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Big Data Analytics Platforms for Electric Vehicle Integration in Transport Oriented Smart Cities:

Computing Platforms for Platforms for Electric Vehicle Integration in Smart Cities

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ABSTRACT

Electric vehicles (EVs) are key players for transport oriented smart cities (TOSC) powered by smart grids (SG) because they help those cities to become greener by reducing vehicle emissions and carbon footprint. In this article, the authors analyze different use-cases to show how big data analytics (BDA) can play vital role for successful electric vehicle (EV) to smart grid (SG) integration. Followed by this, this article presents an edge computing model and highlights the advantages of employing such distributed edge paradigms towards satisfying the store, compute and networking (SCN) requirements of smart EV applications in TOSCs. This article also highlights the distinguishing features of the edge paradigm, towards supporting BDA activities in EV to SG integration in TOSCs. Finally, the authors provide a detailed overview of opportunities, trends, and challenges of both these computing techniques. In particular, this article discusses the deployment challenges and state-of-the-art solutions in edge privacy and edge forensics.

KEYWORDS

Big Data Analytics (BDA), Edge Computing, Electric Vehicles, Intelligent Transportation System (ITS), Internet of Things (IoT)

INTRODUCTION

Due to rigorous research and development efforts and stringent protocols related to vehicle emissions (Yang, Zhu, & Wu, 2016), fuel economy, constraints in conventional energy reserves and the innate global warming, the electric vehicles (EVs) have been receiving an utmost attention from automobile industries, policy makers, R&D, as well as consumers (He, Venkatesh, & Guan, 2012). The EV

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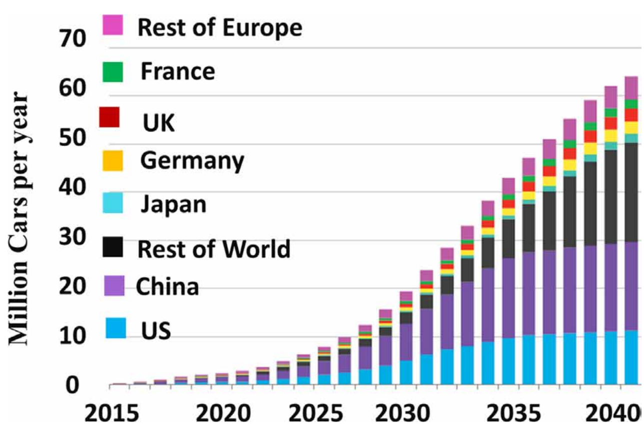
integration programs create potential research thrusts, as they seem to serve as the sustainable and efficient powertrains for the emerging electrified transportation system (Hussain, Alam, & Beg, 2018). The EVs can significantly help emerging transport oriented smart cities (TOSC) to become greener by reducing carbon footprints of the transportation sector (Alam & Beg, 2018). Such characteristic features of EV welcome nations to undertake heavy investments towards EV rollout. According to Bloomberg executive report on global EV forecast (Figure 1), the sale EV will be 41 million per year, which will contribute to 54% of new car sales across the globe (New & Finance, 2017).

While executing a fully electrified fleet, the uncoordinated charging of candidate EVs may pose serious impact on reliable and efficient operation of the associated electric utility (Bitam, 2012). Thorough study of literatures reveal that perforation of large scale EVs fleet can pose a huge challenge and will disrupt the operation of underlying Smart Grid (SG) network, unless their operations are monitored and coordinated properly (Kumar, Singh, Zeadally, Rodrigues, & Rho, 2015). The side effects may be in the form of power losses, incremental investment on the pre-existing network, potential violations of statutory voltage limits, degradation in power quality etc (Hussain, Alam, & Beg, 2018). Lack of coordinated charging strategies can also create demand peaks during rush hours which in turn put pressure on the power grids. However, use of proper charging strategies may circumvent significant proportion of burdens from the overall architecture. Indeed, it has been empirically estimated that even if all the vehicles on the road are made to run by electricity, the existing power backbone can withstand the hike in power demand provided that they are intelligently managed (Eurelectric, 2015).

These days, due to development of Information and Communication Technologies (ICT), Internet of Things (IoT) devices, and sensor networks etc, the data generation and consumption landscape in EV networks changes (Stimmel, 2015; Hussain, Alam, & Beg, 2017). The sensor equipped EV fleet creates enormous data volume while in execution (Faouzi, Leung, & Kurian, 2011). The advancement in Intelligent Transportation Systems (ITS) has favored progresses over existing data collection, storage and processing devices (Zhang et al., 2011). The IoT devices, Vehicle on-board units (OBUs), roadside units (RSUs), intelligent sensors and metering devices, etc, had revolutionized the ITS telematics (Services, Shojafar, Cordeschi, & Baccarelli, 2016). Collecting real-time spatial & temporal characteristics such as traffic volume, occupancy, EV speed, surveillance data etc, become convenient with smart road sensors such as inductive loop detectors, optical detectors etc. Motivated by these avenues, the manifold growth in smart EV count has created an alluring interest in the contemporary automotive industry to invest their assets in data driven fleet management activities.

Figure 1. Annual global EV sales forecast across different Nations



Contribution and Organization

The key contribution of this paper is as follows:

- We provide an overview of Big Data Analytics (BDA) activities in EV to SG integration, for different use-cases, viz. roadside infrastructures, EV charging infrastructure, EV Range Estimation framework, and miscellaneous Smart City Services;
- We present the scopes of edge computing, paradigms towards supporting the mission critical requirements of BDA activities for successful EV fleet integration in Transport Oriented Smart Cities;
- We provide a comprehensive overview of prospective challenges and future research directions for successful deployment of these computing paradigms (specifically edge computing).
- We highlight the potential privacy and forensics challenges in edge computing and also examine the state-of-the-art solutions in edge security.

