM [34], which scholars and professionals widely use. Nonetheless, many other deep learning techniques are available and are also being introduced by the research community.

Time Series Analysis

The forecasting theory is based on the premise that future forecasts can be generated by utilizing information from the past and present. There is a notion known as pattern recognition, which suggests that it is possible to identify patterns in past data and effectively utilize them to forecast future values, particularly in the context of time series analysis. Future values are expected to be inaccurate. Various options exist for forecasting a single time series in a future period, including an expected value (sometimes called a point forecast), a prediction interval, a percentile, and a complete prediction distribution. Time series decomposition is an essential initial step in most forecasting approaches. Seasonal decomposition can represent a time series about other time series or its components. Additive and multiplicative decompositions are commonly used, where the corresponding operations are summing and multiplication. If logarithms can be applied to time series data, every additive decomposition technique can be transformed into a multiplicative one. Temporal data often become the focus of unexpected and unforeseen behaviors, resulting in a range of abnormal observations. It is difficult to find a single, application-specific explanation for an anomaly because of the intricate Nature of domain-specific difficulties. An anomaly is commonly defined in the literature on time series and forecasting as a deviation from the expected behavior within a specific context or about past patterns. Box et al., 1976 pioneered introducing the first Auto-Regressive Integrated Moving Average (ARIMA) model [35].

SARIMA, also known as seasonal ARIMA, is a method that takes a seasonal approach to ARIMA. Neural Prophet is a newly developed algorithm that is a substitute for Facebook Prophet. It has set a standard for forecasting tools that are transparent, scalable, and easy to use [36].

According to Barker, predicting techniques that do not describe how data is generated, such as by a set of equations, are referred to as ML. It allows for the automatic instruction of data correlations. Neural Networks (NN), Decision Trees, Support Vector Machines (SVM), and

Gaussian Processes are considered machine learning (ML) methodologies due to their use of unstructured, non-linear regression algorithms [37].

Data Analytics and Artificial intelligence/machine learning used in smart city

Mohapatra et al. reviewed machine learning usage regimes in smart cities: healthcare, home, weather, control, market analysis, and traffic segments. The corresponding algorithms are plausible to use [38], viz., supervised, and unsupervised techniques. The smart city eventually comprises a smart grid, i.e., smart metering, which distribution companies are contemplating using especially for deciphering any cyber frauds for purposefully evading the billing. Predicting power consumption is also one of the sort-after areas [39]. In their work, Chin et al. investigated the possibility of using artificial intelligence (AI) to enhance the Internet of Things (IoT) and Big Data in order to facilitate personalized services in Smart Cities. They specifically focused on using machine learning (ML) techniques to establish a connection between weather conditions and short-cycling routes in London. The study is predicated on the amalgamation of two disparate datasets.

The first model is based on a convenient self-service system called the Santander Cycles scheme (formerly Barclays Cycle Hire). This scheme is owned by Transport for London (TfL) and offers more than 10,000 bicycles and 700 docking stations. These stations are strategically placed throughout the city core of London, with a distance of around 300 to 500 meters between each station [40]. Mohammadi et al. reviewed machine learning in the smart city context, categorically water, energy, and agriculture sectors [41]. The advent of big data is ushering in a new era when the use of instruments, data collection, and computational processes are becoming more and more prevalent in urban environments. The utilization of big data technology has become indispensable for the operation of urban areas. As a result, urban processes and practices are increasingly adapting to a type of data-driven urbanism, which is the primary production method for smart cities. This form is increasingly focused on addressing the difficulties of sustainability in response to the growing trend of urbanization. However, there are practical and justifiable aspects of the growing data-driven smart city, explicitly focusing on the development and implementation of novel solutions for sustainability [42].

A Use Case of Birmingham Car Parking Data

As data plays a huge role in understanding realistically the smart city ecosystem, so does the role of open-source data. Christelle et al. surveyed 2015 to 2022 the open data paradigm of smart cities from a data analytics point of view [43]. They depict smart city dimensions: smart mobility, environment, people, governance, economy, and living. Data availability, albeit from open source, is a crucial criterion for research, especially future direction.

Smart mobility comprises the use of smart vehicles. However, parking in an intelligent city is equally paramount from the point of view of ease of traffic movement, traffic congestion, and time management. A typical use case of Birmingham, United Kingdom, which ranks 83 in SCI 2024, parking data [44] available in UCI machine learning repository, collected by NCP using pandas open-source python library [45] data frame in Google colab environment [46], [47] has been provided below for exploratory data analytics purpose (EDA).

