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SMART TSS: Defining transportation system behavior using big data analytics in smart cities

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ABSTRACT

A smart city improves the quality of its citizens by providing access to ubiquitous services. Intelligent Transportation Systems (ITS) have a fundamental role in transforming a metropolitan area into a smart city. In the past two decades, many applications of ITS, e.g. city-wide traffic management and monitoring, smart parking, public transportation information services (bus, train, taxi, plane, etc.), logistics, real-time traffic, road speed limit monitoring and management etc., are deployed in smart cities. The sensors or mobile objects in ITS constantly generate mobility data and the scale at which this data is generated is witnessing an exponential increase in volumes. To store and subsequently analyze such massive data generated by sensors, new architectures are needed which are primarily designed for working with big data. In this work, we propose a big data analytics architecture for ITS. The proposed architecture has a built-in storage and analysis capability to work with ITS data and is composed of four modules, namely (1) Big Data Acquisition and Preprocessing Unit (2) Big Data Processing Unit (3) Big Data Analytics Unit and (4) Data Visualization Unit. A detailed analysis of ITS big data for monitoring the average speed of a vehicle at w.r.t. the time attribute is provided. The proposed architecture is evaluated using Hadoop thus validating the proof of concept. The empirical results are encouraging and open directions for future research.

1. Introduction

The advancements in technology and the advent of smart devices is advocating the way cities of future will have their ecosystem, i.e. transport systems, education, healthcare, libraries, water and gas supply, etc., managed (Khan, Silva, & Han, 2016). The idea to develop smart cities of future is an attempt to transform existing cities and plan new ones in a manner which maximizes the use of technologies of future, i.e. smart devices and big data analytics, for improving the city ecosystem. The objective is to integrate Information and Communication Technologies (ICT) and Internet of Things (IoT) in a secure manner to manage and use the assets of a city effectively. Ideally, a single centralized system should be able to collect, process and support decision-making for all the assets of a city. Practically, it is not possible to develop such a magic box with the available computing architectures. However, multiple systems deployed in parallel and processing the data generated by smart devices in different domains may help in achieving the goal.

A city-wide intelligent transportation system has many actors in place including, metro-train, metro-bus, cars, bikes, people carrying smart devices, etc. The incorporation of ICT and IoT in transportation systems is capable to bring a big change in the way people travel and the way transportation systems are managed. This gives a new direction to urban planning, i.e. incorporating intelligence in to the transportation systems. ITS focuses in bringing improvements in traffic efficiency, road safety, assistance for drivers and passengers. However, achieving the true benefits of the use of modern ICT and IoT requires a lot of efforts and the resolution of many critical challenges like issues related to dependability, reliability and real-time communication between users and infrastructure (Bouk, Ahmed, Kim, & Song, 2017). For example, real-time communication may help in getting dynamic road traffic information for selecting the most appropriate route.

Data is collected from sensors which are essentially all over the city installed on moving objects, mobile phones, etc. As the collected data comes from a range of devices, it is in many formats, structure, granularity and complexity which may make it difficult to process with conventional data storage and processing technologies, e.g. relational databases, which are designed to work with relational data. Big data technologies like Hadoop, MapReduce, Spark and GraphX need to be used for the processing of big data generated in smart cities. In general, Hadoop is efficient in processing offline data, while Spark and GraphX are mostly used for processing online data with some processing