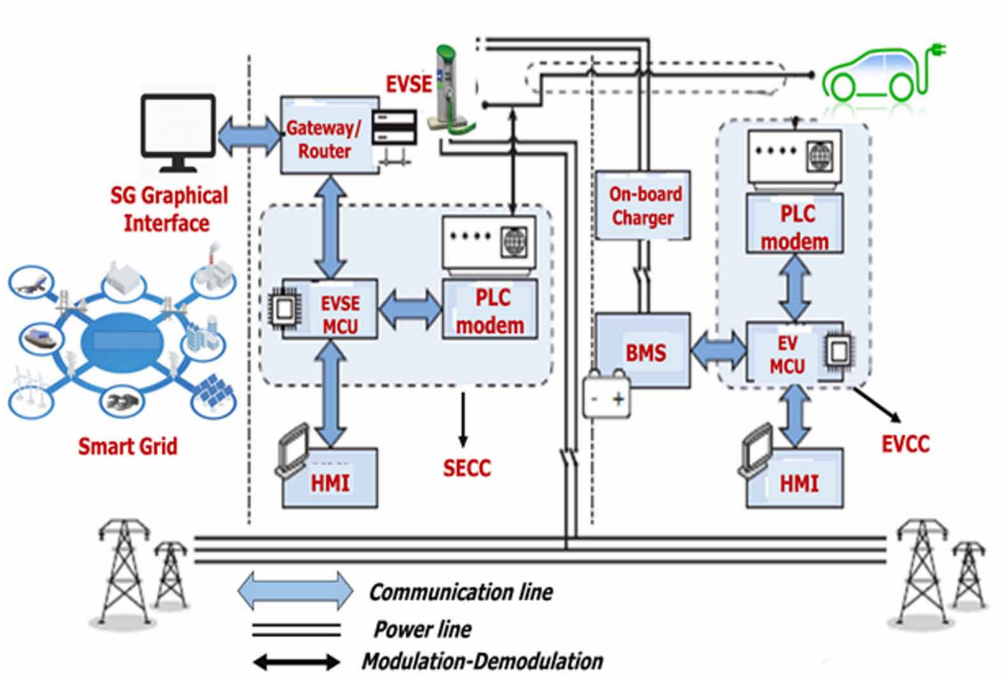
The manuscript is organized as follows. Section 2 identifies the BDA activities their computing requirements in the context of EV-to-SG or EV-to-TOSC integration. In section 3, the characteristic features of distributed cloud computing and edge computing platforms are discussed. In section 4, the futuristic challenges and future directions are highlighted. Section 5 presents the privacy and forensics challenges in edge computing while section 6 concludes the paper.

BIG DATA ANALYTICS (BDA) FOR EV APPLICATIONS

The goal of IoT technologies is to ensure seamless connectivity to ITS components, thereby forming a Connected Transportation Web (CTW) (Lee, Gerla, Pau, Lee, & Lim, 2016). The IoT integrated EV entities are also anticipated to be the drivers of green smart cities as they enable efficient integration of renewable energy with lower carbon footprints (Rehmani, Reisslein, Rachedi, Erol-Kantarci, & Radenkovic, 2017). The TOSC vision anticipates almost all flat surfaces, including roads, covered by solar panels to maximize the utilization of solar energy (Arshad, Zahoor, Shah, Wahid, & Yu, 2017). The EVs carry dozens of sensors that consume and generate volumes of data. The data attributes may include user driving behaviors via GPS system, battery security via battery management system (BMS), and grid charge management via charging stations (Li, Kisacikoglu, Liu, Singh, & Erol-kantarci, 2017; Perera, Qin, Estrella, Reiff-marganiec, & Vasilakos, 2017). Drivers carry smart devices and wearable(s) that also contribute to the data generated on roads. With smart, autonomous, self-driving cars, those data will be continuously moving from cars to servers and cars to cars, etc (Hou, Li, Jin, Wu, & Chen, 2016).

In the case of EV to Grid integration (EVGI), the EVs are either completely or partially powered by their onboard Vehicle Batteries (VB), charged by the SG. Thus, in a growing EV market, the impact of EVs on the SG is of prime concern, specifically at the distribution level. Such effects on SG may be manifested in the form of peak loading, increased energy losses, voltage unbalance/deviations, and need for additional network reinforcements, etc (Gungor et al., 2013). Moreover, in EVGI mode, charging and discharging pattern of EVs is tightly coupled with the operation, security, and efficiency of the SG (Chekired & Khoukhi, 2017). Thus, efficient data management in EVGI plays a vital role for integration of these EVs into the future green smart cities. Generally, the EVs are charged using onboard chargers and Electric vehicle Supply Equipment (EVSE), also called as charging stations. These charging sockets may be placed at residential premises, parking lots of commercial buildings, and any roadside charging facility. An EV-SG integration framework enables EVs to be controlled by the SG or aggregators, through EV-EVSE-SG communication interface. In an IoT aided EV network, the communication can be a mix of wireless and wired technologies including PLC, Zigbee, WiFi, LTE, and fifth generation (5G) wireless networks. An overview of EV to SG interaction and the EVGI system with bidirectional power and communication architecture is presented in Figure 2.

Figure 2. EV-SG integration scenario (HMI-Human Machine Interaction, EVSE-Electric Vehicle Supply Equipment, SECC- Supply Equipment Communication Controllers, EVCC-Electric Vehicle Communication Controllers, PLC-Programmable Logic Controller)



In a nutshell, for successful roll out of EVs, the supporting ITS infrastructure should be leveraged with Advance Metering Infrastructures (AMI), SG, smart EVSE (Kumar et al., 2014). This in turn generates avalanche of multi-dimensional datasets. Preliminary estimation discovers that the transactions of merely two million smart meters generate more than 20GB of data every day (Alam & Beg, 2018, b). In case of autonomous EVs, the volume of data generated is much higher. In fact, IHS[1] Automotive forecasts that there will be 152 million actively connected vehicles on global roads by 2020. The combination of new car features and aftermarket devices could mean nearly 2 billion connected cars on the world's roadways by 2025. Conservative estimates from IHS Automotive state that an average car will produce up to 30 terabytes of data each day. Hidden in the data are valuable clues regarding the performance and State of Health (SoH) of the EVs (e.g., how, when and where the vehicle is driven; the driver's driving style and preferences, and much more). Only by analyzing those data-streams we can reveal meaningful connections, trends and patterns that can help provide a better driver experience and improve vehicle quality and reliability (QoS and QoE). The result is a stronger competitive position and new revenue opportunities. The opportunities from analyzing connected EV data are numerous; some of which are depicted in Figure 3. In essence, the installation of such architecture requires robust BDA analytics framework for gathering, storing, processing and managing the data originated from the intelligent utilities (Xu, Qian, & Hu, 2015). In this section, we discuss few but not the least scenarios, on how the wide scale penetration of smart EVs will create data driven silos and how the BDA framework will potentially address them.