The data is from 04-10-2016 to 19-12-2016. The size of initial Birmingham, UK parking data, tables 3 and 4, is (35717 X 4) post-pre-processing of data, i.e., 35717 rows and eight columns of attributes. The data pre-processing entailed any missing value treatment, adding derived data based on the datetime column in day, weekday, month, and year. The occupancy column has also been driven to another percentage occupancy column for better data visualization analytics purposes. The pre-processed dataset now exhibits nine attributes, as given in table 3 and 4 below, depicting the top and bottom five rows, respectively:

Table 3: The top 5 rows of the dataset as in the pandas data frame post-pre-processing

Sl No.	SystemCodeNumber	Capacity	Occupancy	LastUpdated	Occupancy%	month	year	weekday	day	hour
0	BHMBCCMKT01	577	61	2016-10-04 07:59:42	11.0	10	2016	1	4	7
1	BHMBCCMKT01	577	64	2016-10-04 08:25:42	11.0	10	2016	1	4	8
2	BHMBCCMKT01	577	80	2016-10-04 08:59:42	14.0	10	2016	1	4	8
3	BHMBCCMKT01	577	107	2016-10-04 09:32:46	19.0	10	2016	1	4	9
4	BHMBCCMKT01	577	150	2016-10-04 09:59:48	26.0	10	2016	1	4	9

Table 4: The bottom five rows of the dataset, as in the pandas data frame post-pre-processing

Sl No.	SystemCodeNumber	Capacity	Occupancy	LastUpdated	Occupancy%	month	year	weekday	day	hour
35712	Shopping	1920	1517	2016-12-19 14:30:33	79.0	12	2016	0	19	14
35713	Shopping	1920	1487	2016-12-19 15:03:34	77.0	12	2016	0	19	15
35714	Shopping	1920	1432	2016-12-19 15:29:33	75.0	12	2016	0	19	15
35715	Shopping	1920	1321	2016-12-19 16:03:35	69.0	12	2016	0	19	16
35716	Shopping	1920	1180	2016-12-19 16:30:35	61.0	12	2016	0	19	16

The visual analytics are displayed in Fig 10 to 16 below. The systemCodeNumber categorical variable bar chart plot is depicted in Fig 10, which illustrates the type of car park used with the corresponding code provided by NCP, the car park operator. The occupancy vs occupancy percentage chart is provided in Fig 11, and Fig 12 depicts the capacity and occupancy chart. The occupancy bar chart for the hours of the day is provided in Fig 13, wherein the figure depicts car park occupancy from 7 hours in the morning to 16 hours in the afternoon, a generic trend in city car park occupancy. In the afternoon, 13 hours, the mode value is around 800 numbers, and the minimum occupancy in the morning, 7 hours, is around 250.

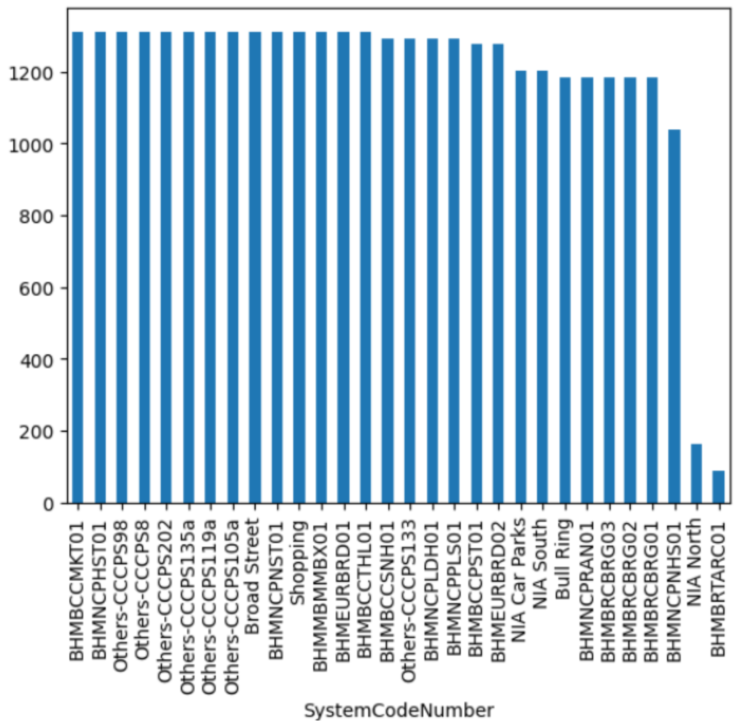

Figure 10: The systemCodeNumber column depicts the value counts

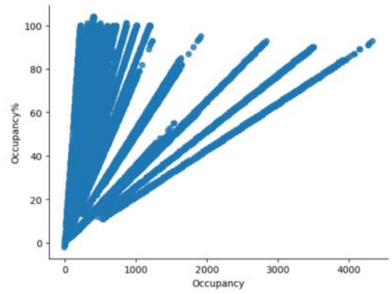

Figure 11: The occupancy and occupancy percentage plot

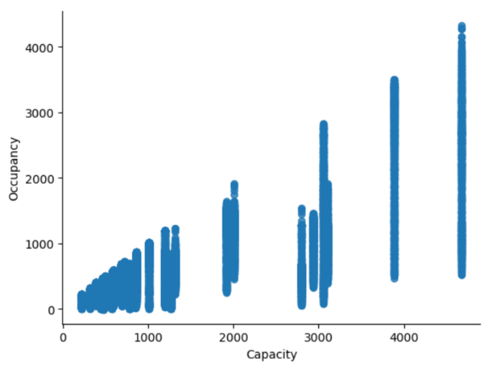

Figure 12: The Capacity and Occupancy plot

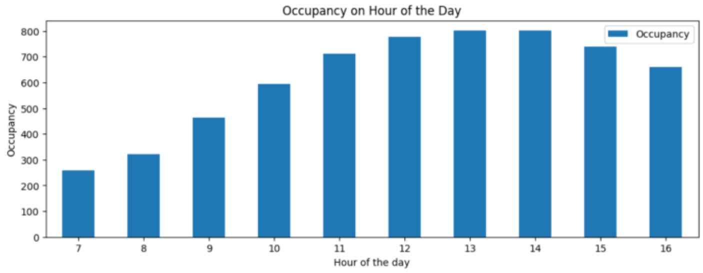

Figure 13: The occupancy bar chart in the respective hours of the day in the car park

Figure 14 depicts a two-month occupancy plot of the data provided, with an increasing trend, though single, apparently linear in Nature, for individual months rather than a generic trend for the total two months.

