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Federated Cloud Analytics Frameworks in Next Generation Transport Oriented Smart Cities (TOSCs) - Applications, Challenges and Future Directions

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Abstract

Electric, plug-in electric and plug-in hybrid electric vehicles (xEVs) are receiving a global attention from automotive industries, vehicle vendors, R&D organizations, power sectors and policymakers in the intelligent transportation era. Penetration of xEV fleet into the contemporary charging infrastructure(s) in the absence of robust integration network imbalances the power grid and potentially jeopardize the execution of emerging distributed generation systems. However, smart grid technologies in collaboration with smart charging management strategies can circumvent such operational disparities, thus enabling a reliable, efficient, consistent and optimal electric energy management in the power system. This work employs the notion of Cloud of Things (CoT) to propose a comprehensive cloud aware Transport Oriented Smart City (TOSC) framework intended to provide intelligent solutions to the contemporary transportation infrastructures in the emerging sustainable smart cities. The proposed work also demonstrates a commercially viable vehicle to cloud (V2C) fleet charging framework for charging management of xEVs through micro grids/ smart grid. The unprecedented data breeding across V2C, cloud to grid (C2G) and grid to vehicle (G2V) bidirectional communication interfaces elucidates the need for computationally efficient analytics. A state-of-the-art Big-Data to Knowledge (B2K) workflow structure is thus proposed for translating the generated data into efficient knowledge for noble decisions and inferences. Finally, the substantial Mobility as a service (MaaS) adoption challenges and data science prospects are outlined along with the emerging technologies that can co-work with the proposed framework to ensure commercial viability and optimal implementation in emerging TOSCs.

Keywords: Big-Data, Cloud of Things (CoT), Electric Vehicle range Anxiety (EVRA), smart grid (SG), Mobility as a service (MaaS)

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1. Introduction

With the advent of rigorous industrial research and development efforts and stringent protocols related to vehicle emissions [1], fuel economy, constraints in conventional energy reserves and the innate global warming, the electric, plug-in electric and plug in hybrid electric vehicles (xEVs) have been receiving an utmost attention from automobile industries, government agencies, R&Ds, vehicle vendors as well as consumers. The xEV programs became a business motto for the automotive industries as they seem to serve as the sustainable and efficient powertrains for the emerging electrified transportation system. According to survey in [2], and [3], during the short span of six years from 2008 to mid-2014, a quarter million plug-in hybrid electric vehicles have been launched into US roads. As of 2013, more than 129,500 Americans were driving xEVs manufactured by all major automotive original equipment manufacturers (OEMs) [4], while the xEV adoption process is still on fast pace in countries like China, France, Germany, India etc. In 2015, the global xEV population exceeded the 1 million threshold, closing at 1.26 million, a reflection and symbolic of achievements due to the joint efforts from governments, policymakers, R&Ds, and automotive industry over the last decades [5]. The tremendous increase in the xEVs count has created an alluring interest in the contemporary automotive

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industry to invest their assets in profitable deployment of this emerging class of vehicles. To achieve this stringent goal, an immediate issue being addressed by the automotive industry in conjunction with the power sector enterprises is the “Electric Vehicle range Anxiety (EVRA)” syndrome prevalent in the xEV customer(s) that usually becomes acute during long drive scenario when the driver is deprived from accurate information of charging station statistics. While executing a fully electrified fleet, the uncoordinated charging of candidate xEVs may pose serious impact on reliable and efficient operation of the associated electric utility [2], [6]. Thorough study of literatures reveal that perforation of large scale xEVs fleet can pose a huge challenge and will disrupt the operation of underlying power grid distribution network unless their operations are monitored and coordinated properly [7], [8]. The prominent side effects may be in the form of potential violations of statutory voltage limits, degradation in power quality, blackouts, incremental investment on the pre-existing network, etc. Lack of coordinated charging strategies can also create demand peaks during rush hours which in turn put stress on the SGs [2]. However, use of data driven charging strategies will potentially circumvent significant proportion of burdens from the supporting smart grid architecture [2]. It has been empirically estimated that the current power system can withstand the power surge caused due to full xEV rollout. provided that they are intelligently managed [9].

The current advancement in intelligent transportation technologies has favored progresses over existing data collection, storage and processing devices. Vehicle on-board units (OBUs), roadside units (RSUs), intelligent sensors and advanced metering infrastructure (AMI) and Vehicle to Infrastructure (V2I) elements had revolutionized the transportation telematics. To ensure real-time processing, analytics and decision making, the utilities demand efficient synchronization infrastructure. As estimation discovers, the transactions of merely two million smart metering populations generate more than 20GB of data every day [10]. Trends reflect that the vast scale roll out of smart transport system leveraged with Advance Metering Infrastructures (AMI), smart grid, smart charging stations and the innate smart xEVs is still in its infancy. Installation of such architecture requires robust and efficient analytics framework for collecting, storing, processing and managing the data originated from the candidate intelligent utilities.

Collaboration of distributed paradigms such as cloud computing technologies with transportation & data analytics modules will ensure robustness and resiliency in penetration of xEV fleet of any size. Hiring cloud services is envisioned to stimulate the development of storage, execution and analytics framework for the aforesaid components. The clouds can be virtualized to act as cache for the generated data. Furthermore, the notion of internet of things (IoT) ensures connectivity to all such entities, forming a connected transportation web (CTW) [11]. However, connecting such varying data sources directly to cloud data centers is inefficient and commercially impractical. The major issues with traditional centralized cloud models are associated with latency, network bandwidth, communication overheads, security and reliability [10].

Under such circumstances an alternative approach is to inherit the notion of CoT and employ multiple micro datacenters corresponding to dedicated stakeholders, interconnected via communication linkages of varying bandwidths. Involvement of CoT utilities with the prevalent transportation infrastructures triggers an unprecedented breeding of data, that further magnifies the exertion on the storage and processing elements. By 2020, the predicted size of IoT enabled devices estimated to surpass by 200 billion entries across the globe [12], trend suggests that more than two and half quintillion databytes are produced per day from such entities [13]. However, voluminous datasets produced from these objects if properly mined have latent peculiarities to bestow pools of knowledge and decisions. There has been a consensus acquiescence in the automotive industries as well as research arena on the fact that an intelligent and duplex trading of data and control between the xEVs and charging infrastructure through the optimal deployment of CoT enabled V2C, C2G, G2V and V2I [14] communication interfaces would empower in prototyping strong decision making paradigms, as outlined in Figure 1.

