

# Predictive Operational Strategies for Smart Microgrid Networks

by

Ahmed Mohamed Elsayed Omara

Thesis Supervisor : Dr. Burak Kantarci

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## Abstract

There have been significant advances in communication technologies over the last decade, such as cellular networks, Wi-Fi, and optical communication. Not only does the technology impact peoples' everyday lives, but it also helps cities prepare for power outages by collecting and exchanging data that facilitates real-time status monitoring of transmission and distribution lines. Smart grids, contrary to the traditional utility grids, allow bi-directional flow of electricity and information, such as grid status and customer requirements, among different parties in the grid. Thus, smart grids reduce the power losses and increase the efficiency of electricity generation and distribution, as they allow for the exchange of information between subsystems. However, smart grids is not resilient under extreme conditions, particularly when the utility grid is unavailable. With the increasing penetration of the renewable energy sources (RES) in smart grids, the uncertainty of the generated power from the distributed generators (DGs) has brought new challenges to smart grids in general and smart microgrids in particular. The rapid change of the weather conditions can directly affect the amount of the generated power from RES such as wind turbine and solar panels, and thus degrading the reliability and resiliency of the smart microgrids. Therefore, new strategies and technologies to improve power reliability, sustainability, and resiliency have emerged. To this end, in this thesis, we propose a novel framework to improve the smart microgrids reliability and resiliency under severe conditions. We study the transition to the grid-connected operational mode in smart microgrids, in the absence of the utility grid, as an example of emergency case that requires fast and accurate response. We perform a comparative study to accurately predict upcoming grid-connected events using machine learning techniques. We show that decision tree models achieve the best average prediction performance. The packets that carry the occurrence time of the next grid-connected transition are considered urgent packets. Hence, we perform an extensive study of a smart data aggregation approach that considers the priority of the data. The received smart microgrids data is clustered based on the delay-sensitivity into three groups using k-means algorithm. Our delay-aware technique successfully reduces the queuing delay by 93% for the packets of delay-sensitive (urgent) messages and the Packet Loss Rate (PLR) by 7% when compared to the benchmark where no aggregation mechanism exists prior to the small-cell base stations. As a mitigation action of the utility grid unavailability, we use the electrical vehicles (EVs) batteries as mobile storage units to cover smart microgrids power needs until the utility grid recovery. We formulate a Mixed Integer Linear Programming (MILP) model to find the best set of electrical vehicles with the objective of minimum cost. The EVs participating in the emergency power supply process are selected based on the distance and throughput performance between the base station and the EVs.

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# List of Abbreviations

|                 |                                     |
|-----------------|-------------------------------------|
| <i>ADSL</i>     | Asymmetric Digital subscriber Line  |
| <i>AON</i>      | Active Optical Network              |
| <i>AML</i>      | Advanced Metering Infrastructure    |
| <i>ANN</i>      | Artificial Neural Network           |
| <i>BAN</i>      | Building Area Network               |
| <i>BB – PLC</i> | Broadband PLC                       |
| <i>BS</i>       | Base Station                        |
| <i>BFS</i>      | Backward Feature Selection          |
| <i>bps</i>      | bit per second                      |
| <i>CNR</i>      | Carrier-to-Noise Ratio              |
| <i>CR</i>       | Cognitive Radio                     |
| <i>DER</i>      | Distributed Energy Resources        |
| <i>DMS</i>      | Distribution Management System      |
| <i>DG</i>       | Distributed Generator               |
| <i>DSL</i>      | Wireless Local Area Network         |
| <i>DSM</i>      | Dynamic Spectrum Management         |
| <i>DSSS</i>     | Direct Sequence Spread Spectrum     |
| <i>DSRC</i>     | Dedicated Short Range Communication |
| <i>DTV</i>      | Digital TV                          |