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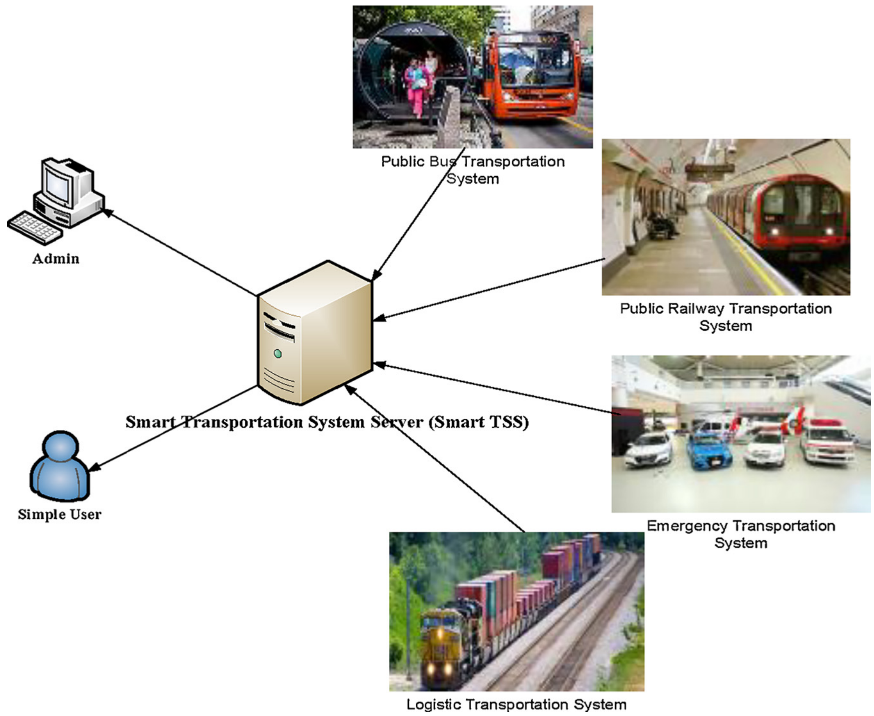

Fig. 1. Overview of the proposed System Design.

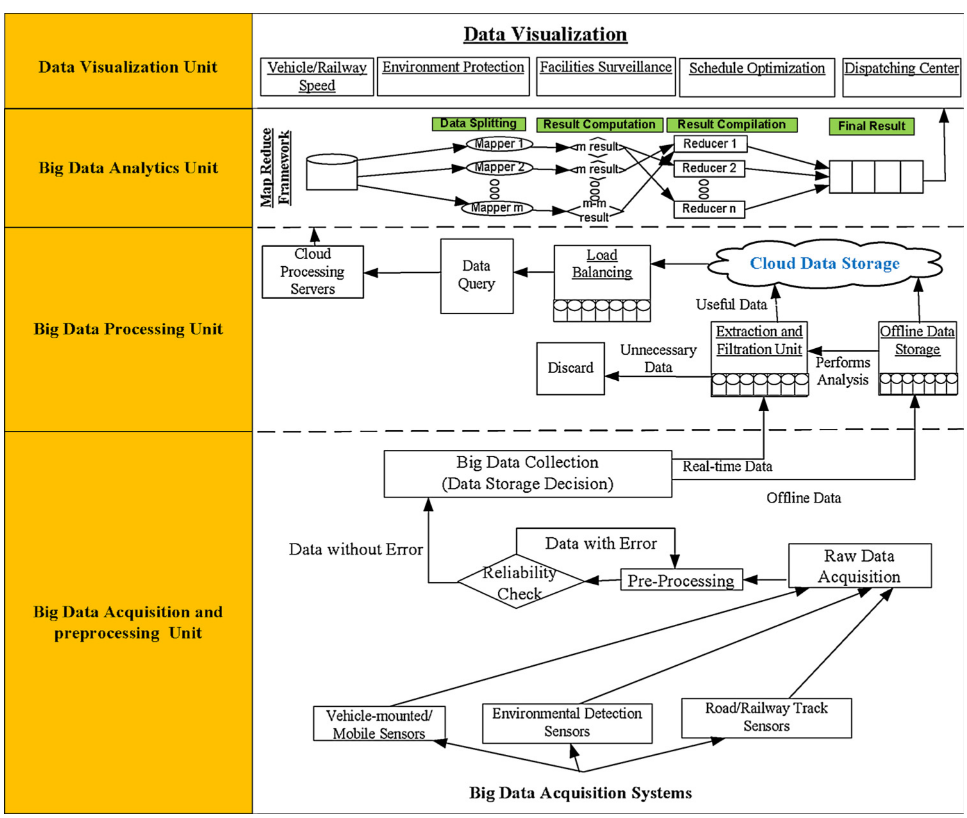

Fig. 2. Big Data Analytics Architecture for Intelligent Transportation System.

limitations. The management and analysis of the online and offline data has many challenges. In some cases, processing online and offline data simultaneously is the requirement of a purpose-built system (Ahmad, Paul, & Mazhar Rathore, 2016a). Big data analytics systems are required to have a modular architecture which makes them easy to develop and fix whenever an issue arises.