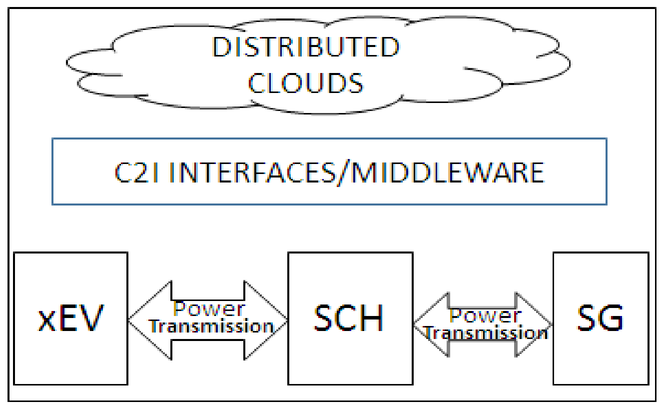

Fig.1: Outline of the proposed model

Recent investigations for commercial deployment trends reflect that the contemporary cloud prototypes are not designed for the V’s of Big Data generated by CoT utilities [15]. The need for fundamental restructuring is strongly perceived in existing cloud settings, to overcome the scalability, latency and security concerns [16],[17]. In response, analytics frameworks have been developed for validating massive datasets generated in cloud aware transport system execution and translating them to build meta-data models [18]. Heavy investments from utility companies on big data analytics of smart grid data are in continuum from nations across the globe. Figure 2 depicts the investment trend as forecasted from GTM research obtained from an exhaustive survey of electric utilities across specific regimes on SG analytics [19].

A As evident from the forecast, till 2020, the cumulative global investment on electrified transportation and SG analytics is expected to reach $16 billion, 40% of which is shared alone by US. In fact the annual global investment is estimated to reach $4.6 billion by 2022 which is more than a half of the cumulative amount from nine year span 2012-2020.

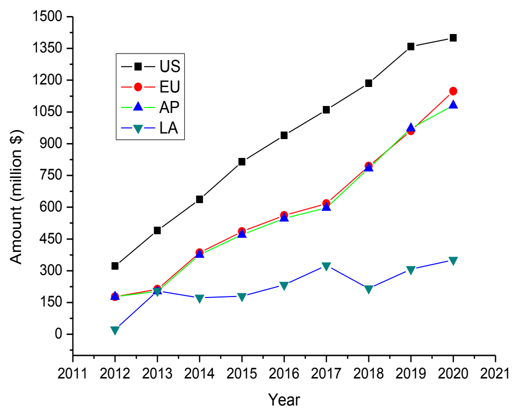

Fig.2: Trends in investments on transportation and smart grid analytics

Motivated by the above-mentioned facts, challenges and opportunities, this work proposes a state of the art Transport Oriented City (TOSC) framework based on the notion of Cloud of Things (CoT). As one utility of TOSC framework, the proposed work provides a commercially viable ready to be prototyped V2C model, incorporates cloud data analytics into the infrastructure claimed by proposing a smart V2C remote charging infrastructure for the electric/plug-in electric/plug-in hybrid electric vehicles (xEVs). In addition this work also discusses data science prospects and challenges that will evolve in/during the implementation of V2C framework over TOSCs by proposing a Big-Data to Knowledge (B2K) framework that defines control flow model for transforming information in transportation telematics into valued knowledge and rightful decisions. The major contributions of this work can be encapsulated as

1) Proposed a state of the art cloud aware TOSC framework using the notion of CoT, where the "things" in CoT comprises of intelligent entities like **S**mart grid, **S**mart charging station, **S**mart car and **S**mart meters, described in detail in section II.

2) Presented a commercially viable realization of V2C framework in TOSCs destined to smart charging management of incoming flux of smart xEVs fleet satisfying three criteria namely (i) **M**inimum charging tariff, (ii) **S**hortest travelling distance and (iii) **M**inimum queuing delay, in section III.

3) Formulated a prototype for B2K control flow for translating the produced big data into knowledge for rightful decisions, in section IV.

4) Outlined the significant Mobility as a service (MaaS) adoption challenges and data science prospects to realize commercial viability and optimal implementation of the proposed frameworks, in section V. Section VI concludes the work.

2. Transport Oriented Smart City (TOSC) Architecture

Intelligent transportation systems (ITS) play the strategic role for emerging smart cities. Deployment of smart cities is envisioned to constitute an ITS based urban development for optimally managing the city's assets while sustaining a green and clean environment for the citizens [20]. Thus, policymakers as well as R&Ds across the globe have joined the smart city development consortium engaged in employing relevant expertise and funds towards the deployment of transport oriented cities (TOSC). These cities are uniquely distinguished by provisions for intelligent data connectivity. Plenty of claims and proposals are found in the open domain which are being implemented independently in diverse ITS domains such as security in information management of smart grids [4], smart grid dynamic energy management (DEM) [21], agent based simulation of electric vehicles fleet charging strategies and several other areas [1].

However, the said methodologies are localized in silos and yet to realize the synchronization aspects, management tractability and commercial viability of the complete transportation system. Establishing a data driven analytics framework is the need of hour in current transportation architectures in the emerging smart cities through the notion of TOSC. To realize the anticipated TOSC objectives, a cloud aware Transport Oriented City frame work is proposed in Figure 3.