Use-Case 1: Roadside Infrastructures

The autonomous self-driving EVs are leveraged with hundreds of sensors and are integrated with IoT services (Lee et al., 2016). Also, the road infrastructure is also underway with large deployment of connected IoT technologies (i.e., traffic lights, signs, and road cameras). The IoT technologies,

Figure 3. Big data analytics opportunities in electric vehicle to transport oriented smart city

specifically Internet of Vehicles (IoV), will enable these smart vehicles to be able to communicate with the road-side infrastructure and peer vehicles. Autonomous connected vehicles and their integration into TOSC will escalate the velocity and veracity of data that is generated and shared. In that case, a distributed cloud frameworks can facilitate the store and compute requirements of those applications. Onboard and on-body devices have limited storage and processing capabilities. Meanwhile, their communication capability opens the door to accessing backend cloud data centers. The data from EVs, drivers, EVSE, and infrastructure constitute the big data of EVs, which requires data analytics tools running on TOSC clouds or edge nodes.

Use-Case 2: EV Charging Infrastructure

Many automobile vendors allow drivers to check the status of their EVs and remotely control their charging through mobile apps. These applications collect vehicle and trip data. EV data mostly come from onboard sensors (OBSs) and Battery Management Systems (BMS). Also, the State of Charge (SoC) of EV batteries serve as a key driver for most charging and discharging decisions. BMS logs show the SoC information and capture the dynamics of EV battery. Other details such as tracing of malfunctio6ning batteries, and heating and cooling details (Battery Thermal Management (BTM)), etc, can be recorded by such logs. Based on BMS logs, state of health (SoH) information can be obtained, and the impact of Vehicle to Grid (V2G) services on battery life can be estimated (Zhang et al., 2011). In addition to the data directly collected from EVs, the commuters can voluntarily share information about their driving charging profiles. The IoT/IoV network enables tracking other details such as how much air conditioning is used, or how a driver accelerates or breaks. Such varying modalities of data are prime candidates for decision making through data analytics tools and techniques that both consistent and reliable.

Use-Case 3: EV Range Estimation

An important performance and reliability factor for EV to SG integration is the electric vehicle range anxiety (EVRA). For a long time, the adoption of EVs was low due to this factor. It is defined as the condition where the EV user is driven by fear that his vehicle battery (VB) will run out of power before the destination or before a suitable EVSE is reached. It usually becomes acute during long drive scenario when the driver is deprived from accurate information of charging station statistics (Griggs, Yu, Wirth, Husler, & Shorten, 2016). While executing a fully electrified fleet, the uncoordinated charging of candidate EVs may pose serious impact on reliable and efficient operation of the associated electric utility. An ideal EV infrastructure will have minimal EVRA per vehicles. The prediction algorithms running on their BDA engines, installed at the TOSC clouds, estimate the driving range at precise time quanta, which may be an efficient way to diminish the range anxiety (Kumar et al., 2014; Erol-Kantarci and Mouftah, 2016). For instance, regression methods can be used to predict parking demand variables, including total vehicle hours per zone, neighborhood and parked time per vehicle trip, etc, as a function of site accessibility, local jobs, population densities, and trip attributes. As cities become smarter, such data will have vast volume, and mining them along with EV data will provide more opportunities for planning (Hannan, Azidin, & Mohamed, 2014). An illustrative range estimation framework is shown in Figure 4.

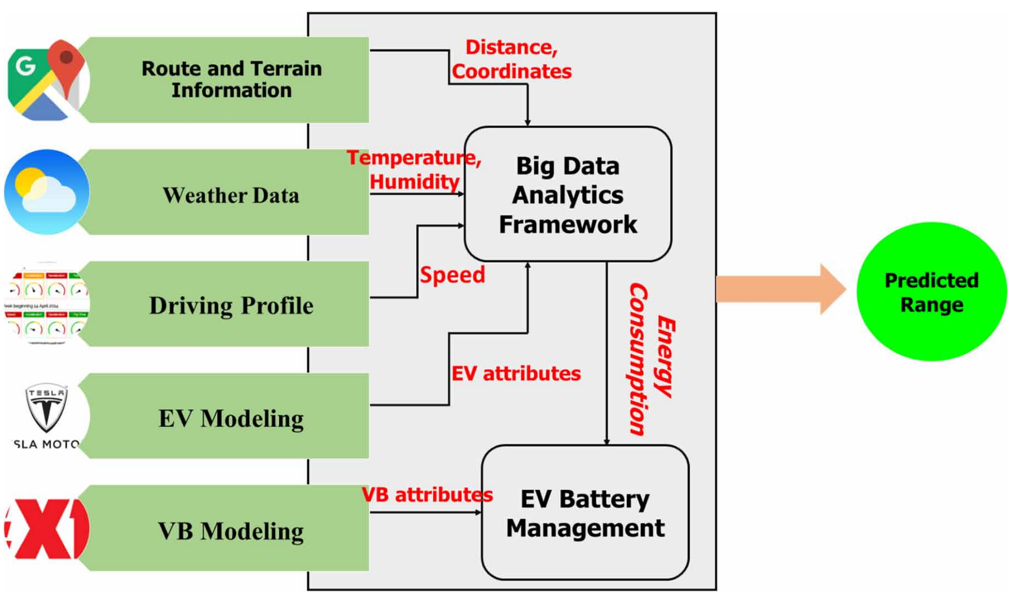
Use-Case 4: Other Smart City Services

Besides range estimation, big data generated from EV fleet dynamics can be used by municipal bodies (Emergency Response Corporation) to make decisions on stand-alone public charging stations. In this respect, the key factor is the prediction of charging load. Various kinds of data have been employed such as road traffic density, distribution of gas stations, and vehicle ownership. There are also several studies that use travel patterns of taxi fleets in order to derive optimal routing of charging stations. Figure 4 shows the key domains where BDA will create rich use-cases, depicts the potential data generation sources, analytics tools and applications for BDA. In the next section, we present state of the art computing platforms that will support the BDA activities, for successful integration of EVs to SG.