This paper proposes an architecture for intelligent transportation systems in a smart city environment. The architecture is composed of four layers and various tasks are performed at each layer. A proof-of-the-concept is implemented using Spark and GraphX with custom Hadoop eight (08) node setup on UBUNTU 14.04 LTS coreTMi7 machines with 3.2 GHz processor and 8 GB memory.

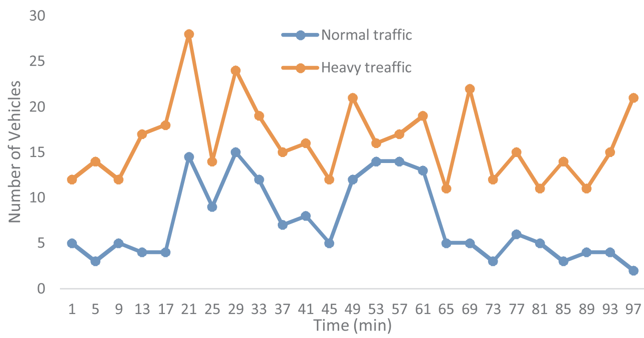

Fig. 3. Vehicles on road.

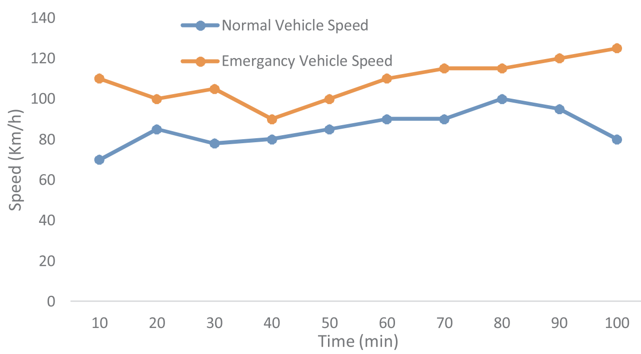

Fig. 4. Vehicles speed on road.

Fig. 5. Throughput of the system depending on data size.

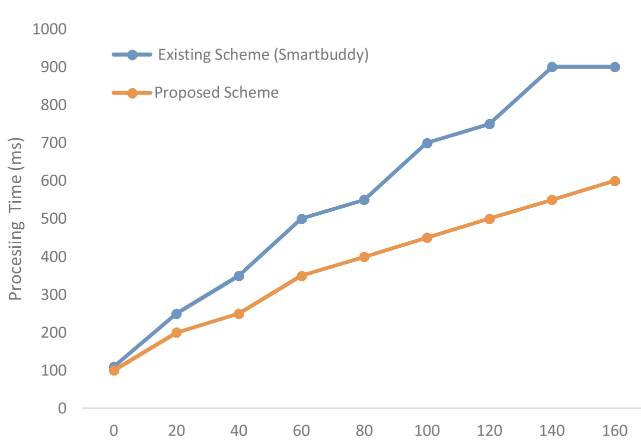

Fig. 6. Processing time of the system depending on number of nodes.

The rest of this paper is organized as follows: The next section presents the related work. Section 3 is about the detailed architecture of the proposed system and Section 4 presents a detailed analysis and evaluation of the system implemented. Section 5 concludes this work and gives some future directions.

2. Related work

2.1. ITS in smart cities

Smart cities are rather complex entities which are comprised of objects like sensors, smart meters, mobile devices, embedded hardware, etc. and the instrumentation that defines the intelligence of cities (Albino, Berardi, & Dangelico, 2015). The intelligence of cities can be described as the collective intelligence of its residents which benefit from online collaborative learning by focusing on people-driven innovation. The instrumentation and interconnection of smart devices including mobile devices, sensors, actuators, etc. allows data to be processed, i.e. collected and analyzed, in real-time. The volumes in which data is generated by smart devices are massive and the term 'big data' generally refers to the large volumes of data.