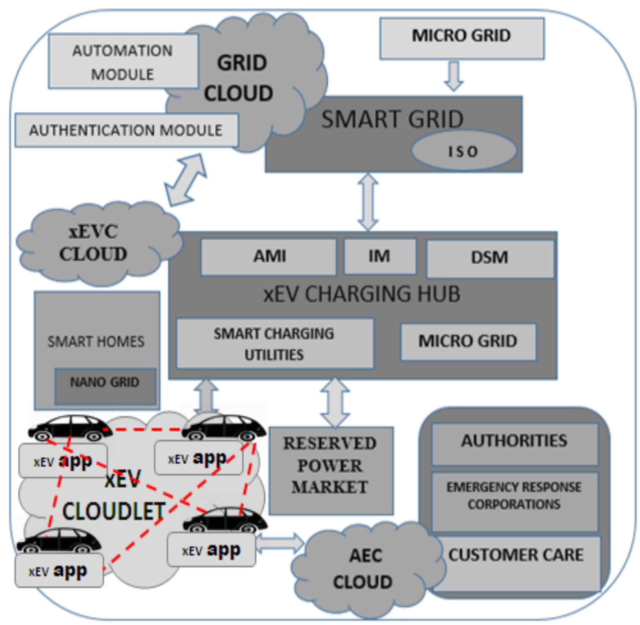

Fig. 3: Architecture of the Cloud aware Transport Oriented Smart City

The prime ideology on which the proposed framework is established is remote accessibility and remote management. The framework manages the control and data trafficking through federated clouds namely Grid cloud, xEVC cloud, xEV cloud and AEC cloud. The grid cloud interfaces SG with the xEV charging stations, AMI and demand side management (DSM) utilities. The grid cloud is designed to support bidirectional data and power transport among these entities to ensure optimization of power system utilities in terms of efficiency, availability, reliability and sustainability. The objective of analytics involved in grid cloud is to establish a platform for supporting stakeholder's services like dynamic energy management (DEM), demand response (DR), integrating micro grids and any other renewable energy based distributed generation system. The cloud applications serve as virtual communication platform for TOSC components, thus ceasing the need for inter-entity communications. The data centers in SG install efficient virtualization mechanisms to ensure cost reduction, resource optimization, and server management. Since the SG is interfaced to intelligent transportation devices such as smart meters, smart sensors, and privately managed charging station or aggregator cloud, scalable Software as a Service (SaaS) applications can be developed that facilitate rapid analysis and integration of data streams in order to shape the real-time xEV flux and power supply curves. It also engage intelligent agents for successful integration of virtual energy sources such as micro-grid, nano-grid, smart homes etc, into existing energy storage and executes robust power exchange mechanisms to successfully meet the requirements of xEV users.

The xEV charging hub in this framework acts on behalf of aggregators to participate in the real time power market operations. The charging stations hire hybrid cloud services from xEVC cloud substructure where in public mode the resources and computation are shared with SG, xEVs and other stakeholders. The xEVC cloud is interfaced to smart grid and vehicular applications through dedicated datacenters. The public deployment mode also allows the charging station vendors to hire IaaS infrastructure equipment like virtual machines, servers, storage and network hardware etc. Through virtualization techniques, IaaS reinforces computational and storage capabilities and enforces load balancing protocols to provide intelligent charging solutions to the xEV users. The xEVC clouds employ IoT enabled intelligent recommender systems that collect multivariate attributes from varying road and vehicle telematics, metering information, state information of SG, forecasting & day-ahead status data etc, and provides charging recommendation to the vehicle users. It also employs application specific infrastructure and power management softwares modules for task scheduling and effective renewable integration respectively.

The dynamic xEV cloudlets formed from clusters of parked and semi-parked vehicles provide platform where corporate computing, sensing, communication and physical resources are shared, allocated and coordinated dynamically. The IoT paradigm enables the design of mobile vehicular clouds that possess powerful storage and processing capabilities [22], where the “things” in IoT includes vehicular components such as external sensors (GPS, camera), internal automotive and cockpit sensors/actuators (brakes, steering wheels, xEV battery state of health (SOH) and state of charge (SOC) monitor, accelerators etc, intelligent and autonomous vehicles, smart drivers etc. Such xEV cloudlets are formed autonomously from the road traffic (parked vehicles, vehicles in traffic congestion, platoons etc.) and employ “computing on wheels” approaches to offer smart transport services in TOSCs. Besides the resources and services provisioned on demand from the generic public vendors such as Amazon EC2 [23], the consumers can hire underutilized vehicular resources such as computing power, network connectivity, sensing capability, and storage through diverse business models such as Storage as a Service (SaaS), Network as a Service (NaaS), Cooperation as a Service (CaaS) etc. Such self-organizing cloudlet infrastructures can work independently and can be complemented with conventional cloud vendors to offer intelligent utilities not only to xEV users, smart passengers, pedestrians, traffic managers, TOSC planners but also provide reciprocate advantages to xEV cloudlets in terms of scalability, dynamic computation capacity and Quality of Service (QoS).

For maintaining the legislative and regulatory protocols across administrative regimes, the infrastructure employs hybrid AEC cloud that provides services associated to authorities, emergency response corporations, service centers and customer care services etc. AEC clouds have communication interfaces to the xEVs, drivers, traffic management entities and other cloud-cloudlets to ensure real-time monitoring set up for the TOSCs.

