Microgrid Data Aggregation and Wireless Transfer Scheduling in the Presence of Time Sensitive Events

Ahmed Omara
School of Electrical Engineering and Computer Science, University of Ottawa
Ottawa, Canada
aomar020@uottawa.ca

Wendong Yuan
School of Electrical Engineering and Computer Science, University of Ottawa
Ottawa, Canada
wyuan011@uottawa.ca

Michele Nogueira
Department of Computer Science, Federal University of Paraná
Curitiba, Paraná, Brazil
michele@inf.ufpr.br

Burak Kantarci
School of Electrical Engineering and Computer Science, University of Ottawa
Ottawa, Canada
burak.kantarci@uottawa.ca

Lei Wu
Department of Electrical and Computer Engineering, Clarkson University
Potsdam, NY, USA
lwu@clarkson.edu

ABSTRACT

Microgrids enable a network of distributed energy generators to sustain energy needs off-the-grid. Microgrids can experience islanded operational mode, being this mode a time sensitive event that affects costs of power generation and distribution. The detection of time-sensitive events is important because the control unit needs to be aware of changes in the grid to avoid losses in power quality and costs. This requires a quality of service (QoS)-aware data aggregation and queuing mechanism in the core of the network infrastructure to convey microgrid data to a central server (considered as a macro base station). This paper investigates the impact of time sensitivity-based microgrid data aggregation on message delivery under different priority and time-sensitivity levels. Hence, we propose a framework to cluster the electrical data based on the time sensitivity criteria using unsupervised machine learning. We introduce a multi-class queuing system in the pico-cells to ensure that clustering reduces the processing time for high priority data. The results show that the proposed approach significantly reduces the delivery delay of messages carrying time sensitive events from the microgrid.

CCS CONCEPTS

• **Networks** → **Cyber-physical networks**; **Wireless access networks**; • **Computing methodologies** → **Machine learning**;

KEYWORDS

Smart grid; HetNets; Microgrids; Picocells; Data aggregation; Clustering

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1 INTRODUCTION

Smart grid is an electric power system formed of sensors, communication technologies, and control units to provide the customers with better power services [6]. Power system reliability and sustainability, as two of the major concerns in smart grids, call for proactive emergency preparedness and self-recovery solutions [11]. Smart microgrid is defined as small scale of the smart grid. In terms of the microgrid operational mode, it is classified into two categories, namely the islanded mode and grid-connected mode [13].

In the islanded mode, the utility grid is unable to supply/control the newly formed island [2]. Thus, according to the IEEE standard, islanding events must be detected within two seconds [1]. We also need to notify the utility grid about the microgrid transition to a different mode (either islanded or grid-connected) for the sake of preparedness and sustainability in microgrids. Hence, we need to reduce the processing time of the information messages (that identify the islanding events) in the communication infrastructure. This means that islanding events not only need to be detected within two seconds but also the information messages need to be transmitted to the control unit in the utility grid as soon as possible. In other words, the incidence of islanding and grid-connected events, which could be defined as time sensitive events, could result in remarkable hikes in the operational expenditures of the utilities [8].

In smart grids, the impact of islanding and grid-connected events can be significantly reduced by integrating a reliable communication infrastructure with the smart grid [7]. A heterogeneous network (HetNet) infrastructure can process and communicate the time sensitive events faster and more accurately in comparison to a single-tier network infrastructure. In this paper, we introduce a multi-class queuing mechanism for aggregating of microgrid data in the pico-cells. We compare the proposed framework to a baseline data aggregation approach that would work on first come, first serve basis as opposed to multi-class priority queue-driven aggregation. Our simulation results show that the delivery delay of higher priority messages can be significantly reduced if our proposed data aggregation approach is adopted.

The paper proceeds as follows: Section II reviews the related work while Section III describes the proposed system model in detail. Section IV presents our simulations along with thorough discussions. Section V concludes the paper and gives future directions.

2 RELATED WORK

Wireless networks are considered as viable candidates for their flexibility, ubiquity, and low cost of deployment. For instance, the authors in [14] state Wireless Lan (WLAN) and Long Term Evolution (LTE) as potential wireless technologies for effective management of microgrids while identifying round robin polling-based time division multiple access (TDMA) as a viable option for wireless access in a microgrid network. The wireless communication network serves to address the distributed load shedding and supply-demand balancing problems. The wireless communication networks deal with particular challenges, in the integration of wireless networks with the microgrids, ensuring the stability of microgrid in the presence of wireless link delays. The authors in [5] study the stability of a microgrid through analysis of wireless communication channels between actuators and controllers.