In recent past, the emergence of internet of things has evolved the concept of intelligent and smart cities. The intelligence in smart cities comes essentially from the smart devices which are continuously producing multidimensional data in the social, geo-spatial, digital spaces which can potentially be used for improving not only the physical infrastructure management in smart cities but also the socio-economic activities (Batty et al., 2012a) thus enhancing the problem-solving capabilities for intelligent smart cities.

As mentioned already, an essential component of smart cities is Intelligent Transportation Systems. Broadly speaking, ITS is a three-tier architecture which has roads, vehicles and users at its core which collaborate as a network (Komninos, Schaffers, & Pallot, 2011). The transportation in cities has many aspects to it, e.g. real-time traffic information, mass transit, speed limits, emergency vehicle assistance, etc. (Xiong, Sheng, Rong, & Cooper, 2012) A smart city has all these transportation modes coordinated and implemented in a way that the social problems caused by the road congestions are minimized. The advantage of ITS thus comes in reduced traffic congestion and consequently the fuel consumption and most importantly saving lives by reducing road accidents and having an effective emergency vehicle assistance. We now highlight some key components in ITS.

2.1.1. Live traffic information (LTI)

A live feed on the state of current and developing congestions and the public transport schedules including delays if any (Neirotti, De Marco, Cagliano, Mangano, & Scorrano, 2014). Route-planning applications consider the live feed for planning the route for a better commuting experience. Intelligent traffic management using for example, smart signals, by the city traffic police is also based on the LTI.

2.1.2. Smart public transportation (SPT)

Smart public transportation is aimed at facilitating the transportation of passengers as well as goods' in a way that the costs in time and money are minimized and the safety of the passengers is ensured (Kitchin, 2015). All public transport means including metro-train, metro-bus, etc. are components of SPT.

2.1.3. Smart logistics (SLo)

Another important component focused on transport vehicles is Smart Logistics which is aimed at providing goods in time and on demand in a cost-effective way (Dobre & Xhafa, 2014). The logistics are transported using all the transportation mediums and should be transported effectively to improve the customer satisfaction with the minimum costs involved.

2.1.4. Smart parking (SP)

Current state of parking disseminated by the sensors is used by the smart parking applications to readily provide the available parking slots to the users (Strohbach, Ziekow, Gazis, & Akiva, 2015) thus, improving the user experience of the road along with achieving fuel efficiency.

2.1.5. Emergency vehicle assistance (EVA)

The system broadcasts the upcoming route for the emergency vehicle to the vehicles on road to facilitate prioritized access to the emergency vehicle. The smart signals could also be activated (Castro, Jara, & Skarmeta, 2013) to improve the response time of the emergency vehicle.

2.1.6. Variable speed limits (VSL)

Ideally, the current traffic conditions should be used to define the speed limits on roads. Electronic sign boards can thus be employed to setup varying speed limits on roads to avoid congestions in peak hours or in emergency situations.

2.1.7. Smart vehicle charging (SVC)

Pollution is a major concern in smart cities and electric vehicles including automobiles are the future of transportation. Smart charging of electric vehicles helps in charging electric vehicles cost effectively, i.e. during low demand electricity hours, and time efficiently, i.e. avoiding congestions at charging points, thus achieving user-satisfaction (Buhalis & Amaranggana, 2013).

Next, we discuss the significance of Big Data Analytics in the context of intelligent smart cities.

2.2. Big data analytics and ITS

As mentioned above, the essence of smart cities is the hardware including sensors, mobile devices, etc. which generate data and essentially the information that is used to make cities smart (Ahmad, Paul, Rathore, & Chang, 2016b; Ahmad, Paul, Din, et al., 2017; Ahmad, Paul, Khan, et al., 2017; Ahmad et al., 2018; Jara, Genoud, & Bocchi, 2014). However, all the data generated by the smart city hardware has no meaning if it is not processed and analyzed (Ahmad, Paul, Rathore, & Chang, 2016c; Bonomi, Milito, Natarajan, & Zhu, 2014; Söderström, Paasche, & Klauser, 2014). Therefore, along with the hardware infrastructure and applications that produces and record the data, an analysis framework is fundamental to an intelligent smart city (Kitchin, 2014). This is referred to as big data analytics and in simple words, the idea is to extract some meaning from the data that is produced in large volumes. Thus, from a big data perspective, a smart city has to manage, process and regulate live data using information and communication technologies (Townsend, 2013). The huge amounts of data produced in smart cities can be used to better illustrate city processes (Al Nuaimi, Al Neyadi, Mohamed, & Al-Jaroodi, 2015), e.g. object moving patterns using trajectory mining (Fan & Bifet, 2013), ultimately providing guidelines for future developments (Batty et al., 2012b; Rathore, Ahmad, Paul, & Rho, 2016).