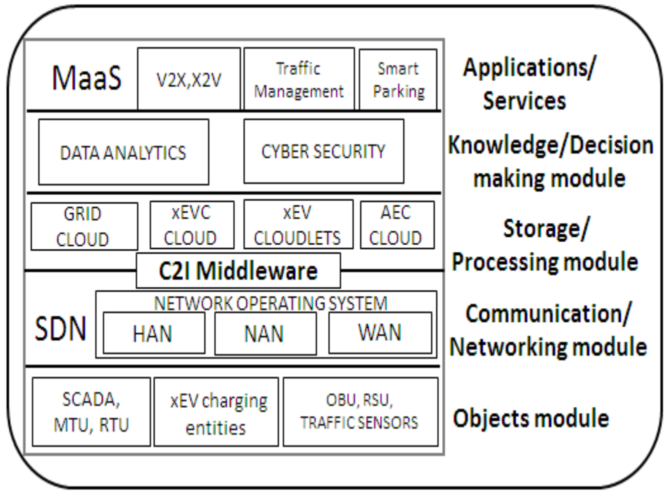

Fig.4: Service Oriented Architecture (SOA) for TOSCs

The objective of the execution strategy outlined for the proposed TOSC framework is to granulize the traditional cloud paradigms into a hierarchical structure to multimodal execution setup. The decisions for offloading and analysis tasks are decided by the degree of service criticality and reliability. The operational modes of the miniaturized cloud versions also termed as cloudlets are defined to be dependent or independent based on the type of service it is intended to support for. In the former mode, the operation of such peer clouds are managed under hierarchical control of large master data center. In independent mode of service, the architecture relinquishes the centralized control and the federated datacenters were managed as one larger data center. Distributing the cloud abstraction to deeper levels of control in TOSCs offers an extended range of advantages over the traditional cloud deployments architectures. The key advantages are but not limited to:

1. Distributing the clouds to finer grained control in TOSCs will overcome the overhead and latency issues by offering proximate storage and computation service.

2. Distributed data locality paradigms will improve the authenticity and privacy concerns that often occur with traditional single mega datacenters.

3. This paradigm shift in cloud computing fundamentals provide optimal feasibility to the transportation and power system architectures in the emerging smart cities that

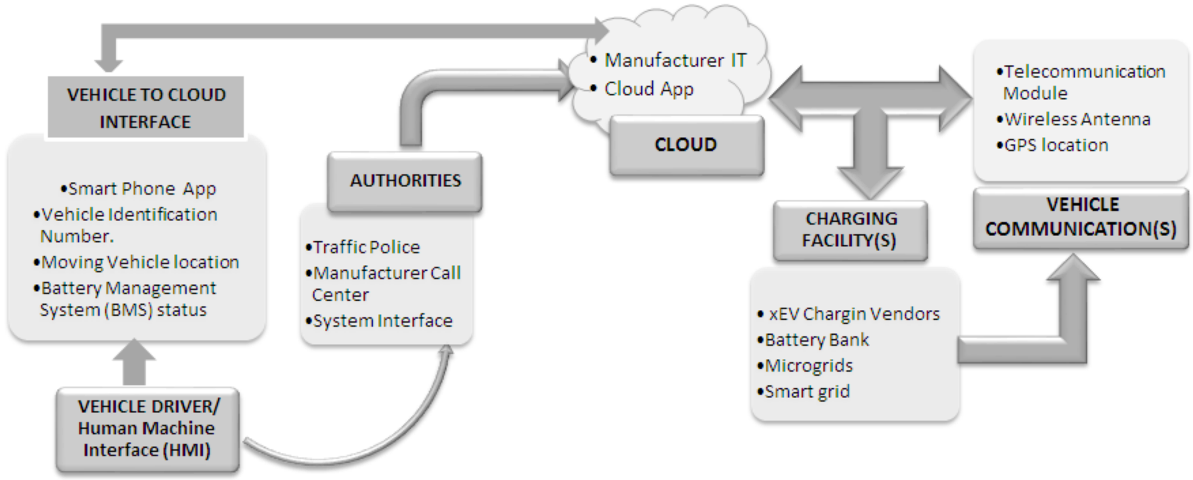

Fig. 5: Federated V2C framework for smart charging of xEVs.

encompass incongruent political regimes, multiplicity of cultures, psychology and stakeholders.

4. This also ensures greater business agility by invoking developers to adopt mobility as a service (MaaS) utilities for the TOSCs and deploy them according to stakeholder's need.

5. The multimodal cloud infrastructure shall provide lower operating expenses and deeper insights through local storage and analytics instead of offloading the whole universe of datasets for cloud analytics.

The TOSC infrastructure once efficiently deployed will extend the smart city services to a new horizon by providing a reference for domain specific applications such as smart parking, smart traffic management, smart charging etc. Fig.4 describes the modular service oriented architecture of typical cloud aware next generation TOSCs. In order to demonstrate the expediency of developed TOSC infrastructure, in the next section an analytical vehicle to cloud (V2C) framework is proposed for coordinating smart charging management of contemporary xEV fleet.

3. Vehicle to Cloud (V2C) Framework for Smart Charging of xEVs

In this section a vehicle to cloud (V2C) remote charging management infrastructure is devised as one of the TOSC package, to coordinate charging of xEV fleet. The cloud-cloudlet hierarchy and inter-cloud interaction for the V2C framework is shown in Fig. 5. In the proposed V2C scheme, the entities involved in the vehicular infrastructures will have seamless interaction through the dedicated TOSC data clouds. The federated clouds described in section II will regulate the trade of control and data in V2C through robust network interfaces as shown in Fig.6. The clouds will represent in varying interfaces each with the TOSC entities such as xEVs, the charging station, and the smart grid etc. The APIs at the xEVs end needs only to interact with the xEV cloud, without any needed to communicate directly with the charging station or smart grid vendors. This requires implementation of efficient and secure communication as well as interfacing procedures [11].

The API at xEVs end would be interfaced to the cloud mesh through authentication mechanisms. The peer data centers would be under the administration of master cloud and communicate with other stakeholders through appropriate and legal mechanisms. Keeping a major portion of control under government administration ensures proper pricing schemes/power rates. At the same time, it also hides the implementation details from casual users by enforcing stringent protocols thereby assuring a secure infrastructure. The centralized control also removes redundancy in the computation.

The application running at xEV driver's end has bidirectional information exchange with the cloud computing utilities to obtain real-time power system updates. Such updates can be in the form of energy pricing status, state of charge of xEV battery as well as smart grid, trip description etc. In turn, the real-time scenario information related to energy pricing status, state of charge of xEV battery, optimal location of charging station, best route/ shortest route etc are fed by coordination and monitoring modules in the data centers to intelligently regulate the driving behavior of the xEV fleet. The data center implements efficient algorithms on such scenario attributes to compute the degree of range anxiety in the xEV user and correspondingly recommends charging option to the latter under the criterion triad's namely minimum charging tariff, shortest travelling distance and minimum queuing delay in decreasing degree of criticality.