EDGE COMPUTING PLATFORMS FOR SMART ELECTRIC VEHICULAR NETWORKS

The predicted size of IoT connected devices seems to bounce beyond a trillion in coming decade (MIT, 2016). In fact, according to International Data Corporation's (IDC's) visionary presentation

Figure 4. Range estimation framework based on big data analytics of EV data



on "The Digital Universe of Opportunities," the overall created and copied data volume worldwide was 4.4 zetabyte (ZB) in 2013, which will exceed 44 ZB by 2020 (Jalali, Vishwanath, De Hoog, & Suits, 2016). Besides the volume, the velocity of the data is growing as a result of the advances in communication technologies and IoT. Distributed cloud models are envisioned to stimulate the development of storage, execution and analytics framework such scenario (Yvonne Coady, Hohlfeld, Kempf, Mcgeer, & Schmid, 2015). The generated by EV-SG interfaces contain plenty of hidden information. For instance, the usage data in ITS telematics such as vehicle localization mechanisms, telecommunications, data processing, smart metering, traffic sensors, roadside units (RSUs) and on-board units (OBUs) can be exploited to discover useful patterns, which may further be evaluated to design smart charging decisions (Connected & Programme, 2015). However, connecting such diverse data sources directly to cloud data centers is inefficient and impractical (Hussain, Alam, & Beg, n.d.a). Involving cloud utilities into the prevalent transportation infrastructures trigger an unprecedented breeding of data, that further magnifies the exertion on the storage and processing elements. Moreover, contemporary cloud prototypes are not designed for the V's of Big Data that the IoT generates (Birman, Ganesh, & Renesse, 2010). The major issues associated with traditional centralized cloud models are (Hussain & Alam, 2017).

Latency

Time critical applications like cloud robotics, motion control of drones, anti-locking brakes for EVs etc, require real-time response. The distribution of storage and processing elements off-the source in the prevailing cloud computation paradigm fails to meet such requirements, as moving all data from the network edge to the data center for adds intolerable latencies. Thus, by the time the data makes its way to the data centers for analysis, the opportunity to act on it might be gone (Osanaiye et al., 2017).

Security and Reliability

The data generated from EV network demands protection services both in transit and at rest. The traditional cloud designs many a times fail to provide secured and automated response environment across the entire attack continuum: before, during, and after. Since the transportation services are primarily dedicated to support actions that affect citizen safety, the integrity, availability and reliability of the infrastructure services mustn't be in question.

Network Bandwidth

The transportation modules such as smart metering, and EV fleets etc, generate tera-peta bytes of data in span of minutes and hours. Transporting whole data traffic everytime from multitudes of edge nodes to the cloud data centers ultimately outstrip the network bandwidth capacity.

Communication

The cloud servers are destined to communicate only through internet protocols (IP). However, IoT devices in transportation domain employ diverse range of industrial protocols and standards that are different from IP. For successfully transporting the data from billions of edges to data centers for storage and analysis, such protocol needs to be retranslated to IP, adding futile computational overhead.

However the edge model will potentially abridge the silos between personalized and bulk level big data analytics in EV systems. In edge computing the application specific logic is embedded not only in remote clouds, but also across the intermediary edge infrastructure components. A robust edge topology allows dynamic augmentation of associated edge nodes, thus significantly improvising the elasticity and scalability profiles of mission critical infrastructures. Table 1 compares the features of the generic cloud models with distributed cloud platforms and edge platforms. The cloud-based vehicular applications employ a data center as a central server to process data that is generated by IoT devices, such as OBUs, driver's handheld devices and

Table 1. Features of Cloud, Distributed cloud and Edge computing

Features	Centralized Cloud Computing	Distributed Cloud Computing	Edge/Fog Computing
Architecture	Centralized	Decentralized	Decentralized
Vertical Scalability	Average	High	Very High
Availability	High	High	High
Latency/Delay Jitter	High	Low	Low
Mobility	Limited	Supported	Supported
Context/Location Awareness	No	Yes	Yes
Geo-Distribution	No	No	Yes
Content Generation/ Distribution	Centralized	Decentralized	Decentralized
Service Generation/ Distribution	Within the internet	Within the internet	At network edges
Energy Consumption	High	Low	Low
Renewables Integration	No	Yes	Yes
Carbon Footprint	High	Low	Low
Virtualization	At Centralized Data Centres	At micro-data Centres	User and Network Equipment
Control and Orchestration	Centralized	Both Centralized and Distributed	Highly Distributed
Client-Server Distance	Multi-hops	Lesser number of hops	Often Single hop
En-route Threat Probability	High	Average	Very low
Last mile Connectivity	Leased Lines	Wireless	Cognitive Wireless

wearable, etc. Such model places ever increasing demands on mission critical communication and computational infrastructure with inevitable adverse effect on both Quality of Service (QoS) and Quality of Experience (QoE). The concept of Edge Computing is predicated on moving significant proportion of this computational load towards the edge of the network to harness computational capabilities that are currently untapped in edge nodes, such as OBUs, Base-Stations (BS), autonomous vehicles, gateways and switches (Coady, Hohlfeld, Kempf, McGeer, & Schmid, 2015). The edge/fog based ITS solutions offer EV utilities, the required storage, control, and networking resources with minimal delays because of "being near" to the users or terminal devices along the cloud-to-things continuum (Chiang & Zhang, 2016). The utilities enforcing edge/fog based Big Data Analytics aimed at minimizing the response delay by servicing the user's request at the network edge instead of mere servicing it at remote cloud data centers (Hu, Patel, Sabella, Sprecher, & Young, 2015). Doing so also minimizes the downward and upward traffic volumes in the network core, ultimately leading to energy efficiency and data cost reductions. There are many versions of edge based technologies, often encountered in literatures, such as edge computing, fog computing, cloudlets, micro-data centers, and nano-data centers (Bilal, Khalid, Erbad, & Khan, 2018; Mao, You, Zhang, Huang, & Letaief, 2017; K. Zhang, Mao, Leng, He, & Zhang, 2017). In this paper we use the edge and fog terms synonymously. In this section, we list some distinguishing features of edge platforms that will potentially support mission critical BDA activities towards successful EV integration.

Reduced Network and Data Traffic

The number of IoT endpoints in EV networks is growing at an enormous rate, as can be revealed from the smart meter installation landscape in ("M. M. Insights). Consequently, the data traffic generated from these sources is also growing exponentially. Consider a smart metering device that is reporting data at frequency 4 times per hour. It will generate 400MB of data a year. Thus, any utility implementing AMI to only one million customers will generate 400TB of data a year. In 2012, BNEF predicted 680 million smart meter installations globally by 2017, leading to 280PB of data a year (M. M. Insights). This is not the only data that utilities are dealing with, the generated data volume is anticipated to come from other SG attributes such as consumers load demand, energy consumption, network components status, power-line faults, advanced metering records, outage management records and forecast conditions etc.