|                 |                                               |
|-----------------|-----------------------------------------------|
| <i>DT</i>       | Decision Tree                                 |
| <i>DWT</i>      | Discrete Wavelet Transform                    |
| <i>EPC</i>      | Evolve Packet Core                            |
| <i>EV</i>       | Electrical Vehicle                            |
| <i>FD</i>       | Frequency Domain                              |
| <i>FL</i>       | Fuzzy Logic                                   |
| <i>FFS</i>      | Forward Feature Selection                     |
| <i>GEO</i>      | Geostationary Earth Orbits                    |
| <i>GPR</i>      | Gaussian Process Regression                   |
| <i>GSM</i>      | Global System for Mobile Communications       |
| <i>HetNet</i>   | Heterogeneous Network                         |
| <i>HSPA+</i>    | Evolved High-Speed Packet Access              |
| <i>IoT</i>      | Internet of Things                            |
| <i>LEO</i>      | Low Earth Orbits                              |
| <i>LTE</i>      | Long Term Evolution                           |
| <i>LP – WAN</i> | Lower Power Wide Area Networks                |
| <i>mmWave</i>   | millimetre Wave                               |
| <i>MEO</i>      | Medium Earth Orbit                            |
| <i>MIMO</i>     | Multi-Input, Multi-Output                     |
| <i>MILP</i>     | Mixed Integer Linear Programming              |
| <i>NB – IoT</i> | NarrowBand Internet of Things                 |
| <i>NDZ</i>      | Non-Detection Zone                            |
| <i>NB – PLC</i> | Narrowband PLC                                |
| <i>NREL</i>     | National Renewable Energy Laboratory          |
| <i>OFDMA</i>    | Orthogonal Frequency Division Multiple Access |
| <i>OFDM</i>     | Orthogonal Frequency Division Multiplexing    |



|              |                                            |
|--------------|--------------------------------------------|
| <i>PCA</i>   | Principle Component Analysis               |
| <i>PDSCH</i> | Physical Down-link Shared Channel          |
| <i>PON</i>   | Passive Optical Network                    |
| <i>PLC</i>   | Power Line Communication                   |
| <i>PLR</i>   | Packet Loss Rate                           |
| <i>PMU</i>   | Phasor Measurement Unit                    |
| <i>QoS</i>   | Quality of Service                         |
| <i>RAN</i>   | Radio Access Network                       |
| <i>RSN</i>   | Roadside Unit                              |
| <i>RMSE</i>  | Root Mean Square Error                     |
| <i>SAE</i>   | Stacked Auto-Encoder                       |
| <i>SCADA</i> | Supervisory Control And Data Acquisition   |
| <i>SVM</i>   | Support Vector Machine                     |
| <i>SNR</i>   | Signal-to-Noise Ratio                      |
| <i>SPD</i>   | Signal Produced by Disconnect              |
| <i>TCP</i>   | Transmission Control Protocol              |
| <i>TD</i>    | Time Domain                                |
| <i>TGVP</i>  | Throughput Guarantee Violation Probability |
| <i>TTI</i>   | Transmission Time Interval                 |
| <i>UDP</i>   | User Datagram Protocol                     |
| <i>UMTS</i>  | Universal Mobile Telecommunications System |
| <i>UE</i>    | User Equipment                             |
| <i>V2G</i>   | Vehicle-to-Grid                            |
| <i>VANET</i> | Vehicular Ad-hoc NETwork                   |
| <i>VDSL</i>  | Very-high bit rate Digital Subscriber Line |
| <i>V2I</i>   | Vehicle-to-Infrastructure                  |

|              |                                                 |
|--------------|-------------------------------------------------|
| <i>V2V</i>   | Vehicle-to-Vehicle                              |
| <i>WLAN</i>  | Wireless Local Area Network                     |
| <i>WWAN</i>  | Wireless Wide Area Network                      |
| <i>WiMAX</i> | Worldwide Interoperability for Microwave access |
| <i>WPAN</i>  | Wireless Personal Area Network                  |