1. Minimum Charging tariff

The prime motive of an xEV user is to have charging services at the least possible rate. Many a times the consumers have constrained alternatives with unaffordable charging options that further add to the range anxiety. The V2C application will communicate with various charging stations located in the vicinity of the xEV to track the dynamic power pricing tariffs and recommend the one with optimum rate. It is discovered from the predominant charging strategies that in regulated power market, the consumers often have to endure the unrealistic power tariff caused due to vendor's monopoly in the market. The distribution of dominion over several dealers as in a deregulated power market will enhance competitiveness among them and the consumers could grab the edge. The application will also be equipped to surveil the forthcoming pricing agenda and correspondingly prepares the user to be managed for the trade. Moreover, the system will offer varying incentivization schemes based on intra-brand or inter-brand charge transfers, mode of charging viz. fast, regular or slow charging rate and time of charge viz. off peak/ rush hour etc to extend the range of services sufficing a range of customers.

The real-time cost optimization operations enforced by SG and charging hub clouds respect the power pricing interests of each power system stakeholders thus realizing a win-win climate for whole TOSC infrastructure. Equation (1) dictates a integer linear programming (ILP) based cost minimization strategy motivated to realize multi-location remote charging of xEVs, with concentration on minimizing the xEV battery degradation.

$$\min_{d_i^h, c} \; Cost_i = \sum_{h=1}^{H} \left\lfloor (p.\Delta h).\chi_h (c_i^i - d_i^h) + \; .d_i^h.(p.\Delta h) \right\rfloor \tag{1}$$

Subject to constraints:

$$\Psi_i^{h+1} = \Psi_i^h + \left\{ p.\Delta h(c_i^i - d_i^h) \right\} \;, \; h \in \left[h_{in} - h_{i,n}^d \right] \tag{2}$$

$$\Psi_{h_{i,n}^d} - \Phi_{i,n} = \Psi_{i,n+1} \tag{3}$$

$$\Psi_{i,j}^{\min} < \Psi_i^h < \Psi_{ij}^{\max} \tag{4}$$

$$d_i^h + c < 1 \tag{5}$$

The terms in objective function (1) shows the charging cost and xEV battery degradation cost respectively under time of use (TOU) price. Equation (2) and (3) captures the stored energy dynamics of xEV battery when the xEV is in transit among three states defined by decision variables d_i^h and c_i^h showing charging and discharging events respectively, at a time slot h as described by (6). Constraint (4) defines the inherent regulatory limits imposed on the xEV state of charge (SOC) while (5) enforces the integrity and synchronization mechanism by drawing the fact that charging and discharging of xEVs are mutually exclusive events.

$$d_i^h, c = \begin{cases} 0/1 & If \quad h \quad \left[h_{in} - h_{i,n}^d \right. \\ 0 & otherwise \end{cases} \tag{6}$$

2. Shortest Travelling Distance

When the xEV battery SOC starts reaching below a threshold level and the xEV user is driven by the fear of being stuck in the midway, the xEV user opts for the shortest route. The V2C application recommends in accordance to the adopted shortest path first (SPF) algorithms such as Dijkstra's algorithm. Further, every shortest route is not guaranteed to be the least time consuming one, thus the application dynamically adapts according to the forecasted traffic uncertainties. The application can also implement geometric planning strategies to obtain a optimal route under such adversaries [24].

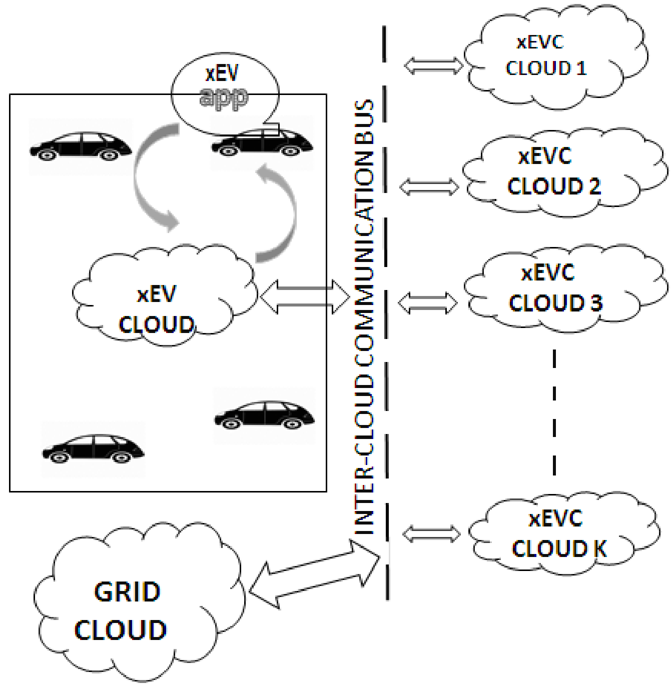

Fig.6. Communication interfaces among Federated Clouds

3. Minimum queuing delay

Here the driver has time constraints and it generally occurs during miscellaneous contingency hours viz. office hours, school hours etc. For such case, the road which is shortest as well as having least traffic is the ultimate option. Many a times, the driver has to confront to useless delays due to infrastructure uncertainties such as at traffic jams, queuing at charging stations. The V2C recommendation system software can implement robust routing protocols to manage the charging schedules of xEVs. It can further use the fundamentals of queuing theory to configure the stationary and non-stationary distributions of xEVs incoming flux in a way that guarantee minimal queuing delay, maximum charging hub utility and curtail the burden from backend SG.

However, the proposed V2C algorithm would undertakes all these criteria into consideration to achieve an optimal output termed as the state of “triangle equivalence”. There exist a range of xEV consumers that often wish to get rid of the delays while the vehicle battery is plugged. To address such disputes the V2C recommender system (RS) will mine the fuelling, driving, social and psychological profile data of the xEV user to predict the mode of charging that he shall adopt such as fast charging, normal or slow charging etc.

