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Impact of PMU and smart meter applications on the performance of LTE-based smart city communications

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Abstract: Electrical distribution network operators require measurements from phasor measurement units (PMUs), micro-PMUs (μPMUs), and smart meters (SMs) in order to develop efficient distributed management system (DMS) applications. The high data-rate transmission of those measurements is a burden to the underlying communication system and its feasibility needs to be investigated. In this paper, we propose a method to characterize the traffic generated by a DMS application in a smart city scenario and an analysis of its impact on a realistic LTE infrastructure. Real geographic data on the position of SMs, PMUs, and μPMUs are employed to accurately model this DMS application and its generated traffic. A realistic LTE infrastructure is used to measure the load of DMS traffic at each eNodeB. The impact of synchronous and asynchronous DMS traffic on the LTE access is discussed, and bottlenecks in the LTE communication network are identified.

1 Introduction

According to the World Bank [1], the world percentage of urban population grew from 33% in the 1960s to the 55% in 2016. This shows the pressure that cities are facing to sustain the standard of living of their increasingly large population. To provide that growing population with a suitable trade-off between livability and sustainability, cities are becoming *smarter* and that transformation is affecting city transportation, food/energy supply and social interactions. The power grid will also be impacted by the smart-city paradigm since, for sustainability reasons, stakeholders are increasingly pushing for the use of more renewable energy sources. Therefore, the penetration of non-conventional energy sources in urban areas will very likely increase, which will impact their distribution systems (DSs).

Conventional electrical DSs operate as passive, radial grids whose states, e.g., power flows, voltage profiles, and power quality, are easily predicted and managed. In recent years, however, DSs are becoming more complex and active due to the growing integration of distributed energy resources (DERs) including microgrids, small and medium-size photo-voltaic/wind generation, combined heat and power, energy storage systems (ESSs), electric vehicles, and demand-response systems. Daily changes frequently happen in DSs and impose several challenges such as modeling and management. Therefore, distribution network operators require smart grid technologies, advanced distributed management systems (DMSs) and wide-area monitoring systems (WAMSs) to manage recurrent events including extreme voltage variations, congestions, disturbances, and faults [2].

Phasor measurement units (PMUs), micro-PMUs (μPMUs), smart meters (SMs), digital relays, and intelligent electronic devices provide a great opportunity to improve the performance of WAMSs and to increase the DS observability [3]. PMUs are measurement devices capable of reporting GPS-synchronized sets of phasor, frequency, and rate of change of frequency (ROCOF) of voltage and current signals, also known as synchrophasors. The synchrophasor data have been efficiently used in developing wide-area monitoring, protection, and control [4]. SMs can also play a major role in the development of DSs toward the concept of the smart grid. Besides providing basic automated meter readings of consumers, SMs offer various functionalities that can be used to develop applications such as integrating building area networks, power quality indicators, and event alarms [5]. These capabilities provide the opportunity to utilize the widespread SMs to access valuable, free, and reliable information.

The development of WAMS, DMS, and energy management system (EMS) in smart cities relies on the underlying communications system. That system must provide effective bidirectional communication between the DMS and a large number of PMUs, μPMUs, and SMs. That flow of information is subject to several communication performance requirements such as delay and the reporting rate of data, that span from sub-milliseconds for synchrophasors to few seconds for SM data. Power studies often make abstraction of the communication infrastructure, assuming that it will be highly reliable and performant. That is the case for dedicated telecommunication networks that are typically overdimensioned for the sparse traffic that they transport. In smart cities, however, such will not be the case. First, transmitting elements will not be just a few PMU elements, but the scale will be much larger as SMs, PMUs, and μPMUs are widely distributed in the cities. Second, the messages from the DS will be using the same infrastructure as millions of messages coming from other smart-cities applications.

The objective of this paper is to investigate the effect of a largely distributed measurement devices on a realistic smart-city LTE communication infrastructure. LTE is a well-known technology, actively promoted by the 3GPP group to be used in the Internet of Things (IoT) sector. LTE is currently widespread in urban areas due to its large coverage, speed and the possibility of dealing with a large number of users. Note that a new standard (i.e., NBIoT) has been recently proposed to support the communication requirements of smart systems, such as the capability to cope with a large number of devices, low bandwidth, and limited power consumption. However, the suitability of LTE to support smart grid/smart city applications, e.g., DMS, needs to be further investigated.