One solution to cope with the Big Data avalanche is to have an expansion of data center networks that can mitigate the analytical workloads. However, this again raises concerns related to sustainable energy consumption and carbon footprint of those data centers. Attempts to undertake analytics only on front-end device is restrictive due to their resource limitations and in many case aggregated and collective analytics becomes unfeasible. Added to this is the volume of network traffic and complexity in EV network that worsens the reliability and availability of analytics services. Leveraging the EV with dedicated edge/fog nodes deployed at a few hop distances (mostly one hop) from the core network, will complement the computations of both front end device as well as back-end data center to cope with the growth of data as well as distributing traffic in a network. In Vehicular Infotainment Services (VIS) (Hou, Li, Chen, et al., 2016; Vehicular & Computing, 2017), if edge/fog nodes are used as data delivery and sharing points across the road-side infrastructures, huge volumes of transit data between content Distribution Networks (CDNs) and network edge can be saved . Caching at the mobile edge (base stations/eNodeBs) may save significant percentage of backhaul network traffic. For such latency critical applications, the edge nodes can perform on-the-fly video transcoding to create required video representation versions. It may host dedicated services at edge to provide real-time response and data filtration. Such strategies reduce the memory requirements, minimize access delays, and improve the viewer's QoE (Alam & Beg, 2018).

Decentralized Low Latency Analytics

In a data driven EV network, the data generation and consumption nodes are sparsely distributed across the whole infrastructure. For efficient EV-SG integration, together with a centralized control, the sensor and actuator nodes deployed across the smart homes or EV networks also demand geo-distributed intelligence. Often, the domain of SG information visibility may need to be extended from mere SCADA systems to a scale that ensures national level visibility. Since majority of the EV services are consumer centric, the applications demand location aware analytics to be performed closer to the source of the data to improve the service that is delivered. The contemporary cloud infrastructures pose serious latency issues for SG-EV integrating applications operated by real-time decisions. For instance, real-time visual guide mapping services work only when the response time is less than 50ms. Also, the SCADA system employed in a modern data driven SG is so timed that it can malfunction when operated over ubiquitous TCP/IP protocols and cannot sustain the out-of-the-box TCP flow control latencies. Thus, content deployment at local ISPs (edge nodes) is critical for areas with low connectivity and high response time. Nowadays, a number of ISPs have opened their edge services to other providers and subscribers, and offer various edge-based solutions, such as cloudlets, network functions virtualizations, and mobile edge computing. The edge model provides low latency and reduced data traffic, as the applications are localized to the region where the edge is deployed. The mobile edge computing can also harness the store and compute resources latent in the underutilized infrastructure resources such as vehicles, for Vehicular fog computing (Hou, Li, Chen, et al., 2016). In that case, edge/fog model complements the cloud computations with dedicated and ad hoc computational resources, to be performed on the edge nodes of an IoT aided EV network and circumventing the networking latency.

Offloading Cloud Traffic and Computation

The sudden upsurge in location aware vehicular services leads to avalanche of data generation per day. A typical EV user/commuter is leveraged with smart handheld devices having installed sensors such as GPS, accelerometers, gyroscope, and temperature sensors, body sensors, etc. The data logged by such applications is often sent to cloud in the form of tuples. Each tuple contain several pieces of information, such as user id, longitude, latitude, time, distance, speed, duration, and SoC etc. For instance, a recent study on Endomondo revealed that a single workout generates 170 GPS tuples, and average number of tuples generated per month is between 2.8 and 6.3 billion (Jalali, 2015). In a population of 30 million users, the number of tuples generated per second could reach 25,000 tuples/sec. In an IoT aided EV infrastructure, this number will be manifold. When such high velocity real-time data-streams are dispatched to remote cloud servers, the skeleton network will get congested and the cloud servers may get overburdened. Interestingly, not all of the sensed data is useful. Under such circumstances, the edge nodes can be deployed to locally process and filter unnecessary data, thereby reducing the network traffic and processing burden from cloud servers.

The edge nodes can also be exploited to offload computation from data centers that require limited resources to the edge nodes. In vehicular infotainment services, uploading/sharing high resolution photos and videos from user endpoints to the cloud servers occupy excessive bandwidth and may cause intolerable delay in places where internet connectivity is poor. Similar issues arise in case of ERC services, where live streams surveillance data from cameras and Visual Sensors Nodes (VSN) needs to be uploaded to cloud. Prior to uploading to the cloud servers, the geodistributed edge/fog nodes can be utilized to transfer specific compression related tasks near to the end users., . Moreover, instead of uploading the raw data to the cloud, such nodes can also be used to encrypt the user data, thus ensuring security and privacy of user data in the immediate hops.

Reduced Load on EV User Devices

As the end-user/EV driver's smart phones are resource constrained, it often cause battery drainage when subjected to such complex tasks and processing. The heterogeneous IoT/IoV datasets may also create compatibility concerns. Under that scenario, these devices may offload some of their high processing tasks to the nearby edge to reduce their load. Also, not the whole data generated from the end device may contribute in the computation of useful information. In a study conducted on Endomondo sports activity tracking application, it is observed that even if a jogger stops to take rest, his sensors stores the same values at regular intervals (Foster, Harrison, Freedman, Rexford, 2011). In that case, the edge nodes may employ efficient filtering techniques to dispose-off the redundant data and only filtered data is sent to the cloud. Similarly, in interactive infotainment services such as video on vehicular demand (VoD) applications (Alam & Beg, 2018), the resource intensive tasks may deplete VB. Processing such datasets at the edge of the network, and delivering synthesized virtual view may result in significant bandwidth and energy savings at client's end-points.