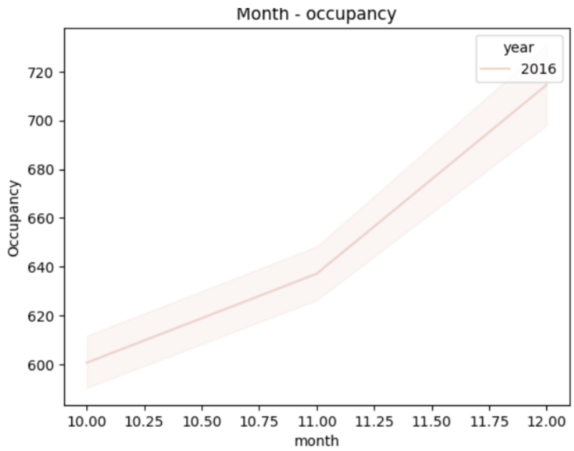

Figure 14: The two-month occupancy plot for 2016

Figure 15 exhibits the occupancy line plot for the weekdays, which depicts the low occupancy on weekends compared to weekdays and weekdays.

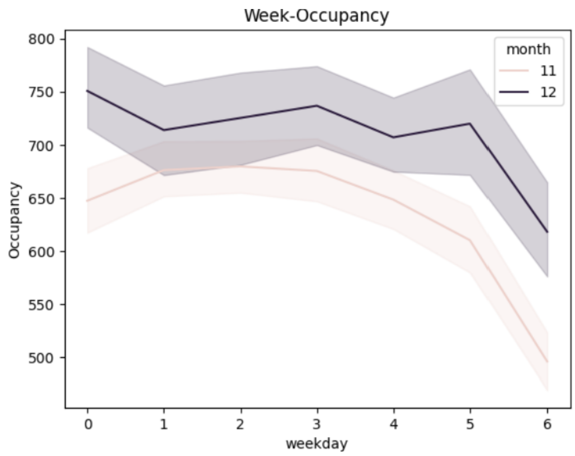

Figure 15: The weekday plots for two months in 2016 occupancy

Fig 16 exhibits the occupancy plot for the entire month of 30 days, and it is for the different weekdays. Nonetheless, the pattern shows some variation, which is noticeable in Fig.

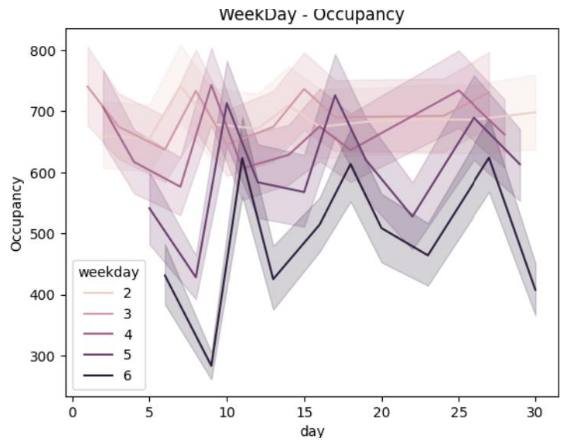

Figure 16: The monthly occupancy plot for the respective weekdays

As the dataset comprises both categorical and numerical variables, categorical ones are converted into numerical forms, and the correlation heatmap plot of all the variables is depicted in Fig 16. The correlation value explains the dependency of each variable with the others and provides a scope of inspection and gaining insight into the data, especially which data shows any trend of multi-co-linearity and thus enables to ponder the relevance of the variable to consider or discard concerning the target result cum meaningful information.