The role of Heterogeneous Networks (HetNets) in microgrid control and management has been considered in the last few years by several researchers. In [9], the authors presented the first work that introduces multi-agent coordination via a HetNet infrastructure in order to address the trade-off between two cost components: communication and power generation. In [12], the authors tackle the automation problem in microgrids, and propose a heterogeneous and converged fiber-wireless network infrastructure as the communication medium for the addition and/or deployment of renewables as well as storage systems into the power grid. To address the interoperability issues, the proposed system utilizes the IEC 61850 standard for the power grid end, whereas off-the-shelf automation protocols such as PROFINET and Modbus TCP are utilized for the interoperability within building automation.

3 SYSTEM DESIGN

The system under study consists of four layers: power generation, data analytics, data processing and communication. The power grid generation layer denotes a smart microgrid that is aimed to be sustained by renewable resources. The data analytics layer consists of a data analytics framework running machine learning algorithms to cluster time sensitive events. The data processing layer is responsible for processing the data rapidly based on their clusters/priorities. The data analytics and processing layers are located in each picocell. Finally, the communication layer is the data carrier between the HetNet tiers. In this paper, we consider upcoming grid-connected events as possible time sensitive events affecting the cost of electricity consumption.

3.1 Power generation layer

This work considers a microgrid with two distributed generators (DGs) as in the literature. The first DG is assumed to be a diesel generator which serves as the base power supplier of the microgrid to reduce the uncertainty of the power generation in the microgrid. The second DG is assumed to be a photovoltaic (PV) panel with an efficiency of E_e, which represents the average efficiency found in the market. The PV panel is a simple example of the renewable energy sources in the microgrid which causes uncertainty in the amount of the generated power. The PV panel generated power depends on its area following Eq. 1. [4]:

$$E_{out} = A_e E_e G \tag{1}$$

where E_{out} is the electricity production in kW; A_e the total surface area of solar cells in m^2; E_e the mean power conversion efficiency for the PV pane; and G the total solar irradiation in kW/m^2.

3.2 Data analytics layer

The data analytics layer plays the key role in our proposed approach. This layer aims to cluster the electrical data generated from the power layer into subcategories based on specific features by implementing data analytics framework in the layer. Unsupervised machine learning is one of the most viable techniques to cluster the data based on hidden patterns and similar features in the data. One of the well-known and popular algorithms used in data clustering is k-means, proposed by Lloyd [10].

However, defining the time sensitivity of the raw data requires the measurement of the electrical cost variation over a period of time. In other words, we can identify whether the raw data is time sensitive or not by calculating the difference in electrical costs between every two consecutive minutes over 24 hours, as described in Eq. 2. In the equation, δ is the difference in the electrical cost of two consecutive minutes. Each microgrid is defined by a sequence of δ values that indicate the time sensitivity of the data.

$$\delta = x(t) - x(t-1) \tag{2}$$

In order to accurately calculate variations of the δ values, root mean square (RMS) can be used to measure the level of variation of electrical cost. Higher RMS means that the data varies rather frequently which is more likely to be delay sensitive. Lower RMS means that the data remains on a reasonable level which is more likely to be delay tolerant.

3.3 Data processing

In order to process three different types of power consumption data /messages (i.e. highly time-sensitive, moderately time-sensitive, and delay-tolerant), the queuing system becomes vital to the integration of microgrid data in a timely manner. With the integrated queuing system deployed within a wireless network environment, different power consumption messages can be handled asynchronously to speed their processing time with delay-sensitive feature or higher level of urgency. The system processes the high priority messages first and after the lower priority messages.

The proposed queuing system for microgrid data aggregation introduces a single priority queue into a system, which means the priority queue contains all types of messages (Figure 1). In a priority queue, an element with high priority will be served earlier than an element with low priority, making it possible for important messages to be processed first in the system. To use a single priority queue, less memory is required for queue structures in the heap

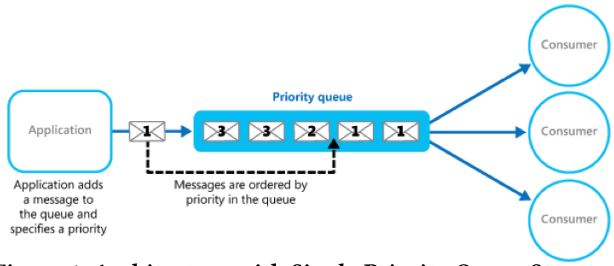

Figure 1: Architecture with Single Priority Queue Structure

during the initialization stage. At the same time, only one comparator module is needed to realize the selection on the message with the highest priority in the queue system. When the queuing system scales with more types or classes being added, the queuing system can still perform the same level of functionality and does not require any modification since the queuing system still performs the selection procedure based on the values of priority levels.