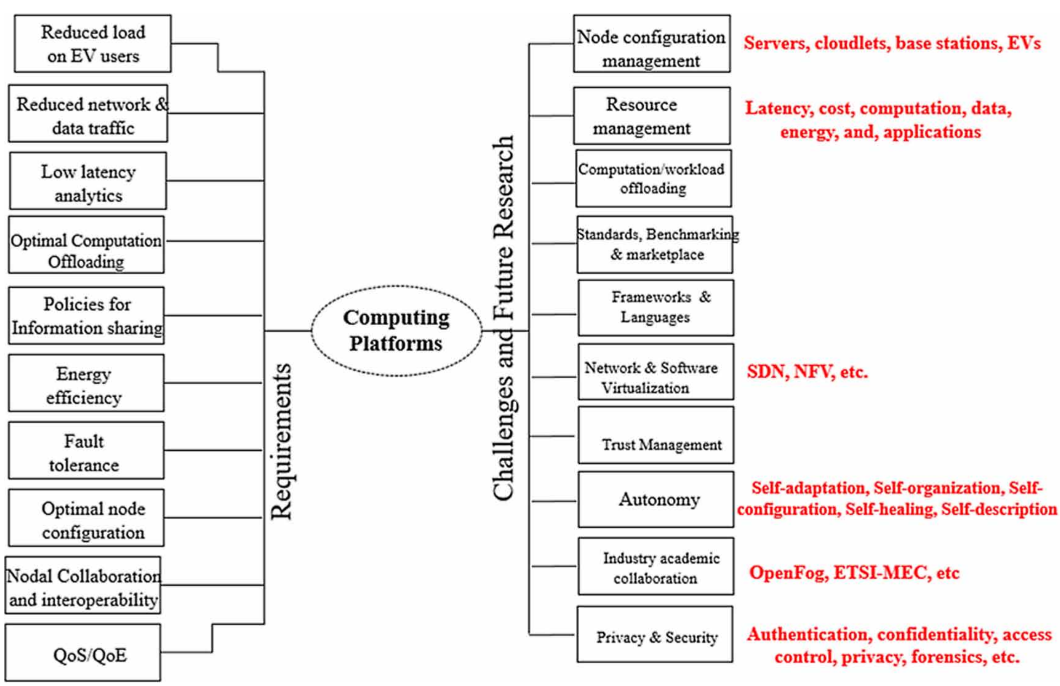
CHALLENGES AND FUTURE RESEARCH PROSPECTS

As with others, the distributed cloud as well as edge/fog paradigms also faces deployment challenges. Such infrastructures will seldom be designed from scratch, but grow out of existing infrastructures. Thus, while some of the challenges are inherited from cloud computing, many challenges arise due to the non-standardization of edge technologies. Moreover, how to best program such platforms, also depends on the context, the specific application, and the objectives. There are several challenges that must be overcome in order to create an ecosystem where all actors (end users, service providers, infrastructure providers) benefit from the services provided by any distributed computing paradigms. The whole range of edge computing requirements and research taxonomy is shown in Figure 5.

General Purpose Computing on Distributed Cloud/ Edge/Fog Nodes

Theoretically, the edge/fog techniques can be implemented on a wide range of featuring devices, from discrete and low power edge nodes to dedicated aggregator nodes viz. gateways, access points, base-stations etc. However, majority of these components and devices are not tailored to perform analytical tasks that the edge based framework is meant for. For instance, Base Stations (BS) in cellular networks are equipped with signal processing units (e.g. DSPs), transducers to manage tasks like routing, mobility and hand-off management etc. It is not readily known whether they can be evolved to do with the analytical loads, previously are not leveraged for, or what additional plugins needs to be installed. Intel's Smart Cell Platform (Corporation, 2000) is among the notable attempts to make the edge resources upward compatible to analysis workloads and upgrading them for multi-purpose analytics. Recently, plenty of solution providers taken steps to realize edge computing using software solutions, thanks to Software Defined Networking (SDN) and Network Function Virtualization (NFV) technologies that serve as primers for edge based computation in IoT aided vehicular environments ("IoV - IOT FORUM Milan, 2015). Similar efforts can be seen from Nokia, where the attempt is to enable cellular BS for mobile edge computing (MEC) (OpenFog Consortium Architecture Working Group, 2017), or it may be Cisco's IOx3 execution environment for its integrated service routers. Moreover, portable and cross-platform solution needs to be developed so that the applications are decoupled from hardware dependencies and can be executed in heterogeneous environments. Design of micro operating systems or microkernels is still a nascent research thrust, as they can leverage deployment of applications on heterogeneous edge nodes. Since the edge/fog nodes are not equipped with heavy computational resources as a server, utilities should foresee quick deployment, reduced boot up times and resource isolation strategies that will allot fewer resources to such adhoc and dedicated

Figure 5. Requirements, challenges and future opportunities in next generation computing platforms



computing endpoints. QoS can be improvised by developing mobile containers such as *Docker*, that support cross platform multiplexing into virtual clones or devices and enable quick deployment of applications on heterogeneous platform (Colman-Meixner, Develder, Tornatore, & Mukherjee, 2016).

Programmability and Abstractions

For both distributed cloud as well as edge models, a key research challenge is to identify suitable programming models, primitives, and abstractions. Robust programming model is missing even for contemporary cloud platforms, relying on virtualization techniques. Considerable progress has been made over the last few years in the design of network programming languages providing higher levels of abstractions. For instance frenetic language family (Foster, Harrison, Freedman et al., 2011.), where the authors used SDN to describe the recent convergence of multi-tenant clouds, cloudlet, and distributed clouds etc. For edge platforms, different components and their interconnections will likely be programmed in different languages and still there is no lingua franca, no "one size fits all." Often, it is convenient to use constrained, domain-specific languages to provide the right, hopefully high-level abstractions, to allow programmers to focus on the important concepts. In contrast to Turing complete languages where the bugging is efficient, edge based solutions still introduce verifiability concerns.

Resource Management

Determining resources and services in cloud models is a well explored area and easily understood, but exploiting network edges in decentralized network settings call for efficient node discovery algorithms that can schedule jobs to optimal nodes (Skarlat, Schulte, & Borkowski, 2016). Resource discovery in fog/edge computing is not as easy as in both tight and loosely coupled distributed environments. Manual mechanisms are not feasible because of sheer volume of processing nodes available at fog/edge layer. For instance, if an EV-SG integration utility wants to execute machine learning or BigData tasks, resource allocation strategies also need to cater for data-stream of heterogeneous devices from multiple generations as well as online workloads. Benchmark algorithms need to be developed for efficient estimation of edge node availability and capability. These algorithms must allow for seamless augmentation (and release) of these devices in the computational workflow at varying hierarchical levels without added latencies or compromised QoE. Autonomic node recovery mechanisms needs to be developed to ensure consistency and reliability in fault detection in edge networked architectures, as the existing cloud based solutions don't fit to them. Besides, the one potential research aspect to ponder is workflow partitioning in fog/edge computing environments. Though numerous task partitioning techniques, languages and tools have been successfully implemented for cloud data centers, but research regarding work apportioning among edge nodes is still in concept phase. Without specifying the capabilities and geo-distribution of candidate processing devices, coming up with automated mechanisms for computation offloading is perplexing. Maintaining a ranked list of associated host nodes through priority aware resource management policies, making hierarchies or pipelines for sequential offloading of workloads, developing schedulers for dynamically deploying segregated tasks to a multiple nodes, algorithms for parallelization and multitasking of only edges, edges and data centers or only data enters etc, are potential research hypes in academia as well as R&D community.