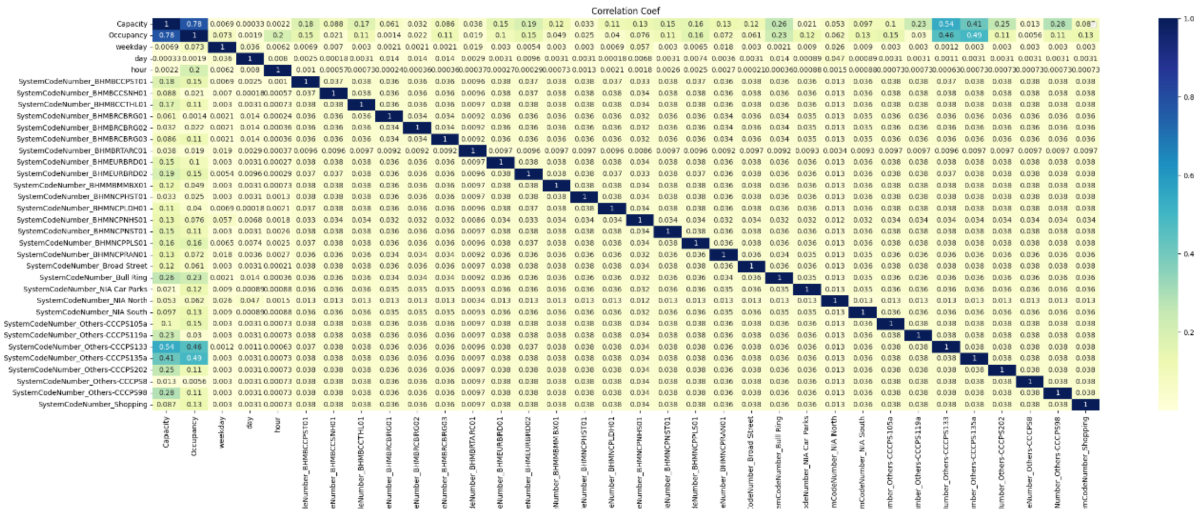

Figure 17: Correlation heatmap plot of the parking dataset, categorical variables converted to numerical forms

Post data analytics of the Birmingham parking dataset, the parking occupancy dependency of any other variable has been investigated through the machine learning paradigm. The problem is a supervised technique of regression where any dependent variable relation with other independent variables can provide insight based on a data-driven approach. However, any relation with other variables should ideally be linear or non-linear, for which appropriate machine-learning techniques are available. Scikit learns [48] library in Python has been used as a software resource to be run in a laboratory environment.

Table 5 provides a summary of linear regression, reflecting all the variables and their dependencies. Nonetheless, closer inspection suggests that the problem is unlikely to be of a linear regression kind; hence, a non-linear approach should also be undertaken for this dataset.

Table 5: OLS Regression Results

```
==============================================================================
Dep. Variable:           Occupancy   R-squared:                       0.779
Model:                         OLS   Adj. R-squared:                  0.779
Method:              Least Squares   F-statistic:                     2749.
Date:             Sat, 08 Jun 2024   Prob (F-statistic):               0.00
Time:                     12:36:45   Log-Likelihood:            -1.7875e+05
No. Observations:            25001   AIC:                        3.576e+05
Df Residuals:                24968   BIC:                        3.578e+05
Df Model:                       32
Covariance Type:         nonrobust
==============================================================================================
=
                 coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------------
const                       -635.1923     15.896    -39.958      0.000    -666.350    -604.034
Capacity                       0.4736      0.004    114.813      0.000       0.466       0.482
weekday                      -24.5858      0.983    -25.000      0.000     -26.513     -22.658
day                            0.5082      0.236      2.152      0.031       0.045       0.971
hour                          49.9721      0.745     67.044      0.000      48.511      51.433
SystemCodeNumber_BHMBCCPST01       93.3734     15.218      6.136      0.000      63.546     123.201
SystemCodeNumber_BHMBCCSNH01      275.1553     13.672     20.126      0.000     248.358     301.953
SystemCodeNumber_BHMBCCTHL01      211.6733     14.973     14.137      0.000     182.325     241.022
SystemCodeNumber_BHMBRCBRG01      281.7977     13.651     20.644      0.000     255.042     308.554
SystemCodeNumber_BHMBRCBRG02      108.4142     13.145      8.248      0.000      82.649     134.179
SystemCodeNumber_BHMBRCBRG03      -49.1459     13.951     -3.523      0.000     -76.491     -21.801
SystemCodeNumber_BHMBRTARC01      272.4172     39.104      6.967      0.000     195.772     349.063
SystemCodeNumber_BHMEURBRD01      191.9426     14.573     13.171      0.000     163.378     220.507
SystemCodeNumber_BHMEURBRD02      140.7438     15.518      9.070      0.000     110.328     171.160
SystemCodeNumber_BHMMBMMBX01      264.8827     14.110     18.772      0.000     237.226     292.540
SystemCodeNumber_BHMNCPHST01      101.7902     12.668      8.035      0.000      76.959     126.621
SystemCodeNumber_BHMNCPLDH01      278.9634     14.201     19.644      0.000     251.129     306.797
SystemCodeNumber_BHMNCPNHS01      214.7191     15.605     13.760      0.000     184.133     245.305
SystemCodeNumber_BHMNCPNST01      166.3539     14.703     11.314      0.000     137.535     195.173
SystemCodeNumber_BHMNCPPLS01      -16.2889     14.754     -1.104      0.270     -45.208      12.630
SystemCodeNumber_BHMNCPRAN01      208.6930     14.735     14.163      0.000     179.812     237.574
SystemCodeNumber_Broad Street      219.4094     14.156     15.500      0.000     191.663     247.155
SystemCodeNumber_Bull Ring      109.6956     10.041     10.925      0.000      90.014     129.377
SystemCodeNumber_NIA Car Parks     -286.5330     12.900    -22.211      0.000    -311.819    -261.247
SystemCodeNumber_NIA North      -51.5394     31.384     -1.642      0.101    -113.053       9.974
```