As suggested by Schaffers et al. (2011), a smart city originates from small city-based clouds which progressively become open and federated content platforms, leading to the emergence of cloud-based fully connected cities. However, for such kind of cloud computing models, many issues have been highlighted in literature (Cheng, Longo, Cirillo, Bauer, & Kovacs, 2015; Hashem et al., 2016). We discuss some of the important issues with cloud-based systems in ITS: (1) When data is being collected from multiple heterogeneous sources, the abstraction at which data is recorded, semantics, storage mechanisms, structured or unstructured, user understanding of the data, etc. have an impact on the quality of the results (Khan, Anjum, & Kiani, 2013). Thus, data representation is of fundamental importance in such smart systems which are heterogeneous in nature. (2) Another challenge is the scales at which data is being collected. Most of this data will never be looked again and thus must be processed on the fly. Therefore, a live data processing system is essential to producing meaningful results from the data. (3) The Analytics engine employed determines the kind of results that will be produced from the data. Thus, the computational cost of the analysis algorithms and the processing powers of the underlying hardware along with the distributed computing architecture becomes a major challenge in big data systems. (4) Privacy is a major concern when dealing with data produced by individuals. There are limits to which extent such data could be stored and processed. For most big data service providers, maintaining the confidentiality of the data is a major challenge. (5) When data is being stored and processed at such large scales, the energy consumption for data centers which manage and process big data is also a concern both from economic and environmental perspectives.

Keeping in view the above points, it is rather clear that such models and frameworks are required which generate useful data from intelligent smart cities in general, and intelligent transportation systems in particular, and then such systems be employed which can manage and process big data for future while developing ITS in smart cities.

3. Proposed architecture of big data analytics for intelligent transportation system

In urban areas, public transport is the major transportation medium. Many applications including city-wide traffic management, smart parking assistance, public transportation services (e.g., bus, train, taxi, and plane), logistics, real-time traffic, and road speed limit monitoring and management, etc. have been introduced for ITS. An overview of the proposed system is shown in Fig. 1.

As the smart devices generate a continuous stream of data, that data is stored and managed by a central big data analytics unit which primarily is comprised of four units namely (1) Big Data Acquisition and Preprocessing Unit (2) Big Data Processing Unit (3) Big Data Analytics Unit and (4) Data Visualization Unit. The proposed big data architecture is presented in Fig. 2. Each unit of the architecture is explained in the sequel.

3.1. Big data acquisition and pre-processing unit

The vehicle mounted or mobile sensors, environmental detection sensors, road/railway track sensors are deployed. These devices generate continuous ITS data streams. ITS are made up of heterogeneous sensor devices where data originates from different sources. Therefore, data generated by each sensor device is collected separately. In the big data acquisition and pre-processing unit, the incoming ITS data is initially stored as received. We assume that ITS have a lot of metadata containing source information. This storage system handles the ITS data redundancy, removal of noise from the ITS data, and removing other error from the ITS data. After pre-processing, the collected data is transmitted to the data processing unit.

3.2. Big data processing unit

We process the incoming data stream as online and offline data stream. In the case of offline data processing, the data is sent to the cloud data storage. This data is then used for future analysis. However, in real-time data, all the data are transmitted to the extraction and filtration unit. Hence, all the unnecessary or redundant data is discarded by using filtration. Since the data which is collected from different ITS sensor devices need load balancing on the storage servers. In the proposed architecture, the load balancer is used that performs cooperative load balancing load among different storage servers and separates the data from different data sources. The data storage is based on No SQL databases such as Mongo DB, Neo4j DB, Flock DB, etc. for storing big data and indexing final and intermediate results. Different distributed data query mechanisms are required to generate queries, because of the complex nature of big data. After querying, the ITS data is ready for processing. The server intelligently processes the ITS data based on web standard specifications. This processing of ITS data is also based on No SQL databases. After big data processing unit, the data is transmitted to big data analytical unit.