3.4 Communication layer

The communication layer is responsible for carrying the data from and to the base station. The communication network infrastructure followed in this paper consists of two tiers, namely macro-cell and pico-cell, forming a heterogeneous network for microgrid, as shown in Figure 2. The macro-cell base station is a simple type module working as the terminal of all aggregated messages. It receives all the incoming messages from the pico-cells, and –if equipped with edge computing capability– performs data analysis based on priority categories.

The pico-cell component is a compound type module working as the first recipient of the sent messages from the microgrid users. It consists of two submodules: the pico-sink component and the queue component. The pico-sink module is an intermediate submodule within a pico-cell to process the incoming user data. In order to define the corresponding priority levels for each message, machine learning procedure is needed to perform on the dataset.

The message queuing component is another important submodule within a pico-cell. It identifies time sensitivity of incoming messages from the pico-sink. This submodule contains a priority queue and serves as an integrated queuing system. A comparator method is integrated with the queue component as a priority identifier which defines the customized rules to compare each message in the queue for selecting the highest prioritized message.

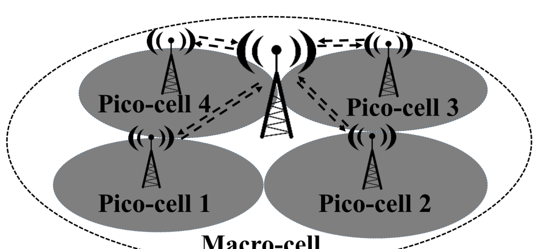

Figure 2: Heterogeneous Network Topology in Microgrid

4 PERFORMANCE EVALUATION

For evaluations, we employ the dataset provided by UMass Smart* Dataset 2013 release which is a microgrid dataset providing electrical data of 443 microgrid users over a single 24-hour period [3]. The electrical data is collected in a time sequence order per minute using timestamps in Unix time. Figure 3 presents clustered data. The simulation environment is built on OMNeT++ development platform using C++ language (C++11). However, due to memory limitation in OMNeT++, the platform only employs data of 48 home users from the 443 microgrids dataset.

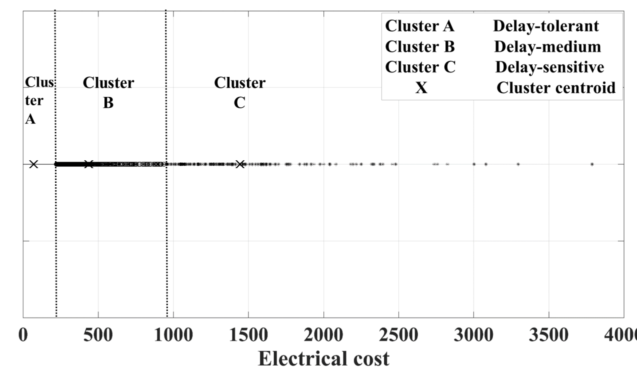

Figure 3: Clusters of Microgrid Data vs. Time Sensitivity

The wireless network consists of one macro-cell and four pico-cells. In order to compare the performance of various cases, two types of networks are simulated, namely *uniform* and *heterogeneous* microgrid networks. In the uniform scenario, the microgrid users are distributed over the pico-cells uniformly (i.e., 12 home users per pico-cell) whereas the heterogeneous scenario considers the certain pico-cells as hotspots. In the heterogeneous scenario, the home users are distributed over the pico-cells 1, 2, 3 and 4 as 5, 10, 15 and 18 users, respectively.

Figure 4 compares the number of the clustered messages based on the time sensitivity feature in both uniform and heterogeneous microgrid network scenarios. In the uniform scenario, 9.6% of the collected data are considered highly time-sensitive messages, whereas the moderately time-sensitive and the delay-tolerant are 27% and 63.4%, respectively. In the heterogeneous scenario, the percentages of highly time-sensitive, moderately time-sensitive, and delay-tolerant messages are 9.7%, 26.7% and 63.6%, respectively. Hence, the data clustered percentages in the heterogeneous scenario are close to those of the uniform scenario.