For immediate actions, the cloud aware TOSC proposed in this work augments the V2C services to another dimension where the xEV user is alarmed of such uncertainties and advocated to undertake the pico-grid service offered by photoactive coatings on the vehicle panes. The RS can also implement risk averse solutions by efficiently quantifying the physical, social and financial uncertainties of the overall environment for optimal commercial viability.

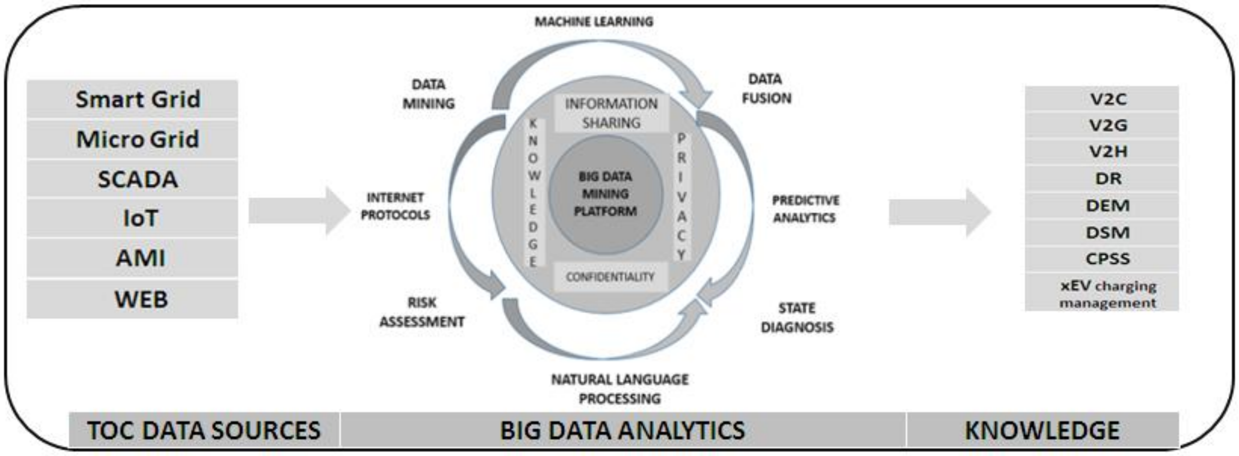

Fig. 7: Workflow model for Big-Data processing in TOSC Architectures

4. Big-Data TO Knowledge (B2K) Framework

The proposed TOSC framework congregates the diverse transportation entities into a clique like structure through CoT paradigm and enables a bidirectional flow of energy and data among the stakeholders in order to facilitate the assets optimization. The major data sources for a data driven TOSC include:

1. SG data aggregation nodes such as Supervisory control and data acquisition (SCADA) system and associated components viz. master terminal unit (MTU), remote terminal unit (RTU), programmable logic controller (PLC) etc.

2. AMI metering and sensing devices.

3. ITS objects such as xEV OBU, RSU, traffic sensors and actuators, GPS devices etc.

4. Web data for recommender systems, crowdsourcing, feedback modules.

Fig.7 depicts the big data to knowledge (B2K) work flow for translating the data generated from TOSC infrastructures. The objective of the proposed B2K framework is to realize a range of data aware TOSC services such as vehicle to cloud (V2C), vehicle to grid (V2G), vehicle to home (V2H), demand response (DR), demand side management (DSM), DEM, xEV charging management etc. In order to effectively meet these but not the least TOSC objectives, the B2K framework defines a multi-tier TOSC analytics framework that encompasses multidisciplinary efforts from data mining, machine learning, data fusion, predictive analytics, state diagnosis etc. It establishes a data driven big-data analytics platform for the cloud to infrastructure (C2I) interfaces and enable the xEVs, SGs, micro-grids etc to act both as producers and consumers, are thus entitled as prosumers. For instance, the xEVs are allowed to participate in power trading services such as V2G, V2H etc. Robust data science and computational analytics synchronizes the active participation of SG entities in power market operations such as bidding, arbitration, unit commitment, forecasting, scheduling, ancillary market etc, and operates diverse energy management services such as dynamic energy management (DEM), real-time wide-area situational awareness (WASA), home energy management systems (HEMS), demand response (DR), frequency regulation etc.

Use of machine learning techniques for TOSCs provides the utilities the ability to adapt to act, grow and change without explicit stakeholder involvement when exposed to time series datasets. Efficient execution of such algorithms on the data generated in proposed TOSC framework setup consistent decision making platform and makes the system reliable and adept to adversaries. The dynamic and time series data from such utilities create high dimensional datasets that create storage, scalability and flexibility concerns for the analytics at the data centers. The B2K framework defines the use of efficient machine learning techniques specifically dimensionality reduction algorithms such as random projection [25], principal component analysis [26] and kernel based algorithms such as support vector machines [27] etc. to develop an efficient storage and analysis platform for such voluminous datasets. The framework advocates the use of advanced dimensionality reduction algorithms based on graph kernels to intelligently summarize the data produced due to the nodal structure of IoT enabled TOSC components such as charging station network, the xEV distribution and human social interaction etc. In addition, the TOSC data centers are equipped with fast and massive storage and computational elements supporting High Performance Computing (HPC).

The framework enables the use of summarization techniques for aggregation analytics and transforms the original TOSC data streams into noble representations to remove the concerns related to scalability, complexity, event detection and process execution. Besides, it also employs data mining tools and techniques such as anomaly detection, rule mining, regression analysis etc.

The B2K framework implements data fusion (DF) paradigms that primarily inherit algorithms from three broad domains namely statistics, probability and AI, essentially employ sequence of tools and techniques for aggregating heterogeneous configurations of data from varying sources to acquire intelligence and inferences for the system. The TOSC utilities and data centers are leveraged with efficient data fusion techniques that collate the multivariate and heterogeneous data from the contemporary transportation and road telematics such as OBUs, RSUs, localization mechanisms viz. GPS, information storage and processing technologies etc to conclude with a comprehensive inference.