3.3. Big data analytics unit

In big data analytics unit, the map-reduce framework is used. In map-reduce framework, the input ITS data is split into small chunks which are then processed by the mapper nodes. Each mapper node works independently on the allocated data and intermediate results are generated for each mapper node. The results are then combined at the reducers which perform the aggregation such that the results generated by the mappers are significant. The results produced by the reducers are then combined into final results which are passed on to the visualization unit.

3.4. Data visualization unit

In the data visualization unit, the ITS data is visualized for the users using various techniques. The visualization techniques help in easy understandability of the results and help in decision-making. The techniques include simple tables, bar charts and graphs with meaningful coloring schemes. As the data is from multiple sensor deployments, different kind of visualizations are put in place to get a cohesive view of the city traffic.

4. Data analysis and system evaluation

The proposed system is implemented using Spark and GraphX with custom Hadoop eight (08) node setup on UBUNTU 14.04 LTS coreTMi7 machines with 3.2 GHz processor and 8 GB memory. For real-time traffic, we generate Pcap packets from the datasets by using Wireshark libraries and retransmit them towards the developed system. Hadoop-pcap-lib, Hadoop-pcap-serde, and Hadoop Pcap Input libraries are used for network packets processing and generating Hadoop Readable form (sequence file) at collection and aggregation unit so that it can be processed by Hadoop and GraphX. GraphX is used to build and process graphs with the aim of making smart transportation decisions. We have considered the massive volume of data (Bischof et al., 2014; Tönjes et al., 2014; Uppoor, Trullols-Cruces, Fiore, & Barcelo-Ordinas, 2014). The intensity of the traffic varies from time to time on the same road. The intensity analysis for a range of time slots a day helps the authorities to manage and make proper plans for the traffic.

Initially, the analysis is performed on Aarhus city traffic data. Fig. 3 shows normal and heavy traffic on road. When the normal traffic is exceeded, the processing unit of the proposed architecture generates warnings and also the corrective measures including speed limit adjustment.

Fig. 4 demonstrates the driving speed of normal vehicles and emergency vehicles of various users on road. It is shown in the figure that normal traffic drives carefully by limiting their vehicle driving speed. However, emergency vehicles (ambulances etc.) crosses the normal speed. In this case, the system generates an alert which is transmitted to the officers on duty.

Since the main contribution of the work is the processing of large data to achieve smart transportation, thus, the system is evaluated on efficiency regarding throughput (in megabytes/sec Mbps) and the response time (in milliseconds). While analyzing the efficiency results regarding throughput, we compare our proposed scheme with the existing scheme (smart buddy) (Paul, Ahmad, Mazhar Rathore, & Jabbar, 2016). we increase the dataset size for both the schemes and perceives the system throughput effects. We noticed that with the increase in the dataset for both the schemes the system throughput is also increased, as shown in Fig. 5. It is shown in the figure that the proposed scheme performs better than the exisiting scheme. To sum up, we can say that the throughput is directly proportional to the data rate. This is because of the parallel processing of the large data on Hadoop ecosystem. When the dataset is larger, the Hadoop system partitions the data into chunks and processes them in parallel. We can observe that the throughput at large datasets, e.g. 7345 MB, the throughput is rather decent. This is the major achievement of the system that with an increase in data size the throughput also increases. However for the smaller dataset. Less than 100 MB, the use of Hadoop is not efficient.

We test the system by increasing the number of nodes from zero to two hundred thousand for the proposed and exisitng scheme (smart-buddy), as shown in Fig. 6. The massive increase in the number of nodes results in a gradual increase in the processing time as shown in the graph for both the schemes. Moreover, even for two hundred thousand nodes, the processing time is quite acceptable, i.e., less than one thousand milliseconds. Therefore, based on the efficiency results, we can say that the system performs well in real-time as comapre exisitng scheme.