# List of Symbols

|                    |                                                                                                                                   |
|--------------------|-----------------------------------------------------------------------------------------------------------------------------------|
| $A_{im}^{nr}$      | Binary variable defines the multiplication of $O_m^{nr}$ by $O_m^{nr+1}$                                                          |
| $C_j$              | The centroid of a cluster $j$ (initial value selected arbitrarily)                                                                |
| $D_n^{\Phi_j}$     | Aggregator to macrocell delay for packets of delay sensitivity category $j$ in small cell $n$                                     |
| $D_{avg}^{\Phi_j}$ | Average aggregator to macrocell delay for packets of delay sensitivity category $j$ in the entire heterogeneous microgrid network |
| $D_m$              | Energy demand of microgrid $m$ (kWh)                                                                                              |
| $E_n$              | Initial battery level of EV $n$ (kWh)                                                                                             |
| $F$                | Total number of small cells                                                                                                       |
| $H$                | Electrical vehicle charging power (kW)                                                                                            |
| $J$                | Set of priority levels of microgrid packets with respect to delay sensitivity                                                     |
| $K$                | Total number of dropped packets                                                                                                   |
| $K_{im}$           | Distance between microgrid $i$ and microgrid $m$ (km)                                                                             |
| $L_s$              | Length of a packet $s$ , including payload and header in (bits)                                                                   |
| $M$                | Number of microgrids                                                                                                              |
| $N$                | Number of participating electrical vehicles (EVs) in the power supply request                                                     |
| $O_m^{nr}$         | Binary variable is one if microgrid $m$ is served by EV $n$ in order $r$                                                          |
| $P_n$              | Electrical energy price offered by EV $n$ (\$/kWh)                                                                                |

|                |                                                                                                                                                                                                  |
|----------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| $P_k$          | Length of a dropped packet $k$ , including payload and header in (bits)                                                                                                                          |
| $R$            | The average uplink transmission rate in (Mb/s)                                                                                                                                                   |
| $S_m^n$        | Amount of energy that EV $n$ provides to microgrid $m$ (kW)                                                                                                                                      |
| $T_m$          | Distance from the initial location of EV $n$ to first microgrid $m$ (km)                                                                                                                         |
| $U_n$          | Revenue of EV $n$ (\$)                                                                                                                                                                           |
| $W$            | Waiting cost per hour (\$/h)                                                                                                                                                                     |
| $Z_j$          | Total number of queued packets categorized in cluster $j$                                                                                                                                        |
| $\alpha_n$     | Percentage value determine the contribution value of the EV $n$                                                                                                                                  |
| $\delta_{(i)}$ | Difference in cost between two consecutive payload packets sent by microgrid $i$                                                                                                                 |
| $\phi_j$       | Label of cluster $j$ with respect to delay sensitivity. Without loss of generality, the label $\phi_j$ denotes higher delay sensitivity than the highest priority level cluster and $\phi_{j+1}$ |
| $d_{dequeue}$  | Time needed to remove the first available packet from the head of an aggregation queue in (s)                                                                                                    |
| $v$            | Constant value defines the cost of the service request made by the microgrid (\$/request)                                                                                                        |
| $x_{(i)}(t)$   | The payload of a packet $s$ sent by microgrid $i$ at time $t$ , carrying information of the cost of the total energy consumption of microgrid $i$                                                |
| $z$            | Average energy consumption per km (kWh/km)                                                                                                                                                       |

## Candidate's Publications During his Studies

### Publications in the Thesis Scope:

- **Ahmed Omara**, Michele Nogueira, Burak Kantarci, and Lei Wu, “Intelligent management for enhanced microgrid sustainability: A machine learning-based feasibility study”, (Submitted)
- **Ahmed Omara**, Burak Kantarci, Michele Nogueira, Melike Erol-Kantarci, Lei Wu, and Jie Li, “Delay Sensitivity-aware Aggregation of Smart Microgrid Data over Heterogeneous Networks”, in *IEEE International Conference on Communications (ICC)*, (Shanghai, China) May 2019
- **Ahmed Omara**, W.Yuan, B. Kantarci, M. Nogueira, and Lei Wu, “Microgrid Data Aggregation and Wireless Transfer Scheduling in the Presence of Time Sensitive Events”, in *ACM International Symposium on Mobility Management and Wireless Access*, (Montreal, QC, Canada), November 2018
- **Ahmed Omara**, Murat Simsek, and Burak Kantarci, “Cost Optimization of EV-Microgrid Integration and its Performance Evaluation over LTE Links”, (Submitted).