Orchestration Challenges

In an IoT integrated EV networks, both physical devices and applications are integrated in mashup style, for effective and controlled development and maintenance cost. As described in above points, the IoT based EV applications are diverse in terms of reliability, scalability, and security constraints. Managing the location, configuration, and served functionalities of fog/edge nodes further amplify such diversities. However, in order to have consumer centric business objectives, an orchestrating framework is necessary to enable proper alignment and mapping of available resource pool to corresponding applications. An orchestration framework schedules proper mapping between IoT devices and edge nodes to realize an optimal workflow while meeting nonfunctional requirements such as security, node availability and reliability, network latency, QoS and QoE. The orchestrator must also scale with the heterogeneous IoT endpoints and edge devices manufactured by competitive vendors and developers. It should also be able to cater the complexity concerns created by customized hardware configurations and protocols with personalized requirements. Besides, the orchestrator should automatically predict, detect, and resolve issues pertaining to scalability bottlenecks arising due to dynamic workflows. Moreover, scaling and extendibility mechanism comes up with raised probability of failure. Fault diagnosis should go parallel since the inception of execution. Even rare software bugs or hardware faults can lead to debilitating effects on system performance and reliability. Meanwhile, numerous research avenues are unlocked while coping with such orchestration challenges. Within lifecycle management of IoT devices and edge nodes, one aspect is optimal discovery and placement in the deployment stage. Installation of dynamic QoS monitoring solutions and providing runtime guarantees via incremental learning, processing, re-engineering and reverse engineering mechanisms are nascent domains to ponder on.

CHALLENGES IN EDGE SECURITY

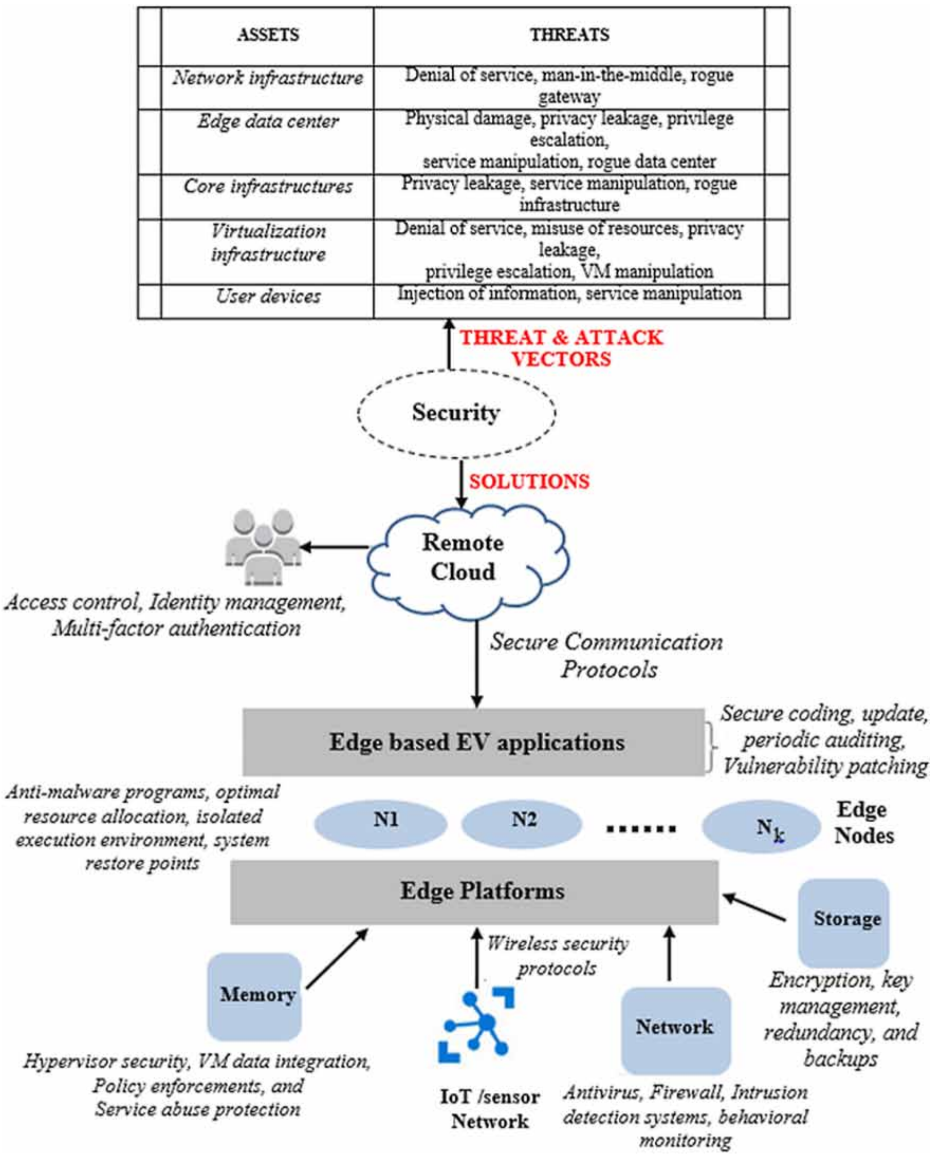
One of the greatest challenges for the creation of edge paradigm ecosystem is security. While edge and fog paradigms inherit several features from cloud computing, most of the existing research is compartmentalized; no synergies have been explored. However, the characteristics of edge models give birth to new security and privacy challenges. This is especially true in the field of edge security, where most analyses focus only on one edge paradigm, while ignoring the others. The existing security and privacy measurements for cloud computing cannot be directly applied to the fog computing due to its features, such as mobility, heterogeneity, and large-scale geo-distribution. In the context of edge computing, key security challenges are related to Identity and Authentication, Access Control Mechanisms, Network protocols, Trust Management, Intrusion Detection Mechanisms (IDM), virtualization, edge privacy and forensics. Figure 6 shows diverse security challenges and solutions that come under edge umbrella. In this section we consider the challenges and future prospects particular to edge privacy and edge forensics. We also holistically analyse the threats and forensics, challenges, and mechanisms inherent in all edge paradigms, while highlighting potential synergies and venues of collaboration.