5. Concluding remarks

This article has envisioned the fundamental role of Big Data analytics for intelligent transportation system (ITS) for smart cities. In this paper, we have demonstrated Big Data analytics architecture for ITS. This architecture analyzes and stores the ITS data efficiently and helps the city administration to make better decisions based on the kind of visualizations available. A detailed analysis of ITS Big Data for the average speed of a vehicle at different time, efficiency of the proposed system is provided in the paper using Hadoop. The proof-of-concept implementation is encouraging, and we intend to deploy the proposed framework for other kinds of real heterogenous data in future and build a cloud-based ecosystem where the intelligent smart city applications are running ideally without the need of human intervention.

References

Ahmad, A., Paul, A., & Mazhar Rathore, M. (2016). An efficient divide-and-conquer approach for big data analytics in machine-to-machine communication. *Neurocomputing, 174*, 439–453.

Ahmad, A., Paul, A., Rathore, M. M., & Chang, H. (Paul, Rathore, Chang, 2016a). An efficient multidimensional big data fusion approach in machine-to-machine communication. *ACM Transactions on Embedded Computing System, 15*(No. 2) Article 39, Publication date May 2016.

Ahmad, A., Paul, A., Rathore, M. M., & Chang, H. (Paul, Rathore, Chang, 2016b). *Smart cyber society: Integration of capillary devices with high usability based on cyber-physical system. Future generation computer systems*, *Vol. 56*, Elsevier493–503. http://dx.doi.org/10.1016/j.future.2015.08.004.

Ahmad, A., Paul, A., Din, S., Rathore, M. M., Choi, G. S., & Jeon, G. (2017). *Multilevel data processing using parallel algorithms for analyzing big data in high performance computing. International journal on parallel programming.* Springer1–20. http://dx.doi.org/10.1007/s10766-017-0498-x.

Ahmad, A., Paul, A., Khan, M., Jabbar, S., Rathore, M. M., Chilamkurti, N., et al. (2017). Energy efficient hierarchical resource sharing management for mobile cloud computing. *IEEE Transactions on Sustainable Computing Year,* (99), 1. http://dx.doi.org/10.1109/TSUSC.2017.2714344.

Ahmad, A., Khan, M., Paul, A., Din, S., Rathore, M. M., Jeon, G., et al. (2018). *Towards modeling and optimization of features selection in big data based social internet of things. Future generation computer system*.

Al Nuaimi, E., Al Neyadi, H., Mohamed, N., & Al-Jaroodi, J. (2015). Applications of big data to smart cities. *Journal of Internet Services and Applications, 6*(1), 25.

Albino, V., Berardi, U., & Dangelico, R. M. (2015). Smart cities: Definitions, dimensions, performance, and initiatives. *Journal of Urban Technology, 22*(1), 3–21.

Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., et al. (2012a). Smart cities of the future. *The European Physical Journal Special Topics, 214*(1), 481–518.

Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., et al. (2012b). Smart cities of the future. *European Physical Journal Special Topics, 214*, 481–518.

Bischof, S., Karapantelakis, A., Nechifor, C.-S., Sheth, A., Mileo, A., & Barnaghi, P. (2014). Semantic modeling of smart city data. *Position Paper in W3C Workshop on the Web of Things: Enablers and Services for an Open Web of Devices, 25-26 June 2014*.

Bonomi, F., Milito, R., Natarajan, P., & Zhu, J. (2014). *Fog computing: A platform for internet of things and analytics. Big data and internet of things: A roadmap for smart environments.* Springer International Publishing169–186.