This paper contributes to the application of a DMS that employs datasets reported by SMs, PMUs, and μPMUs in a smart city scenario. The characteristics of the traffic produced by the DMS applications are studied, and the performance of LTE is thoroughly assessed by means of stochastic simulations. Several types of traffic are used (e.g., periodic, synchronous, and asynchronous traffic) to accurately model the traffic generated in a DMS application. Visual analysis are also included in order to display the load on each element of the LTE network and to identify bottlenecks in the communication infrastructure. We will see that some features, such as the synchronicity of traffic can have a major impact on the application performance. To the best of our knowledge, this is the first time that the performance assessment of DMS traffic is done in a realistic smart-city context.

The rest of the paper is structured as follows. In Section 2 an overview of the current work on DMS/EMS techniques and the applications of PMUs, and SMs in DSs is presented. In Section 3, the DMS under study is described in detail. In Section 4, the smart city case study is described. Preliminary results are included in Section 5. The conclusions of this research work are included in Section 6.

2 State of the art

This section presents a brief review of the work on the DMS/EMS and some of their communication features. A network-oriented energy management system, which utilizes network capacity linear inequality constraints, is proposed in [6] and a multi-objective energy management approach is proposed in [7] to achieve the optimal operation of distribution networks that include DER and ESS units. In conventional power systems, real-time voltage and current measurements were limited, and thus, pseudo measurements were obtained using different estimation algorithms such as weighted least squares (WLS) [8].

The introduction of PMU increased the system observability. The WLS algorithm proposed in [9] exploits PMU measurements to estimate branch currents and to improve the knowledge of the voltage profile. A Bayes's rule distribution system state estimation (DSSE) algorithm capable of addressing the uncertainties of PMU measurements is proposed in [10].

On the other hand, the penetration of SMs and advanced metering infrastructure (AMI) in distribution networks provides the opportunity to enhance the accuracy of DSSE methods. Several DSSE methods that utilize unsynchronized SM measurements, have been developed [11, 12]. An AMI comprising supervisory control and data acquisition (SCADA) and SMs is used in [13] to propose energy forecasting and operational planning services in low-voltage distribution networks. Furthermore, several optimal placement algorithms for PMUs and SMs in distribution networks, to achieve reliable DSSE, have been proposed [14, 15]. However, the effective integration of synchronized PMU data and unsynchronized SM data is not thoroughly addressed.

A comprehensive review of the current advancements in communications to support the smart grid can be found in [16]. In particular, the network performance of AMIs are studied in many research projects, and the main approaches adopted in literature are stochastic simulations ([17]), mathematical analysis (e.g., in [18]), and field trials ([19]). Communications among PMUs and μPMUs are regulated by two major standards: IEC 61850-90-5 ([20]) and IEEE C37.118.2 [21]. In [4], a model to compensate for an unreliable communication system is proposed. In [22], the combination of PMU and smart sensors data is studied, focusing on the interoperability of different types of measurement data and their potential benefits to the power grid. The use of μPMUs to improve the performance of the DS is presented in [23]. Several research projects focused on the suitability of LTE to support the smart grid (SG) monitoring and, more generally, machine-to-machine (M2M) communications [24]. A framework to characterize the traffic generated by a wide M2M application and its impact on the LTE infrastructure can be found in [25, 26].

Differently from the above mentioned papers, we provide the following original contributions:

- We construct a realistic large-scale use case for DMS in smart cities.
- We study for the first time the interaction between the traffic generation patterns and the performance of a largely distributed DMS system.