SystemCodeNumber_NIA South -65.7386 13.901 -4.729 0.000 -92.985 -38.492

SystemCodeNumber_Others-CCCPS105a 298.9705 11.016 27.141 0.000 277.379 320.562

SystemCodeNumber_Others-CCCPS119a -679.4520 9.870 -68.837 0.000 -698.799 -660.105

SystemCodeNumber_Others-CCCPS133 73.8235 10.348 7.134 0.000 53.540 94.107

SystemCodeNumber_Others-CCCPS135a 563.8120 9.646 58.452 0.000 544.906 582.718

SystemCodeNumber_Others-CCCPS202 -269.2572 9.793 -27.496 0.000 -288.451 -250.063

SystemCodeNumber_Others-CCCPS8 144.1891 12.477 11.556 0.000 119.734 168.645

SystemCodeNumber_Others-CCCPS98 -336.0031 9.597 -35.013 0.000 -354.813 -317.193

SystemCodeNumber_Shopping 273.4316 11.022 24.808 0.000 251.828 295.035

==

Omnibus: 3368.155 Durbin-Watson: 1.995

Prob(Omnibus): 0.000 Jarque-Bera (JB): 42915.543

Skew: -0.136 Prob(JB): 0.00

Kurtosis: 9.413 Cond. No. 5.51e+18

==

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The smallest eigenvalue is 2.76e-27. This might indicate that there are

strong multicollinearity problems or that the design matrix is singular.

time: 84.4 ms (started: 2024-06-08 12:36:45 +00:00)

Apart from the linear regression method, support vector machine regressor, decision tree regressor, and random forest regressor have been used on the dataset for comparison of results purpose. From the results, it appeared by inspection that decision tree regressor and random forest regressor worked better than linear regression and support vector machine regressor algorithms. Table 6 compares decision tree and random forest regressor feature importance values wherein feature 0 appears significant compared to the other 31 features.

Table 6: Machine learning Algorithm and feature importance

Decision Tree		Random Forest	
Feature: 0	Score: 0.83392	Feature: 0	Score: 0.71042
Feature: 1	Score: 0.01632	Feature: 1	Score: 0.05079
Feature: 2	Score: 0.00100	Feature: 2	Score: 0.03237
Feature: 3	Score: 0.11291	Feature: 3	Score: 0.13125
Feature: 4	Score: 0.00000	Feature: 4	Score: 0.00009
Feature: 5	Score: 0.00000	Feature: 5	Score: 0.00067
Feature: 6	Score: 0.00201	Feature: 6	Score: 0.00175
Feature: 7	Score: 0.00000	Feature: 7	Score: 0.00163
Feature: 8	Score: 0.00000	Feature: 8	Score: 0.00091
Feature: 9	Score: 0.00000	Feature: 9	Score: 0.00024
Feature: 10	Score: 0.00000	Feature: 10	Score: 0.00009
Feature: 11	Score: 0.00000	Feature: 11	Score: 0.00002
Feature: 12	Score: 0.00000	Feature: 12	Score: 0.00007

Feature: 13	Score: 0.00000	Feature: 13	Score: 0.00064
Feature: 14	Score: 0.00000	Feature: 14	Score: 0.00076
Feature: 15	Score: 0.00000	Feature: 15	Score: 0.00033
Feature: 16	Score: 0.00000	Feature: 16	Score: 0.00005
Feature: 17	Score: 0.00000	Feature: 17	Score: 0.00055
Feature: 18	Score: 0.00000	Feature: 18	Score: 0.00007
Feature: 19	Score: 0.00000	Feature: 19	Score: 0.00010
Feature: 20	Score: 0.00000	Feature: 20	Score: 0.00010
Feature: 21	Score: 0.00000	Feature: 21	Score: 0.01374
Feature: 22	Score: 0.00000	Feature: 22	Score: 0.00744
Feature: 23	Score: 0.00000	Feature: 23	Score: 0.00059
Feature: 24	Score: 0.00000	Feature: 24	Score: 0.00033
Feature: 25	Score: 0.00000	Feature: 25	Score: 0.00221
Feature: 26	Score: 0.01477	Feature: 26	Score: 0.01554
Feature: 27	Score: 0.00000	Feature: 27	Score: 0.00899
Feature: 28	Score: 0.00019	Feature: 28	Score: 0.01021
Feature: 29	Score: 0.00000	Feature: 29	Score: 0.00022
Feature: 30	Score: 0.00000	Feature: 30	Score: 0.00382
Feature: 31	Score: 0.01887	Feature: 31	Score: 0.00371
Feature: 32	Score: 0.00000	Feature: 32	Score: 0.00031

Table 7 depicts the R2 score of the training and testing datasets, which were split with a 70:30 ratio. The random forest technique yielded consistent and better results than support vector machines and decision tree regressors compared to the training and testing datasets.