Bouk, S. H., Ahmed, S. H., Kim, D., & Song, H. (2017). Named data networking-based ITS

for smart cities. *IEEE Communications Magazine, 55*(1), 105–111.
Buhalis, D., & Amaranggana, A. (2013). *Smart tourism destinations. Information and communication technologies in tourism 2014*. Cham: Springer553–564.
Castro, M., Jara, A. J., & Skarmeta, A. F. (2013). Smart lighting solutions for smart cities. *Advanced Information Networking and Applications Workshops (WAINA), 2013 27th International Conference* (pp. 1374–1379).
Cheng, B., Longo, S., Cirillo, F., Bauer, M., & Kovacs, E. (2015). Building a big data platform for smart cities: Experience and lessons from santander. *Big Data (BigData Congress), 2015 IEEE International Congress* (pp. 592–599).
Dobre, C., & Xhafa, F. (2014). Intelligent services for big data science. *Future Generation Computer Systems, 37*, 267–281.
Fan, W., & Bifet, A. (2013). Mining big data: Current status, and forecast to the future. *ACM SIGKDD Explorations Newsletter, 14*(2), 1–5.
Hashem, I. A. T., Chang, V., Anuar, N. B., Adewole, K., Yaqoob, I., Gani, A., et al. (2016). The role of big data in smart city. *International Journal of Information Management, 36*(5), 748–758.
Jara, A. J., Genoud, D., & Bocchi, Y. (2014). Big data in smart cities: From poisson to human dynamics. *Advanced Information Networking and Applications Workshops (WAINA), 2014 28th International Conference* (pp. 785–790).
Khan, Z., Anjum, A., & Kiani, S. L. (2013). Cloud based big data analytics for smart future cities IEEE Computer Society. *Proceedings of the 2013 IEEE/ACM 6th International Conference on Utility and Cloud Computing,* 381–386.
Khan, M., Silva, B. N., & Han, K. (2016). Internet of things based energy aware smart home control system. *IEEE Access, 4*, 7556–7566.
Kitchin, R. (2014). The real-time city? Big data and smart urbanism. *GeoJournal, 79*(1), 1–14.
Kitchin, R. (2015). Making sense of smart cities: Addressing present shortcomings. *Cambridge Journal of Regions, Economy and Society, 8*(1), 131–136.
Komninos, N., Schaffers, H., & Pallot, M. (2011). Developing a policy roadmap for smart cities and the future internet. *eChallenges e-2011 Conference Proceedings, IIMC International Information Management Corporation*.
Neirotti, P., De Marco, A., Cagliano, A. C., Mangano, G., & Scorrano, F. (2014). Current trends in smart city initiatives: Some stylised facts. *Cities, 38*, 25–36.
Paul, A., Ahmad, A., Mazhar Rathore, M., & Jabbar, S. (2016). Smartbuddy: Defining human behaviors using big data analytics in social internet of things. *IEEE Wireless Communications, 23*, 68–74.
Rathore, M. M., Ahmad, A., Paul, A., & Rho, S. (2016). Urban planning and building smart cities based on the internet of things using big data analytics. *Computer Networks, 101*, 63–80.
Schaffers, H., Komninos, N., Pallot, M., Trousse, B., Nilsson, M., & Oliveira, A. (2011). Smart cities and the future internet: towards cooperation frameworks for open innovation. *The Future Internet,* 431–446.
Söderström, O., Paasche, T., & Klauser, F. (2014). Smart cities as corporate storytelling. *City, 18*(3), 307–320.
Strohbach, M., Ziekow, H., Gazis, V., & Akiva, N. (2015). Towards a big data analytics framework for IoT and smart city applications. *Modeling and Processing for Next-Generation Big-Data Technologies* (pp. 257–282).
Tönjes, R., Barnaghi, P., Ali, M., Mileo, A., Hauswirth, M., Ganz, F., et al. (2014). *Real time IoT stream processing and large-scale data analytics for smart City applications. Poster session. European Conference on Networks and Communications 2014*.
Townsend, A. M. (2013). *Smart cities: Big data, civic hackers, and the quest for a new utopia.* WW Norton & Company.
Uppoor, S., Trullols-Cruces, O., Fiore, M., & Barcelo-Ordinas, J. M. (2014). Generation and analysis of a large-scale urban vehicular mobility dataset. *IEEE Transactions on Mobile Computing, 13*(May (No.5)).
Xiong, Z., Sheng, H., Rong, W., & Cooper, D. E. (2012). Intelligent transportation systems for smart cities: A progress review. *Science China Information Sciences,* 1–7.