### Publications out of the Thesis Scope:

- **Ahmed Omara**, Damla Gulen, Burak Kantarci and Sema F. Oktug, “Trajectory Assisted Municipal Agent Mobility: A Sensor-Driven Smart Waste Management System”, in *Journal of Sensor and Actuator Networks (JSAN)*, July 2018

# Chapter 1

## Introduction

Reliable, sustainable, and resilient electric power systems are essential for modern societies. These goals require the distribution and diversification of power sources, which could be facilitated by smart grids [73]. A smart grid is an electric power system that provides reliable and sustainable energy with low losses and high levels of power quality by integrating communication technologies to connect generators and consumers [174]. It enables bi-directional communication between the control units and the end-loads, contrary to the traditional utility grid that uses uni-directional power transmission (generation to consumers) [159]. The integration of the Internet-of-Things (IoT) networks allows smart grids to monitor, control and manage the grid [44]. Power system reliability, sustainability, and resiliency as major concerns in smart grids, call for proactive emergency preparedness and self-recovery solutions [129].

Smart grid reliability is defined as the constant availability of energy, whereas the sustainability of a smart grid conveys that the resources of the energy is continuous. For example, solar power is considered a sustainable resource of energy, however, it is only available at the daytime. Smart grid resiliency is defined as the robustness of the power system under various conditions (e.g., extreme weather and catastrophic disasters). The solution of the aforementioned problems reside in a sub-category of the smart grid named as smart microgrid.

A smart microgrid utilizes Distributed Energy Resources (DERs) to produce power and reduce dependence on the utility grid as much as possible, which decreases consumer costs [56]. Specifically, Community Resilience Microgrids (CRMs) connect loads and DERs of heterogeneous owners to provide reliable and sustainable electricity services for the entire community through distribution lines owned by a local power utility company, especially

during disruption events [164]. CRMs can optimize electrical, economic, and societal goals while serving critical loads, such as pharmacies, gas stations, and hospitals, in the aftermath of a major weather disaster [166]. Therefore, there is an increasing need for deploying smart microgrids to serve multiple electricity customers in the event of long-term unavailability of the main power grid. When representing the next-generation electricity grid paradigms, CRMs introduce unique operation and control opportunities at the local distribution network, mitigate load shedding of local customers, increase renewable integration, and reduce carbon emissions [166].

The utilization of the generated data by the implemented IoT devices (a.k.a MicroGrid Devices (MGD)) and other units in the microgrids such as DERs, controllers and loads, can further help the smart microgrids to become more reliable, sustainable and resilient [49]. Moreover, fast propagation of the data through the communication infrastructure can improve the detection of major issues that face smart microgrids, such as islanding and grid-connected events (see Chapter 3). In addition, a rapid mitigation response towards critical and time-sensitive events can significantly improve as the communication delay of the transmitted data shrinks. However, the huge amount of data generated by the smart microgrids can be a challenging issue for an accelerated data transmission process.

## 1.1 Motivation

Climate change has increased catastrophic weather events in both frequency and intensity, which incurs severe social and economic impacts. One of the critical issues associated with such catastrophes is the sudden loss of electricity [86]. Smart community microgrids can share DERs and improve resiliency of the electricity supply to critical loads during disruptions; the community microgrids are created by connecting multiple facilities owned and controlled by individual partners within a clearly defined electrical boundary. The importance and potential benefits of smart community microgrids are well recognized and understood; however, they may not become widely deployed until several key challenges have been adequately addressed.

Specifically, a community microgrid can operate in both grid-connected and stand-alone modes [84]. It is of crucial importance to have a synchronization control that can ensure the seamless transition between the two modes, i.e., guaranteeing smooth islanding and re-synchronization processes. Indeed, when the main grid is back online after a period of islanding operation, the community microgrid intends to re-synchronize with the main grid [123]. However, such a re-connection needs to pass the synchronization check for ensuring the reliability and stability of the power grid. The synchronization check measures

frequency and voltage at both sides of a circuit breaker, and determines necessary parameters within allowable limits for re-connection. Such re-connection will be approved by the power grid system operator. Thus, it is important and beneficial if the power grid operator could accurately foresee the upcoming islanding and grid-connected events.