Table 7: Performance metrics of different machine learning algorithms

Performance Metrics	Support Vector Machine Regressor	Decision Tree Regressor	Random Forest Regressor
Training R2 Score	0.508	0.872	0.995
Testing R2 Score	0.499	0.872	0.995

Cyber Security Aspects in Smart City

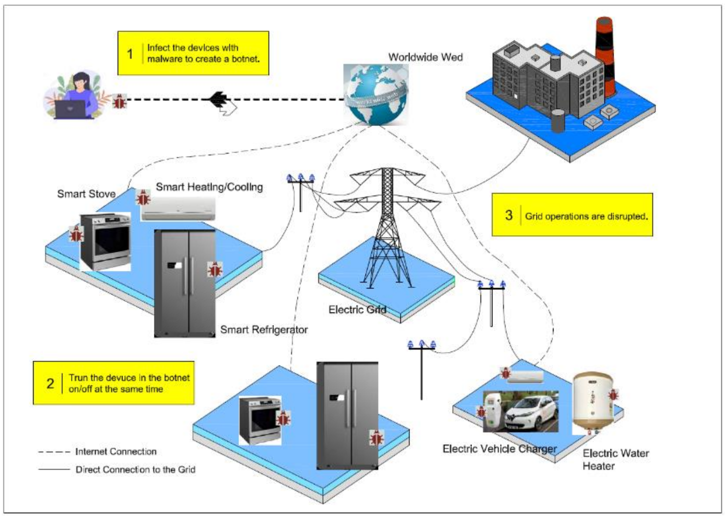

Figure 18: Invisible cyber attacker tends to target smart grid and smart city ecosystem and look for vulnerability

In a smart city, security is approached comprehensively by including all the facets of the city, as well as being integrated into all its constituent elements [49]. Electricity enabled smart cities by connecting smart grids. However, cyber crooks, fig 15, opportunistically look for vulnerabilities. The advancement of technologies in recent years has led to the rapid development of smart grids. In recent years, the utilization of smart grids has been on the rise in Turkey and globally, particularly in essential infrastructures such as natural gas, electricity, water, and energy systems. The rise in the adoption of smart grids has led to a corresponding growth in the significance of security issues. The frequency of cybersecurity assaults targeting these networks steadily rises annually [50].

As cities go on a smartness drive, so is the likelihood of increased threats by cyber-attackers who remain anonymously present in the cyber virtual world. The smart city also needs to cater to the need to safeguard the cyber attackers' malicious intent to cause harm to innocent citizens. Critical infrastructures, banking, hospitals, and public transport are some of smart cities' most common cyber security-sensitive aspects. Even cyber-attackers are recently believed to be eyeing the e-vehicle charging device by tampering with it. One of the most sensitive areas is global positioning systems (GPS) [3], which are used in almost all engineering and daily applications in modern days. GPS spoofing can compromise many of these uses.

Similarly, targeting the Internet of Things, smart meters, and artificial intelligence tools is also becoming a trend. The researchers, Ullah et al., devised a technique based on Deep Reinforcement Learning (DRL) to counteract jamming attacks on airborne Unmanned Aerial Vehicles (UAVs) by GPS. The proposed technique is designed to be applicable regardless of the jammer's geographic location, the channel model, and the UAV channel model. This technique determines the trajectory and power transmission level of UAVs by evaluating the quality of UAV transmission. The simulation findings demonstrate that the technique above enhances the Quality of Service (QoS) of the mission-specific UAVs deployed [51]. Almeida et al. [49] reviewed the cybersecurity risks and depicted a cybersecurity cognitive map for smart cities' risks entailing standards and regulations, the privacy of data, vulnerabilities in networks, access controls, IoT devices, and human behaviors. MITRE frameworks [52], which categorize tactics, techniques, and procedures of cyber attacks, 2023 launched ATLAS [53], which stipulates the adversaries of artificial intelligence use.

In the End

Smart cities offer an auspicious path for the advancement of urban development. In the face of expanding urban areas and mounting intricate problems, incorporating cutting-edge technologies and data-centric solutions can facilitate the development of more environmentally friendly societies [54]. Energy decarbonization and low carbon emissions are the key drivers of sustainable smart cities. The fabric of these is closely knitted through data generated, which was coined by Clive Humby, a British mathematician, in 2006 as the 'The new oil.' To explore further the data usage that the cyber world is generating exorbitantly these days, the use of artificial intelligence is the critical enabler for gathering business intelligence of reality and effectiveness. This chapter briefly presented a global scenario of smart city ecosystem and stressed the potential use of artificial intelligence, albeit ethically, to further explore the benefits. A typical use case of a UK city, which is Birmingham, the second biggest one, has also been presented as a regression problem. Based on the data, there is a much broader scope of applying classification and clustering techniques from the smart city data generated by connecting to the cyber world. As data keeps on growing exorbitantly, streaming in many devices of cyberspace, ripping the benefits by rightly exploring the new ways and avenues of untapped potential by the users, can transform the smart city paradigm in a global albeit local way.

Acknowledgment

The author thanks everyone in the Power Division of WAPCOS Limited, who contributed enormously to the completion of this work. Special thanks to Pawan Kumar, Madhuresh Srivastava, and Rohit Arora for their courage and consistent encouragement throughout the period.

References:

[1] "Smart cities - European Commission." https://commission.europa.eu/eu-regional-and-urban-development/topics/cities-and-urban-development/city-initiatives/smart-cities_en (accessed Apr. 06, 2024).