3 Proposed distribution management system

The integration of the wide-area synchrophasor and AMIs data will facilitate the development of the proposed DMS for the smart grid. Figure 1 illustrates various distribution system DMS/EMS applications and the integrated communications and information flow path of the smart grid including:

1. **Synchrophasor data network** that contains the electrical measurements of medium and low voltage distribution network reported by numerous PMUs and μPMUs, and aligned using phasor data concentrators. Additionally, the data acquired from DER and microgrid local controllers and EMSs are also communicated to DMS.
2. **AMI** that contains the low voltage measurements reported by SMs and collected by data concentrators, and the data processed by and acquired from small industry, building, and home EMSs.
3. **Supplementary data** including weather forecasting and market information that will be used in the DSSE and operational planning.
4. **Distribution network analysis unit** that relies on the reported measurement and data from all available data sources to perform power flow analysis, fault analysis, disturbance detection, etc.
5. **DSSE unit** that employs the available measurements and data along with the results of the distribution network analysis unit, to predict the states of the distribution system. Based on the estimated state of the system, if action from the distribution network operator is needed, early alarms and warnings will be issued. The status of the distribution network will be classified into three categories, i.e., normal, critical, and emergency.
6. **DMS unit** that performs numerous operational and protection actions including voltage regulation, power flow congestion management, DER/microgrid management, and power quality management. In normal operation condition, no action is required. In critical operation condition, the network is operating close its limits and some remedy such as using reserve DER/ESS units is required. In case of the emergency conditions where the network limits are violated, more aggressive load management is required.

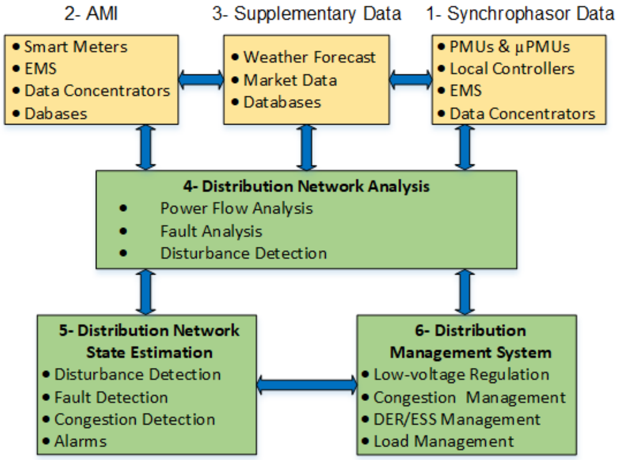

Figure 1: Block diagram representation of measurement, analysis, and management units and the data flow path of the distribution network.

4 Case study: Distribution Network of Montreal

In this study, we focused our analysis on Montreal, second largest city in Canada and recently selected as *Top Intelligent Community of the year* by the Intelligent Community Forum. The metropolitan area under study is displayed in Figure 2, generated using the web application proposed in [25] and available at www.trafficM2Modelling.com.

The web application permits to characterize the traffic generated by M2M applications in a smart city environment. It also allows to assess the performance of a realistic LTE infrastructure, by employing real data on the position of LTE base stations (eNodeB) in Montreal. The metropolitan area of Montreal is further subdivided in regions, as shown in the so-called *Voronoi diagram* (Figure 2). We assume that those regions represent the covering areas of each eNodeB. The Voronoi diagram is used in this context to assign each machine to its closest eNodeB in order to gain access to the LTE network. This is possible thanks to the use of the GPS position of the communicating machines and permits not only to characterize the M2M traffic but also to evaluate its impact on the LTE infrastructure.

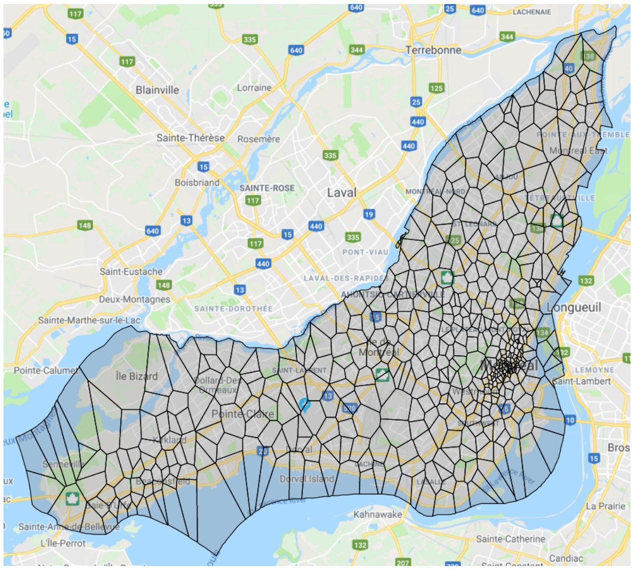

Figure 2: The Voronoi diagram of the Montreal area using the position of 553 eNodeB stations installed by the Canadian cellular provider Rogers.