Data aggregation in smart microgrids is a key component for emergency responses when islanding and grid-connected modes occur [122]. The generated data from smart microgrids meets the 5 V-characteristics of big data (i.e. volume, velocity, variety, veracity and value) [179]. It is difficult for the control units to identify critical and time-sensitive data in smart microgrids. Hence, smart microgrids data require high QoS performance in terms of communication delay and packet loss rate under various heterogeneous network (HetNet) architectures, to guarantee fast time-sensitive data exchange over the network [121]. This requires quick recognition of critical and time-sensitive data. In addition, the mitigation of power unavailability of the power grid, due to unexpected events such as severe weather and islanding to grid-connected transition, is still an open research area to be investigated. Therefore, proposing novel solutions to improve smart microgrids reliability, sustainability and resiliency are essential to assist smart community microgrids to operate in extreme circumstances. It is worth noting that throughout this thesis smart homes and users are used interchangeably. Moreover, smart microgrids batteries are considered drained in our scenario. That is, we modeled the batteries as if they were used already and new alternatives to cover the smart microgrids power demand are needed.

## 1.2 Objectives

In order to improve the Community Resilience Microgrids (CRM) and mitigate power unavailability, we propose a three-stage solution as main objectives of this thesis. The objectives can be summarized as follows.

1. Fast and accurate prediction of transitions to the grid-connected mode during uncertain weather conditions in a smart microgrid.
2. Improve the HetNet data aggregation and the QoS requirements, specifically minimizing communication delay and packet loss rate, of the time-sensitive messages during critical events.
3. Provide alternative solutions to supply smart microgrids with power during a power outage in the grid. Simply, we want to answer the following question, what is the solution if a smart microgrid switch to the grid-connected mode but the utility grid is unavailable?



## 1.3 Contributions

Our contributions in this thesis can be summarized as follows:

- Performing a comparative study in a smart microgrid scenario to accurately predict upcoming grid-connected transitions using Machine Learning (ML) techniques. The study compares the performance of four different ML algorithms, namely Support Vector Machine (SVM), Decision Tree (DT), Linear Regression (LR), Gaussian Process Regression (GPR), in terms of accuracy, prediction speed and training time. Real-time power consumption, power generation and weather forecasting data are used as inputs for the ML algorithms. The results show that GPR algorithm achieves the best prediction accuracy of 98%.
- Introducing data aggregation framework in a smart microgrid network with priority queuing mechanism based on unsupervised (k-means) ML to improve the QoS requirements in terms of the queuing delay and the packet loss rate. The framework is studied under different HetNet scenarios with forty smart microgrids. Based on the message priority group, the Transmission Control Protocol (TCP) and the User Datagram Protocol (UDP) are used. The results conclude that the proposed approach successfully reduces the queuing delay by 93% for the packets of delay-sensitive (urgent) messages and the Packet Loss Rate (PLR) by 7% when compared to the benchmark where no aggregation mechanism exists prior to the small-cell base stations.
- Introducing an operational management framework for Electrical Vehicles (EVs) and smart microgrids integration. The problem is formulated as a Mixed Integer Linear Programming (MILP) model with an objective function of minimizing the smart microgrids' cost. The criterion of selecting the EVs is based on the Physical Downlink Shared Channel (PDSCH) throughput performance in an LTE network to ensure reliable communication links between the EVs and the smart microgrids.

## 1.4 Outline of the thesis

The rest of the thesis is organized as follows:

In Chapter 2 we study the literature works of the following: in Section 2.1 we discuss the various techniques of detecting and predicting the islanding operational mode in smart

microgrids. More specifically two categories are included: Sub-Section 2.1.1 overviews the traditional techniques for islanding detection, where the communication-based and the local-based methods are investigated in 2.1.1 and 2.1.1, respectively; and Sub-Section 2.1.2 discusses the artificial intelligence techniques used for islanding detection. In Section 2.2, we review the communication technologies used in smart grids; Sub-Section 2.2.1 focuses on the wired communication technologies; Sub-Section 2.2.2 discusses the role of wireless communications in power systems management by breaking it into three groups (based on the coverage distance): WPAN in 2.2.2, WLAN in 2.2.2, and WWAN in 2.2.2; and Sub-Section 2.2.3 focuses the communication technologies to enable EV-microgrid integration. In the last Section 2.3, we review different data scheduling techniques to improve traffic management and improve the QoS requirements in different communication environment settings.