For TOSC data, the proposed B2K prototype advocates the installation of comprehensive data fusion pipeline defined and implemented by US Department of Defence (DoD), that involves five execution steps with human in the loop [41]. Level 1 involves data pre-processing i.e. compression, normalization and formatting methods etc, the outputs of which are fed to level 2. In level 3, the real-time data obtained from appropriate sources in level 2 are mingled with standard databases to trace & analyze the possible causes for the events occurring in the data. In the next processing level the patterns, correlations and semantics of information are assessed and aggregated. Level 5 extracts the feedbacks from previous steps and applies successive refinement strategies to predict, assess and evaluate the need for further improvement in the DF methodologies. The overall performance is tuned up by involving human factor in the loop to interpret and utilize the output from the DF pipeline.

The significant correlations, patterns and trends in the transportation dynamics are mined efficiently to devise intelligent schemes for demand response and load balancing. Such datasets can also serve as potential candidates for predictive analytics needed for load forecasting, dynamic pricing, optimal scheduling of resources and bad data correction. Graph pattern mining for distribution statistics of the TOSC elements such as xEVs, charging stations etc and utility mining for the xEV usage profiles allows the V2C to predict the future service adoption scenario, for use in short-term and very short-term demand forecasting.

For load classification (LC) purposes, efficient offline clustering algorithms such as Artificial Neural Networks (ANNs), K-means, Fuzzy c-means etc are executed to discover the latent distributions and groups in the TOSC data. The analytics modules in the data centers also implement online clustering strategies such as XCSc [28], online k-means [29] etc, for effective harvesting and utilization of time-series TOSC and V2C data. To ensure real-time responsiveness, the TOSC implements efficient task scheduling algorithms to have an exact dissemination of resources across the data centers. The application programmers create or port IoT application that assigns the xEV cloudlets to analyse the time-critical datasets and offloads the less sensitive or historical data to data centers at higher levels of hierarchy.

Though V2C infrastructures in transport oriented cities offer great potentiality for data and energy management, switching from conventional power architectures cloud aware smart grid and xEV charging utilities will introduce risk factors that needs to be carefully mitigated. The intensive use of SG's physical components viz. supervisory control and data acquisition (SCADA), master terminal unit (MTU), remote terminal unit (RTU), programmable logic controller (PLC) etc, roadside infrastructures viz. OBU, RSU, V2I elements and AMI coupled with underpinning information and communication technology (ICT) utilities makes the whole TOSC framework a cyber-physical system (CPS). Such cyber configurations can pose serious complications with respect to privacy, security and integrity of both physical as well as ICT subsystems. Moreover, the multiplicities of Big Data applications in contemporary CPSs motivates to solicit the concept of Big Data networking, its formation, features, mathematical and statistical intricalities [30].

The B2K also defining the need for embedding risk analysis modules into design phase of security subsystem in a way that ensures transparency and understandability among the involved stakeholders and curbs the confidentiality, integrity and availability concerns in the transportation and metering utilities. The TOSC software developers also execute robust intrusion and anomaly detection algorithms and install committed firewalls in order to tolerate the vulnerable security threats related to disclosures, power thefts, denial of service (DoS), integrity and cloning.

The millions of IoT based network devices employed in TOSCs are managed through emerging software defined networking (SDN) technologies to reliable operation of the whole infrastructure. SDN upgrades the hierarchical networking configuration of power system that includes home area networks (HANs), neighbourhood area networks (NANs), and wide-area networks (WANs) through the notion of network operating system (NOS). The use of SDN cloud aware transportation and power system architectures provide alluring solutions to the TOSC network management problem by enabling a software-defined centralized control that is flexible with respect to regular software updates, flow control, security patching, and quality of service (QoS) [31]. The NOS programming interfaces are intelligently programmed to remove the labour, cost and complexities prevalent in traditional network management schemes by updating the network elements from the central control plane [32].

As defined in B2K framework, the federated cloud data centers use predictive analytics that involves use of statistical, machine learning and data mining techniques to analyze historic and real-time datasets generate rules and predictive models to predict future events [43], [44]. In order to install TOSC infrastructures from the scratch and to meet the regulatory constraints for renewables and xEV penetration, the TOSC utilities implement robust predictive planning and analytics that can optimize asset replacement expenses and enhance the execution efficiencies under stringent budgetary ordinances. Through predictive forecasting and asset analytics, softwares and services are developed to make the utilities in TOSC infrastructures aware of the potential events for outages and correspondingly execute workforce planning that can undertake proactive measures for event mitigation and routine maintenance. Predictive asset analytics are intelligently used to improve the technological, productivity and business process engagements in a way that assures customer satisfaction, proper route planning, better safety and compliance, and optimized field crews.

5. Adoption Challenges and Future Prospects

The proposed work identifies some of the computing needs for building a data aware management framework for next generation TOSCs. The proposed TOSC infrastructure is potentially viable to bring a paradigm shift in the application specific cloud computing deployments and can co-work symbiotically with numerous intelligent transportation systems (ITS) domains. The work concludes as a wakeup call for multitudes of energy management ideas to develop transportation and SG utilities that not only demand scalability services bestowed by cloud computing but also have additional requirements such as real-time analytics, consistency, privacy, security, etc. that the current cloud computing paradigms doesn't support. However, being the first of this genre, it will elicit proponents as well as skeptics to ponder on future enhancements. This section highlights some adoption challenges and requisites for research thrust in course of TOSCs realization.

1. Scalability

The federated clouds presented for TOSCs will seldom be developed from scratch, but the economics is to grow out of existing architectures. Issues regarding how to best allocate resources and programs to a distributed cloud that can serve the analytics demand of emerging TOSCs remains open book problem. The effectiveness of V2C infrastructures in TOSCs depends on its scalability to handle the dynamically changing xEV flux. The cloud architectures in TOSCs should be potent to tackle the traffic spikes and surges in the xEV demand occurred under emergencies and adversaries. Efficient mobile cloud computing strategies leveraged with data driven demand prediction algorithms can circumvent the scalability concerns caused due to continuous evolution in the xEV network [33].