The EMS application in scope in this paper employs three types of nodes, as previously discussed: (i) smart meters, (ii) μPMUs, and (iii) PMUs.

Smart meters are assumed to be installed in residential premises.[1] PMUs are installed in power substations. μPMUs are expected to be present in the premise where a distributed generation (DG) is installed. We assume DG to be installed in a pre-defined subset of residential premises, randomly generated at the beginning of the simulation. Figure 3 shows the position of the 335158 smart meters, denoted with white circles, and of the 21 PMUs, denoted with red stars. μPMUs are not indicated because they are located in the same positions of the smart meters.

5 Numerical results

To study the performance of this DMS application, we have characterized the telecommunication traffic produced over an hour and measured its impact on the network performance of the LTE system described in Section 4. Results were obtained using a machine with an *Intel(R) Core(TM) i5-8250U CPU 1.6 GHz.*

SMs periodically produce traffic each 10 minutes, whereas PMU/μPMU each second. A packet size of 200 kB is assumed in order to comply with the regulation presented in [21]. As previously mentioned in Section 4, the number of μPMU is variable and depends on the number of houses with DG. We created 4 different instances, with a number of μPMUs equal to 2500, 5000, 10000, and 25000: those values are used to account for different levels of DG penetration in Montreal: a percentage ranging from 0.75% to 7.5% of the residential premises are assumed to have installed DG and consequently a μPMU.

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[1] `http://donnees.ville.montreal.qc.ca/dataset/adresses-ponctuelles`

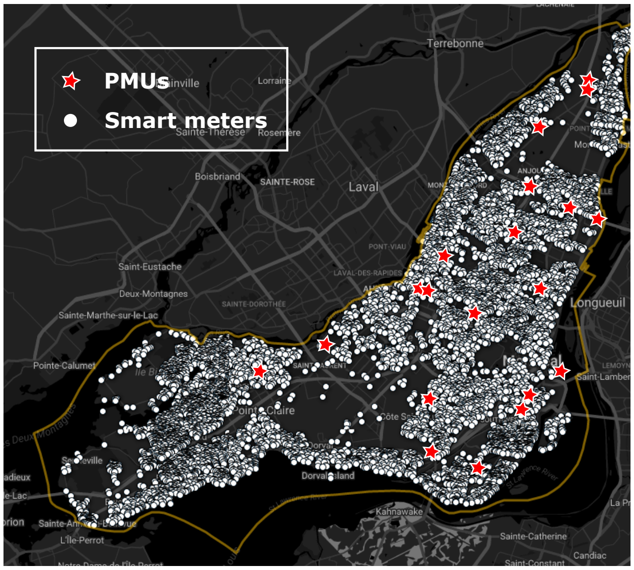


Figure 3: The map of Montreal with the 335158 smart meters (installed in residential addresses) and 21 PMUs, which we assumed to be installed in power substations.

We have implemented two scenarios to test the DMS application:

1. Periodic traffic with synchronous transmissions
2. Periodic traffic with asynchronous transmissions

5.1 Synchronous DMS transmissions

In this scenario PMUs and μPMUs are supposed to take their measurements and transmit at the same time instants. The simultaneous transmission of a large number of devices, alongside the limited number of access resources (i.e., 54 preambles available at each time frame) entails the occurrence of wireless collisions. A collision takes place when two or more devices attempt to access the same eNodeB using the same preamble signal and the same frequency slot, often referred to as *random access opportunity*, as described in [27]. In Table 1, we have reported the values of some performance indexes, such as the collision probability and the access delay, as the number of μPMU varies. The average collision probability ranges from 10.46% to **46.86**% when the number of μPMU is 2500 and 25000, respectively. The increased collision probability has a considerable impact on the average access delay experienced by all the nodes: the value for 25000 μPMUs is considerably larger than the one with 2500 μPMUs (150.30 ms versus 66.70 ms, respectively). A remarkable difference is also observed for the maximum access delay, that goes from 780 ms (with 2500 μPMUs) to 1060 ms (with 25000 μPMUs). The minimum access delay for any machine in the system is 10 ms, i.e. the time frame duration in the LTE network. It is worth remarking that the total traffic produced by the DMS application is higher than 17 GB when the number of μPMU is 25000. This value represents the data volume generated in one hour, leading to a daily traffic generation of 411.65 GB.

5.2 Asynchronous DMS transmissions

The access delays presented in Table 1 can be reduced by relaxing the constraint of simultaneous transmission of PMUs and μPMUs: collision probability is expected to decrease and reduce the access delay. In this scenario, SMs produce packets periodically each 10 minutes, as in the previous scenario; PMUs/μPMUs are periodically transmitting at the rate of 1 packet per second but the transmission of each device is randomized between 0 and δ_{max} ms after the scheduled transmission time. We have considered the following values for δ_{max}: 1, 0.5, and 0.1 s.

When $\delta_{max} = 1s$, we can see that the average collision probability is consistently lower than in the synchronous transmission scenario, as shown in Table 2. The average collision probability ranges from

Table 1: Scenario 1: Synchronous DMS transmissions.

		# μPMU			
		2500	5000	10000	25000
Collision Prob. (%)		10.46	19.98	31.09	**46.86**
Access Delay (ms)	Min.	10	10	10	10
	Avg.	66.70	81.23	103.28	150.30
	Max.	780	830	930	1060
Total Traffic (GB)		2.064	3.74	7.093	17.152
Comput. time (s)		86.4	143.5	324.8	415.3

1.168% to 3.475%. The reduced collision probability reflects into a lower access delay on average, between 55.395 ms and 58.211 ms. Note, however, that even though the network performance with asynchronous traffic is considerably better than in the case with the synchronous traffic, it mayundermine the accuracy of the DMS application. In particular, all the measurements from PMUs and μPMUs are synchronous because of the requirements of the DMS application. Thus, if we delay the transmission of some nodes to produce asynchronous traffic, the average delay for those measurements to be available to the application will increase. For instance, when $\delta_{max} = 1$ s and the maximum access delay is 0.5 s, it means that there can be 1.5 seconds from the measurement time to the time the measurement is available for the DMS application.

Table 2: Scenario 2: Asynchronous DMS traffic with $\delta_{max} = 1s$.

		# μPMU			
		2500	5000	10000	25000
Collision Prob. (%)		1.168	1.193	1.616	3.475
Access Delay (ms)	Min.	10	10	10	10
	Avg.	55.395	55.52	56.077	58.211
	Max.	620.0	760.0	810.0	980.0
Total Traffic (GB)		2.183	3.983	7.583	18.383
Comput. time (s)		45.761	89.382	157.139	412.693

In Tables 3 and 4, we report the values of performance indexes with respect to the number of μPMUs, when δ_{max} is equal to 0.5 s and 0.1 s, respectively. Even though reducing δ_{max} considerably degrades the overall performance, asynchronous DMS traffic is still preferable to the synchronous traffic when measuring collision probability and access delay. We can conclude that a trade-off needs to be done when choosing the value for the parameter δ_{max}: increasing this value permits to release the burden on the LTE infrastructure but increases the time from the moment a measurement is taken to when it is available to be analyzed in the DMS.

Table 3: Scenario 2: Asynchronous DMS traffic with $\delta_{max} = 0.5s$.