In Chapter 3, we present a feasibility study using different machine learning algorithms to predict the grid-connected mode of a smart microgrid: Section 3.1 defines the problem and introduces the solution. Section 3.2 explains the proposed system with detailed discussion of each component of the system in Sub-Sections 3.2.1, and 3.2.2. In Section 3.3 we present a performance comparison among the presented algorithms, where Sub-Section 3.3.1 presents the simulation settings used in the study and Sub-Section 3.3.2 presents the performance comparison. Section 3.4 summarizes the chapter with final remarks.

In Chapter 4, we present a framework for smart microgrid data aggregation with a priority queuing mechanism based on unsupervised machine learning. Section 4.1 defines the problem and introduces the solution. Section 4.2 explains the architecture of the proposed framework. In Section 4.3 we present the simulation settings 4.3.1 and the performance results 4.3.2. Section 4.4 summarizes the chapter with final remarks.

In Chapter 5, we model the interaction between smart microgrids and electrical vehicles for a short-term power supply as an optimization problem. Section 5.1 defines the problem and introduces the solution in Sub-Sections 5.1.1 and 5.1.1, respectively. Section 5.2 explains the proposed solution with an overview of the system in 5.2.1 and detailed discussion of the optimization model in 5.2.2. In Section 5.3 we present the simulation settings and the performance results. Section 5.4 summarizes the chapter with final remarks.

Finally, Chapter 6 concludes the thesis with final remarks, open issues and challenges.

# Chapter 2

## Background and Literature study

### 2.1 Background on Islanding Detection in Smart Microgrid

A smart grid is an electric power system comprising of sensors, communication technologies, and control units to improve customer experience with cost-efficient power services. Smart grids allow bi-directional exchange of electricity and information among different parties in the grid, i.e., generation, distribution, transmission, and consumption subsystems [55]. A smart microgrid is defined as a small scale of the smart grid [70]. There are two operational modes for smart microgrids, namely the islanded mode and the grid-connected mode. Islanding occurs when Distributed Generators (DGs) continue to supply power to loads even after being disconnected from the utility grid. Under these conditions, the utility grid is unable to supply or control the newly formed DG island.

The microgrid transition between the two operational modes, i.e., islanded and grid-connected, is an example of time-sensitive events that require high priority in the queuing systems to reduce processing time. As illustrated in Figure 2.1, the literature on traditional islanding detection techniques can be classified into two categories, namely communication-based and local [91]. In this section we will explain each category and their subcategories, in order to show how the AI-based techniques are formed by integrating traditional techniques, with a focus on the local methods.

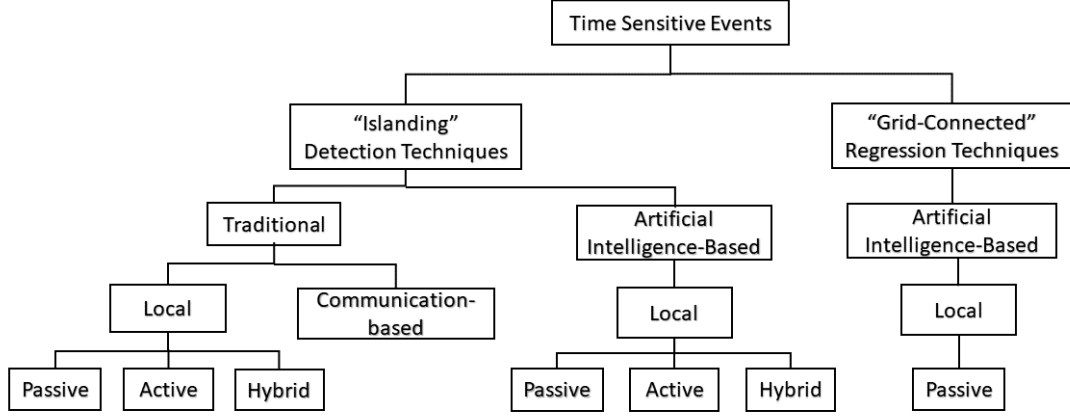


Figure 2.1: Classification of islanding detection techniques in literature

### 2.1.1 Traditional Islanding Detection Techniques

#### Local Methods

In practice, the local category of the traditional islanding detection techniques is more common. The methods are based on local information to detect islanding, which can be further classified as passive, active, and hybrid [116]. The passive methods have been used to detect islanding events by monitoring certain system parameters, without disturbing the system. Such system parameters include Under/Over Voltage (UOV), Under/Over Frequency (UOF), Phase Jump Detection (PJD), frequency derivative, Rate of Change of Power (RoCoP), and Rate of Change of Frequency (RoCoF) [118]. Based on observations in the normal grid-connected mode, thresholds are set to identify any violation when the transition to the islanded mode occurs. Although the passive methods could be easily implemented and cost-effective, they suffer from large NDZ [154] [25].