Privacy in Edge Computing

Since an IoT integrated EV infrastructure comprises of multiple sensors, computer chips and devices etc, their deployment in varying different geographic locations result in increased attack vector of involved objects. As a nontrivial extension of cloud computing, it is inevitable that some issues will continue to persist in such futuristic computing paradigms, especially security and privacy issues (Alam & Beg, 2018). For instance, edge based solutions are deployed by different service providers and utilities that may not be fully trusted and thus devices are vulnerable to be compromised. The edge nodes are confronted with various threats and attack vectors, a landscape of which is presented in Figure 6. The IoT endpoints in EV networks have constrained store, compute, and network resources that are easy to be hacked, broken or stolen. Examples of attack vector may be human-caused sabotage of network infrastructure, malicious programs provoking data leakage, or even physical access to devices (Garraghan, Lin, & Rovatsos, 2017).

The decentralized IoT integrated devices such as switches, routers and base stations etc, if brought to be used as publicly accessible computing processing nodes, the risk associated by public and private vendors that own these devices as well as those that will employ these devices will need revised articulation. Also, the intended objective of such devices, e.g. an internet router for handling network traffic, cannot be compromised just because it is being used as edge/fog node. It can be made multi-tenant only when stringent security protocols are enforced. Although the existing

Figure 6. Potential threats and solutions in edge based computing paradigms



solutions in cloud computing could be migrated to address some security and privacy issues in edge computing, it still has its specific security and privacy challenges due to its distinctive features, such as decentralized infrastructure, mobility support, location awareness and low latency. However, edge computing offers a more secure infrastructure than cloud computing because of the local data storage and the non-real time data exchange with cloud centers. For example, the edge nodes could serve as proxies for end-devices to perform secure operations, if the devices lack of the sufficient resources to do so. Unfortunately, the security and privacy issues and security resources in edge platforms have not been systematically identified. Hence, prior to the design and implement of edge centered EV applications, critical study of threat profiles, security, and privacy goals should be performed. Moreover, holistic security and risk assessment procedures are needed to effectively and dynamically evaluate the security and measure risks, since evaluating the security of dynamic IoT based application orchestration will become increasingly critical for secure data placement and processing.

Edge Forensics

Forensic science is a branch of science that brings together a sequence of scientific principles and methods to identify, discover, reconstruct and analyze evidences to be used for investigation. However, the forensics results cannot be single handedly used, i.e. the court is not bound to rely on the results that are presented and could take into account other metrics to define what the originals are (“Xuejiao Wan et. al. 2015). The main objective of digital forensics is to provide methods that meet the requirements for judicial evidence and could involve the acquisition and analysis of any form of digital data. There are generally two types of evidence in the data that can be retrieved from intelligent IoT devices in any EV network. The first one can be used to prove crimes directly, such as password theft, DoS, DDoS attacks, VM manipulation, denial of service attacks, etc. The other type could be used to support the evidence and build a complete chain of evidence, such as call history, messaging profiles, log files, usage patterns, etc.

In case of cloud computing, digital forensics facilitates digital evidence by reconstructing past cloud computing events (Jusas, Birvinskas, & Gahramanov, 2017). However, due to its centralized and remote nature, it faces many challenges. The first challenge is related to technical dimension that where the key issue are inaccessibility to obtain log data from the cloud, volatile data, integrity and correctness of the data, and multi-tenancy, etc. The second challenge defines organizational dimension where the challenges pertain to lack of forensics expertise. The third but not the least is related to legal dimension that focuses on customer awareness, Internet regulation, and cross-border law(s).

Analogous to cloud forensic, edge forensic is defined as the application of digital forensics in edge computing. According to (Jusas et al., 2017; Mukherjee & Matam, 2017), edge forensics that has many steps similar to cloud forensic, however, is not a part of cloud forensics. Although the challenges in edge/fog forensics are same or similar as cloud forensics (e.g., cyber-physical systems and custody chain dependency, and integrity preservation), many challenges are more significant in edge forensics compared to cloud forensics. For example, since edge model comprises of heavy population of small battery powered edge nodes as infrastructure, retrieving the log data from these nodes becomes very difficult. Moreover, since edge platforms are inherently geo-distributed, the cross-border issue is less critical compared to the centralized cloud forensics. However, due to the huge count of processing nodes, the dependability issue becomes more crucial in edge forensics. The research in edge forensics is still in infancy. Only few works are found that overcome the aforesaid issues. For instance, authors in (Zawoad and Hasan (2013); Fadlullah, Fouda, Kato, Takeuchi, Iwasaki (2011)) considered global unity as a solution to overcome the cross-border issue. Delport et. al (Delport, Kohn, and Olivier, 2012) discussed strategies for solving the multi-tenancy issues. A detailed analysis of the main requirements and status quos of fog computing forensics is presented in (Grispos & Glisson, 2012; Huang, Lu, & Choo, 2017). Three common challenges detected in this work are: a) storing trusted evidence in a distributed ecosystem with multiple trust domains, b) Respecting the privacy of other tenants when acquiring and managing evidence, and c) Preserving the chain of custody of the evidence. The authors also argued that edge and fog based platforms require less computational resources to manage potential evidence. This is because they do not need to manage as many resources (e.g. network traffic, virtual machines) as in centralized cloud infrastructures. Roman et al. (Roman, Lopez, & Mambo, 2016) presented a conceptual Cyber-Physical Cloud Systems (CPCS) forensic-by-design model along with the CPCS hardware and software requirements, and industry-specific requirements. The characteristic factors of a forensic-by-design model identified in this paper are:

1. Risk management principles and practices;
2. Forensic readiness principles and practices;
3. Incident handling principles and practices;

4. Laws and regulation;
5. CPCS hardware and software requirements; and
6. Industry-specific requirements.

How to best integrate forensics techniques and best practices into the design and development of distributed edge architectures, so that it is forensically ready/ friendly is a potential research theme. Having a forensically ready/friendly edge system will allow the real-time identification, collection, and analysis of data that can be used to implement mitigation strategies. Above all, establishment of international legislations and jurisdictions for cross-border forensics is a hot research avenue to ponder on.

CONCLUSION

In this paper we consider the case of Electric Vehicle (EV) to Smart Grid (SG) integration. The EVs are key players for Transport Oriented Smart Cities (TOSC) as they help cities to become greener by reducing emissions and carbon footprint. We analyze different use-cases in EV to SG integration to show how efficient Big Data Analytics (BDA) platforms and techniques can play vital role towards successful EV rollout. We then analyze the scope of distributed edge based computing models, for supporting BDA activities in EV integration. We also provide future research opportunities, trends, and challenges for both these computing techniques. Specifically, we examine the implementation challenges and state-of-the-art solutions in edge privacy and edge forensics.

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