[2] "Smart Cities Mission: A step towards Smart India| National Portal of India." [Online]. Available: https://www.india.gov.in/spotlight/smart-cities-mission-step-towards-smart-india

[3] E. Khalifa, "Smart Cities: Opportunities, Challenges, and Security Threats," *J. Strateg. Innov. Sustain.*, vol. 14, no. 3, pp. 79–88, 2019, doi: 10.33423/jsis.v14i3.2108.

[4] M. E. Milakovich, *Digital governance: Applying advanced technologies to improve public service*, no. September. 2021. doi: 10.4324/9781003215875.

[5] "What Is a Smart City? - Cisco." [Online]. Available: https://www.cisco.com/c/en/us/solutions/industries/smart-connected-communities/what-is-a-smart-city.html

[6] "Smart Cities | United Nations Development Programme." [Online]. Available: https://www.undp.org/sgtechcentre/smart-cities-1

[7] NIST, "A Consensus Framework for Smart City Architectures: IES-City Framework (Internet-of-Things-Enabled Smart City Framework)," *IES-City Framew. Public Work. Gr.*, 2018.

[8] L. Anthopoulos, "Defining Smart City Architecture for Sustainability," *Electron. Gov. Electron. Particip. Jt. Proc. Ongoing Res. Proj. IFIP WG 8.5 EGOV ePart 2015*, no. AUGUST 2015, pp. 140–147, 2015, doi: 10.3233/978-1-61499-570-8-140.

[9] J. Winkowska, D. Szpilko, and S. Pejić, "Smart city concept in the light of the literature review," *Eng. Manag. Prod. Serv.*, vol. 11, no. 2, pp. 70–86, 2019, doi: 10.2478/emj-2019-0012.

[10] J. Stübinger and L. Schneider, "Understanding smart city—a data-driven literature review," *Sustain.*, vol. 12, no. 20, pp. 1–23, 2020, doi: 10.3390/su12208460.

[11] A. M. Toli and N. Murtagh, "The Concept of Sustainability in Smart City Definitions," *Front. Built Environ.*, vol. 6, no. June, pp. 1–10, 2020, doi: 10.3389/fbuil.2020.00077.

[12] T. Bakıcı, E. Almirall, and J. Wareham, "A Smart City Initiative: The Case of Barcelona," *J. Knowl. Econ.*, vol. 4, no. 2, pp. 135–148, 2013, doi: 10.1007/s13132-012-0084-9.

[13] "Smart City Rankings - IMD business school for management and leadership courses." [Online]. Available: https://www.imd.org/smart-city-observatory/home/rankings/#_tab_Rank

[14] M. Gascó-Hernandez, "Building a smart city: Lessons from Barcelona," *Commun. ACM*, vol. 61, no. 4, pp. 50–57, 2018, doi: 10.1145/3117800.

[15] I. Capdevila and M. I. Zarlenga, "Smart city or smart citizens? The Barcelona case," *J. Strateg. Manag.*, vol. 8, no. 3, pp. 266–282, 2015, doi: 10.1108/JSMA-03-2015-0030.

[16] "How moving from the US to Costa Rica's 'blue zone' transformed this family's life forever | CNN." [Online]. Available: https://edition.cnn.com/travel/costa-rica-blue-zone-family-move/index.html

[17] "The 13 healthiest countries in the world to live in as an expat | The Independent | The Independent." [Online]. Available: https://www.independent.co.uk/life-style/healthiest-countries-world-expat-a7564031.html

[18] "Avenida Escazú." [Online]. Available: https://www.avenidaescazu.com/en

[19] "How China's buses shaped the world's EV revolution." [Online]. Available: https://www.bbc.com/future/article/20231206-climate-change-how-chinas-electric-vehicle-revolution-began-with-buses

[20] "THE 17 GOALS | Sustainable Development." [Online]. Available: https://sdgs.un.org/goals

[21] J. D. Sachs, G. Schmidt-Traub, M. Mazzucato, D. Messner, N. Nakicenovic, and J. Rockström, "Six Transformations to achieve the Sustainable Development Goals," *Nat. Sustain.*, vol. 2, no. 9, pp. 805–814, 2019, doi: 10.1038/s41893-019-0352-9.

[22] S. D. G. FUND, "Sustainable development goals," *... //Www. Un. Org/Sustainable development...*, pp. 1–21, 2015, [Online]. Available: https://documents1.worldbank.org/curated/en/106391567056944729/pdf/World-Bank-Group-Partnership-Fund-for-the-Sustainable-Development-Goals-Annual-Report-2019.pdf

[23] J. R. Quinlan, "Learning decision tree classifiers," *ACM Comput. Surv.*, vol. 28, no. 1, pp. 71–72, 1996, doi: 10.1145/234313.234346.

[24] L. Breiman, "Random Forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.

[25] E. Fix and J. L. Hodges, "Discriminatory Analysis. Nonparametric Discrimination: Consistency Properties," *Int. Stat. Rev. / Rev. Int. Stat.*, vol. 57, no. 3, p. 238, 1989, doi: 10.2307/1403797.

[26] T. M. Cover and P. E. Hart, "Nearest Neighbor Pattern Classification," *IEEE Trans. Inf. Theory*, vol. 13, no. 1, pp. 21–27, 1967, doi: 10.1109/TIT.1967.1053964.