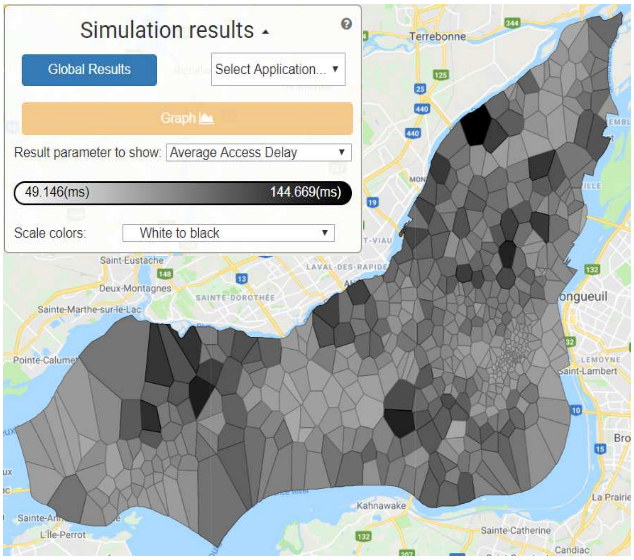
		# μPMU			
		2500	5000	10000	25000
Collision Prob. (%)		1.402	1.762	2.8	6.587
Access Delay (ms)	Min.	10	10	10	10
	Avg.	55.926	56.299	57.372	62.001
	Max.	720.0	740.0	810.0	920.0
Total Traffic (GB)		2.183	3.983	7.583	18.383
Comput. time (s)		40.31	74.505	145.178	456.54

Table 4: Scenario 2: Asynchronous DMS traffic with $\delta_{max} = 0.1s$.

		# μPMU			
		2500	5000	10000	25000
Collision Prob. (%)		3.096	5.72	10.145	21.745
Access Delay (ms)	Min.	10	10	10	10
	Avg.	57.802	61.031	66.563	84.646
	Max.	720.0	790.0	860.0	1000.0
Total Traffic (GB)		2.183	3.983	7.583	18.383
Comput. time (s)		40.151	99.032	154.457	779.797

5.3 Visual performance analysis

When it comes to the analysis of the performance of a large scale application such as the DMS it is important to carry out visual analyses in order to identify bottlenecks in the telecommunication infrastructure. For example, Figure 4 contains a heat-map of the Montreal area in which the color of each region represents the average access delay experienced by all the machines in each eNodeB region. The color bar on the top left of the figure shows the relation between the color and the average access delay. Figure 4 represents the results obtained with 25000 μPMUs and asynchronous traffic. The darkest regions in the figure are the ones that contain the largest number of μPMUs. This depends on the fact that μPMUs, even though less numerous than smart meters, generate access requests at a higher rate which leads to the increased number of collision and a performance degradation.



Result parameter to show: Average Access Delay

Scale colors: White to black

Figure 4: The heatmap representing the average access delay in the scenario with 25000 μPMUs and async. traffic ($\delta_{max} = 0.1$ s).

6 Conclusions

This paper presents an analysis of a novel DMS application in a smart city scenario. The research focuses on the characterization of the traffic produced by the DMS application and its impact on the underlying LTE infrastructure. The proposed DMS application employs data from smart meters, phasor measurement units (PMUs) and μPMUs and it is intended to foster the adoption of Distributed Generation (DG) in smart cities; in particular, different levels of penetration of DG are analyzed ranging from 0.75% to 7.5%.

The use of realistic data on the position of smart meters, PMUs, and μPMUs permits to accurately model the DMS traffic. Moreover, the use of a realistic LTE infrastructure permits to carry out thorough network performance evaluations: in particular, it makes it possible to estimate the load at each eNodeB and to gain valuable insights into the suitability of LTE to support the DMS application under study.

Numerical results show that the introduction of a massive synchronous traffic would consistently degrade LTE network performance with average access delays higher than 150 ms. Another remarkable result is that it is possible to relieve the burden on the LTE network by randomly deferring the transmission of PMU and μPMU data. However, it is important to remark that deferring the transmission has a negative impact on the operation of the DMS application. The choice of the value of δ_{max} (i.e., the maximum deferral of synchrophasor transmissions) is a trade-off between the network performance and the effectiveness of the DMS application.

A visual analysis based on the heatmap of the average access delay permits to highlight the bottlenecks of the LTE infrastructure: this analysis shows that μPMUs are the nodes that mostly affect the network performance: even though they are less numerous than smart meters, they generate traffic at a considerably higher rate negatively impacting on the average access delay.

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