The idea behind the active methods is to inject a probe signal at the DG side and monitor corresponding changes to the system. In other words, these methods create disturbances in the system by a signal to check whether any violation will be induced [17]. Hence, the system power quality degrades because of the changes in the system operation and the detection time becomes longer as we have to wait to monitor the response of the microgrid [132]. However, the NDZ of the active technique is very small [31]. There are many different active islanding detection methods, for example, Sandia Frequency Shift (SFS), Sandia Voltage Shift (SVS), Active Frequency Drift (AFD), Active Frequency Drift

with Positive Feedback (AFDPF), and Slip Mode Frequency Shift (SMS) [28]. Table 2.1 compares the performance of the different passive and the active methods.

Table 2.1: Comparison of different passive and active methods

| Method | Category | NDZ        | Implementation cost | Detection time |
|--------|----------|------------|---------------------|----------------|
| UOV    | Passive  | Very large | Low                 | Short          |
| PJD    | Passive  | Large      | Low                 | Short          |
| UOF    | Passive  | Very large | Low                 | Short          |
| RoCoP  | Passive  | Medium     | Low                 | Short          |
| RoCoF  | Passive  | Medium     | Low                 | Short          |
| AFD    | Active   | Small      | Medium              | Average        |
| AFDPF  | Active   | Average    | Medium              | Average        |
| SFS    | Active   | Small      | Medium              | Average        |
| SVS    | Active   | Small      | Medium              | Average        |
| SMS    | Active   | Very small | Medium              | Average        |

Hybrid technique is the third type of the local island detection methods. As the name implies, the hybrid method is a combination of two stages, passive and active techniques [91]. The passive methods are used in the first stage to ensure that the values of the system parameters are within the required threshold. The active methods are then implemented when values of system parameters fail to be in threshold range [116].

### Communication-based Methods

The communication-based methods (a.k.a, remote methods) rely on transmitting signals over power lines to check if the microgrid remains connected to the grid [66]. This requires a dedicated channel between the utility grid and each individual microgrid in the network. Dedicated channels are associated with a significant infrastructure cost which is usually

difficult to be justified in interconnected DG systems. There are several communication-based methods such as Power-Line Carrier Communication (PLCC), Signal Produced by Disconnect (SPD), and Supervisory Control and Data Acquisition (SCADA) [91]. In the following paragraph, a brief description of each method is given.

The PLCC method transmits signals through the utility power lines to ensure the grid connection [136]. The signal is sent between a transmitter (T) from the utility side and a receiver (R) installed at the microgrid [169]. If the connection is lost, then an islanding formation is detected. Similar to the PLCC method, the SPD method uses a transmitter and a receiver for islanding detection [20]. However, the SPD method uses a different communication link other than the power lines, such as a microwave link and telephone link [80]. SCADA is another method that relies on communication techniques to detect islanding [108]. The SCADA system observes the status of the reclosers and circuit breakers [89]. The system uses voltage sensors to receive DG's voltage measurements [96]. If a voltage measurement is received from a disconnected DG, the transfer trip scheme incorporates with SCADA system to precisely identify the island location [170].

Telecommunication based methods are highly reliable and have theoretically a zero Non-Detection Zone (NDR), and thus have the best performance when compared to the local methods (i.e. passive, active, and hybrid methods) [137]. However, the practical implementation for the communication-based methods is inflexible and complex [39].

### 2.1.2 Artificial Intelligence-based Islanding Detection Techniques

The drawbacks of traditional techniques, such as slow detection time, low power quality, high cost to implement, and low accuracy, created the need for further methods to improve the traditional techniques. Island detection using artificial intelligence techniques have emerged based on certain machine learning algorithms to overcome the drawbacks of the traditional methods [58]. Researchers are currently looking into intelligent methods for detecting and classifying islanding conditions.