[27] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995, doi: 10.1007/BF00994018.

[28] L. P. Kaelbling, M. L. Littman, and A. W. Moore, "Reinforcement learning: A survey," *J. Artif. Intell. Res.*, vol. 4, pp. 237–285, 1996.

[29] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015, doi: 10.1038/nature14539.

[30] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT Press, 2016.

[31] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.

[32] Q. Zhang, J. Zhang, J. Zou, and S. Fan, "A novel fault diagnosis method based on stacked

LSTM," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 790–795, 2020, doi: 10.1016/j.ifacol.2020.12.832.

[33] K. Cho *et al.*, "Learning phrase representations using RNN encoder-decoder for statistical machine translation," *EMNLP 2014 - 2014 Conf. Empir. Methods Nat. Lang. Process. Proc. Conf.*, pp. 1724–1734, 2014, doi: 10.3115/v1/d14-1179.

[34] A. Graves, A. Mohamed, and G. Hinton, "Speech recognition with deep recurrent neural networks," in *2013 IEEE international conference on acoustics, speech and signal processing*, 2013, pp. 6645–6649.

[35] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.

[36] O. Triebe, H. Hewamalage, P. Pilyugina, N. Laptev, C. Bergmeir, and R. Rajagopal, "NeuralProphet: Explainable Forecasting at Scale," pp. 1–40, 2021, [Online]. Available: http://arxiv.org/abs/2111.15397

[37] F. Petropoulos *et al.*, "Forecasting: theory and practice," *Int. J. Forecast.*, no. xxxx, 2022, doi: 10.1016/j.ijforecast.2021.11.001.

[38] B. N. Mohapatra and P. P. Panda, "Machine learning applications to smart city," *Accent. Trans. Image Process. Comput. Vis.*, vol. 5, no. 14, pp. 1–6, 2019, doi: 10.19101/tipcv.2018.412004.

[39] S. Tiwari *et al.*, "Machine learning-based model for prediction of power consumption in smart grid- smart way towards smart city," *Expert Syst.*, vol. 39, no. 5, 2022, doi: 10.1111/exsy.12832.

[40] J. Chin, V. Callaghan, and I. Lam, "Understanding and personalising smart city services using machine learning, the Internet-of-Things and Big Data," *IEEE Int. Symp. Ind. Electron.*, pp. 2050–2055, 2017, doi: 10.1109/ISIE.2017.8001570.

[41] M. Mohammadi and A. Al-Fuqaha, "Enabling Cognitive Smart Cities Using Big Data and Machine Learning: Approaches and Challenges," *IEEE Commun. Mag.*, vol. 56, no. 2, pp. 94–101, 2018, doi: 10.1109/MCOM.2018.1700298.

[42] S. E. Bibri and J. Krogstie, "The emerging data–driven Smart City and its innovative applied solutions for sustainability: the cases of London and Barcelona," *Energy Informatics*, vol. 3, no. 1, 2020, doi: 10.1186/s42162-020-00108-6.

[43] K. D. C. Adje, A. Ben Letaifa, M. Haddad, and O. Habachi, "Smart City Based on Open Data: A Survey," *IEEE Access*, vol. 11, no. May, pp. 56726–56748, 2023, doi: 10.1109/ACCESS.2023.3283436.

[44] D. Stolfi, "Parking Birmingham. UCI Machine Learning Repository.," 2019.

[45] "pandas - Python Data Analysis Library." [Online]. Available: https://pandas.pydata.org/

[46] "Welcome To Colaboratory - Colaboratory." https://colab.research.google.com/ (accessed Nov. 17, 2023).

[47] E. Bisong, "Google Colaboratory BT - Building Machine Learning and Deep Learning Models on Google Cloud Platform: A Comprehensive Guide for Beginners," E. Bisong, Ed. Berkeley, CA: Apress, 2019, pp. 59–64. doi: 10.1007/978-1-4842-4470-8_7.

[48] "scikit-learn: machine learning in Python — scikit-learn 1.3.2 documentation." https://scikit-learn.org/stable/ (accessed Nov. 17, 2023).

[49] F. Almeida, "Prospects of Cybersecurity in Smart Cities," *Futur. Internet*, vol. 15, no. 9, pp. 1–21, 2023, doi: 10.3390/fi15090285.

[50] İ. AVCI, "Investigation of Cyber-Attack Methods and Measures in Smart Grids," *Sak. Univ. J. Sci.*, vol. 25, no. 4, pp. 1049–1060, 2021, doi: 10.16984/saufenbilder.955914.

[51] Z. Ullah, F. Al-Turjman, L. Mostarda, and R. Gagliardi, "Applications of Artificial Intelligence and Machine learning in smart cities," *Comput. Commun.*, vol. 154, no. March 2020, pp. 313–323, 2020, doi: 10.1016/j.comcom.2020.02.069.

[52] "MITRE ATT&CK®."

[53] "ATLAS Navigator | MITRE ATLAS™."

[54] J. S. Gracias, G. S. Parnell, E. Specking, E. A. Pohl, and R. Buchanan, "Smart Cities—A Structured Literature Review," *Smart Cities*, vol. 6, no. 4, pp. 1719–1743, 2023, doi: 10.3390/smartcities6040080.