High performance computation paradigms can be developed to optimize the storage space utilization, coordinate the virtual machines and network bandwidth to shape the server workload. Integrating the proposed TOSC paradigm with next generation technologies such as internet of vehicles (IoV), internet of energy (IoE) etc, for development of middleware for MaaS architectures is still a nascent research thrust [34].

Analytics of dynamically generated voluminous datasets TOSC architecture becomes very expensive under the pay per use computation paradigm. Indeed, the computation expenses vary linearly with the task size and execution time, thus forcing the data scientists to incur heavy investments on storage and analysis. Thus, it opens a doorstep for the industry research and development communities to perform progressive analytics using domain specific sampling strategies to ensure effective user control, determinism and provenance for optimal and commercial viable deployment

2. Performance, reliability and QoS

The incentives of V2C framework is primarily dedicated to promote development of intelligent vehicular services and offer a range anxiety free drive to the naïve xEV users. The TOSC infrastructure assembles the distributed cloud platforms to co-work with each other for smooth and reliable operation of its entities. However, maintaining an optimal balance in the distribution of data, control and computation among the dedicated cloud-cloudlets decides the performance of the system. Commercial realization of the notion of CoT from billions of sensors and low power devices in a sensor network and connectivity with the data centers demand reliable and permanent sources of energy. Efficient fabrication techniques can enable the sensors to generate onsite power from renewables and environment [35].

The V2C paradigm employs dynamic and adhoc data clouds, so intermittent vehicular networking will hamper the service quality. The mesh created by seamless communication among cloud-cloudlet utilities will create galactic volumes of information to flow across the interfaces and data centers, thus uncertain network & communication failure will adversely affect the execution of V2C infrastructure. Intelligent controllers and gateways coupled with mobile networking paradigms can manage the connectivity control of distributed and networked cloud resources in TOSCs cyber infrastructures [36], [37]. For successful installation of the proposed TOSC infrastructure, regular checkpoints can be established to assess the following objectives:-

1. Effect on business strategies adopted by TOSC utility companies in case of fluctuation in performance and QoS parameters.
2. Quantifying the tolerance, response and adaptation of the V2C customers towards risk factors such as latency, variability, power outages, queuing delay etc.
3. Development of real-time evaluation strategies to measure the performance, synchronization, reliability and service quality TOSC data clouds.

3. Cost Uncertainty

Being numerous cloud utility offerings available on the market with varying pricing schemes, decisions on selecting the one commercially optimal to TOSC entities needs to be standardized. A budding informatics thrust is to evaluate the complexity and financial viability of cloud service deployments in price diverse environments. The infrastructure assembles multiple cloud genres into a common platform, thus uncertainties in pricing models is obvious. The stakeholders if are aware of the future service tariffs and incentives, will allow them to ponder for the optimum.

4. Security

Security is among the prime issues in a typical data driven TOSC, as the transportation utility vendors may agonize for the repercussions if the privacy of entrusted cloud data is compromised. Due to the dynamic nature of a transportation and SG infrastructures, it becomes nearly infeasible to create coherent cross-cloud trust relationships. Further, existence of complex relationships and dependencies among varying range of stakeholders in contemporary smart cities hinder the compatibility and cost effectiveness of data clouds employed in TOSCs. Global security standards are essential to cope up with such privacy and flexibility concerns. Decisions regarding selective migration of information hosted in private clouds and vehicular cloudlets to the public storage space require rigor research. Robust and fine grained authorization protocols and access grants should be defined to ensure multiple accesses to federated cloud repositories.

The centrally managed access control policies adopted by SDNs in can cause vulnerabilities and cyber threats for TOSC network topologies. The infrastructures involved in controlling flow dynamics can be susceptible to both active and surreptitious threats caused by method specific, target specific, identity specific and software specific attacks. The attack list can be control plane saturation attack, spoofing, tampering, repudiation, information disclosure, DoS, and elevation of method etc [32]. Thus the integration of SDNs to TOSCs presents ample unique research prospects and challenges to security and networking scientists.

5. High performance analytics

Integration of Human Machine Interaction (HMI) utilities into current intelligent transportation having an elegant communication and computational support opens a doorway for commercial and automotive communities to transform notions of emerging technologies viz. social internet of vehicles (SIoV) [38], social transportation [14], vehicular crowdsourcing [39], platoon research [40] etc, from concept phase to implementation phase. Analytics in such domains will enrich the reliability of decisions obtained in TOSCs and extend the service range to infotainment, safety, traffic scheduling etc. The underutilized vehicular resources if pooled properly, will create realm of supercomputers which can act as beds for real-time as well as offline analytics [16]. Predicting future trend from example data streams forms the basis for an online algorithm and is an efficient method for load prediction and monitoring. The federated cloud computing utilities when coupled to physical systems and cyber systems form cyber physical clouds (CPC). CPCs constitute "CYBER" of cyber physical systems (CPS) and their services can be adopted by SGs, aggregators, independent system operators (ISO) as well as xEV users in social environments as defined by [38],[41], to enhance the controllability, efficiency and reliability of the transport oriented cities.

7. Conclusions

In this work the notion of Transport Oriented Cities (TOSC) is established that comprises of intelligent entities like smart grid, smart charging station, smart car and smart meter and the interaction among these entities is coordinated through the deployment of a federated cloud-cloudlet infrastructure. The hierarchical cloud framework optimally control and monitor the components and entities involved in operation of a transport oriented smart city. A comprehensive and commercially viable realization of vehicle to cloud (V2C) model for smart and coordinated charging of the xEV fleet is proposed. The cloud data centers are endowed with high performance computational elements and robust data analytics algorithms for delivering a real time solution to achieve smart charging management of smart xEVs fleet supporting the criterion triad namely minimum charging tariff, shortest travelling distance and minimum queuing delay at the charging station. The research also developed a Big Data to Knowledge (B2K) framework and highlights the multidisciplinary research trends and thrusts for transforming raw data into rules and decisions. Further, the data science prospects and challenges, research thrust and scope for commercialization in the next generation TOSCs are outlined.

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