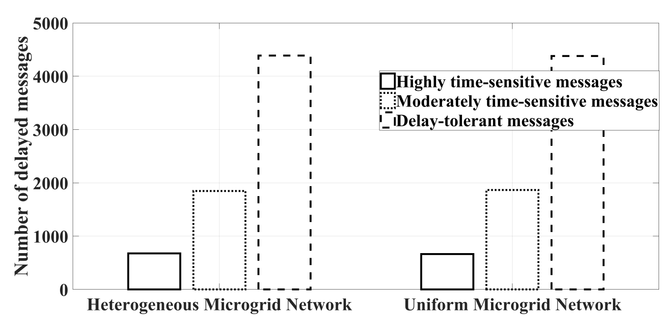

Figure 4: Number of Queue Delay Messages

Figure 5 represents the queue messages delay time regarding the three time-sensitive messages (highly time-sensitive, moderately time-sensitive and the delay-tolerant). The delay time of the queue messages, in both uniform and heterogeneous network scenarios, have exactly the same pattern. The queuing delay is increasing

Table 1: Pico-cells Throughput and Queue Length

	Max Throughput (kbps)	Average Throughput (kbps)	Max Queue Length (B)	Average Queue Length (B)
Uniform Microgrid Network	1.728	1.548	1375	687
Heterogeneous Network (Pico-cell 1)	0.72	0.67	367	51
Heterogeneous Network (Pico-cell 2)	1.44	1.34	1087	303
Heterogeneous Network (Pico-cell 3)	2.16	2.01	1807	754
Heterogeneous Network (Pico-cell 4)	2.592	2.413	2239	1120

when the messages become less time-sensitive. In the uniform microgrid network, the delay time of highly time-sensitive messages is 40.56 seconds, whereas the moderately time-sensitive and the delay-tolerant are 121.3 and 324.19 seconds, respectively. The delay time in the heterogeneous network regarding the highly time-sensitive, moderately time-sensitive and the delay-tolerant are 38.96, 119.3 and 321.5 seconds, respectively.

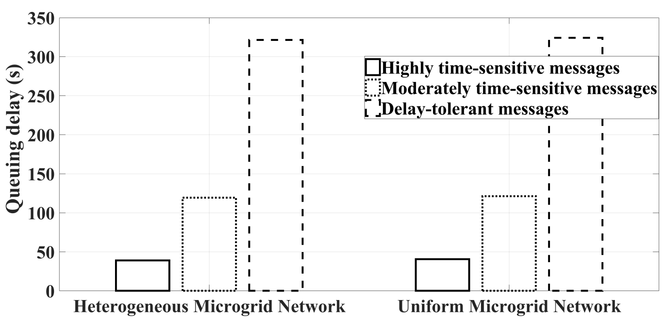

Figure 5: Delivery Time of Queue Messages

With the increase in the number of users per pico-cell, the values of throughput and queue length increase as shown in Table 1. Queue length represents the number of packets in the queue waiting to be transmitted whereas the throughput denotes how fast and successfully the pico-cell can process the data during the transmission time. In the uniform scenario, since the number of users is distributed uniformly among the pico-cells, the pico-cells are set to have identical input parameters. On the other hand, since each pico-cell has a different number of home users in the heterogeneous scenario, the observed values for each metric are different. For the four pico-cells, the maximum values of the throughput vary from 0.70 kbps to 2.592 kbps and the average values vary from 0.67 kbps to 2.413 kbps. Moreover, the maximum values of the queue length vary from 367 to 2239 and the average values vary from 51 to 1120.

From the observation and evaluation mentioned above, we can infer that the priority queuing system has made an impact on the processing time of the delivered messages from the home users. The results show that the delivery delay is reduced for messages with higher level of priority. In other words, the introduction of the machine learning algorithm, particularly k-means clustering algorithm, and the implementation of a priority queue are the key factors behind a lower delivery time for the time-sensitive messages.

5 CONCLUSION

In this paper, to process different types of messages asynchronously according to their levels of urgency, priority queue has been integrated into the system to aggregate microgrid messages in a prioritized manner. Through simulations, we have shown the successful integration of k-means clustering algorithm for time sensitivity analysis of microgrid data and priority queuing system for data aggregation in HetNet. Future work would include analyzing system scalability when the machine learning component and the queuing system are applied to practical scenarios. Moreover, the load imbalance issue will be important to the performance of the system as well.

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