Signal processing techniques have aided researchers in understanding the existence of an island mode operation. The implementation of the signal processing technique allows for extracting hidden features of the measured signals to detect the islanding condition [47]. Various signal processing techniques have been used in the feature extraction process, such as Discrete Wavelet Transform (DWT), Discrete Fourier Transform (DFT), and S-transform. Moreover, feature selection algorithms like Forward Feature Selection (FFS) and Backward Feature Selection (BFS) were also adopted. Extracted features can then serve as inputs to the classifier for recognizing islanding and grid-connected modes.

Al-Bataineh and R. G. Kavasseri in [17] present a comparative performance study among five different classifiers, such as Nearest Neighbour, Bagging, Lazy K, Naive Bayesian, and Random Forest, considering the context of islanding detection. The study used four passive features as inputs to the algorithms including voltage, frequency, and their time derivatives (i.e., rates of voltage and frequency changes). The authors concluded that the Random Forest classifier obtained results of the highest performance in terms of accuracy and detection time. In addition, the Decision Tree (DT) algorithm is used very commonly because of its the high performance. For instance, the authors in [153] [103] [69], used the DT algorithm to predict islanding formation using different types of features extraction methods as an input vector to the algorithm.

Fuzzy Logic (FL) technique was also be applied as a classification technique in islanding detection. Samantaray S. and El-arroudi K. propose a Fuzzy Logic technique that is developed via the Decision Tree algorithm [140]. The combination of fuzzy membership functions (MFs) and the rule-based approach was used to transform the Decision Tree algorithm into fuzzy rule-based approach. The proposed technique was tested on data with and without noise, which performed perfectly with 100% of islanding detection rate. This proposed technique is easy to implement for online islanding detection and can handle uncertainties such as noise; it is thus suitable to be integrated into real-time applications for islanding detection in large power networks. As the DT is an offline data mining algorithm, the Fuzzy Logic technique becomes more preferable for online and real-time implementation.

As islanding detection is a binary problem, many works in literature has used SVM to tackle the problem. SVM is one of best fit to solve a binary problem due to its high accuracy. For instance, the authors in [111] extracted 62 features from voltage and current signals. The results showed a very good pheromones with accuracy of 98.94%. Different number of features were also used in other studies; for example, the authors in [57] [58] used 180 and 21 features with accuracy of 88.83% and 94%, respectively.

Another study pursued by Mishra et al [114]. in 2016 concerning about fast detection of islanding events presented a new scheme for fast islanding event detection in a microgrid, which uses the phase-space technique to extract features of three-phase voltages at the DG terminals. The extracted features were inputs to the Extreme Learning Machine (ELM) classifier. The results showed faster detection of the islanding events, preserving detection average accuracy of 96% at SNR=30 dB.

Deep learning has also been considered to detect islanding events. For instance, most recently, Kong et al., proposed a novel deep learning based hybrid framework to detect islanding events [93]. The authors used Stacked Auto-Encoder (SAE) model as a building

block in the deep network to rapidly and accurately classify the islanding events. They proposed a two-step procedure to train the network, using the greedy layer-wise unsupervised machine learning to initialize the weights of the neurons and fine-tuning the whole network via a supervised machine learning algorithm. The idea of the greedy layer-wise learning algorithm is to train one layer at a time. That is, first, the first hidden layer is trained with the training data as input, and then the second hidden layer is trained with the outputs from the first hidden layer as its input, and so on. A supervised fine-tuning process is then performed on the whole network to properly adjust the weights of the network to drive the loss function to its minimum.

In a related work presented by Elnozahy et al [48], an Artificial Neural Network (ANN) was combined with DWT for islanding detection. The DWT is used to extract the feature vector from the current signals. However, the feature vector includes some unnecessary information that may affect the detection performance. Therefore, the authors used the correlation coefficient to extract the characteristic signatures from the feature vector that only contain the necessary information and validated them via ANN. Only one signal was analyzed, and only one of the ANN inputs is used to detect the islanding condition. The results showed a detection accuracy of 96%. As the number of extracted features changes, the classification accuracy of the islanding events may also change. With 21, 35, and 64 features, the authors in [58] [42] [112], reported detection accuracy of 97%, 97.9%, and 99.28%, respectively. Table. 2.2 summarizes the AI techniques used to detect islanding formation.

Table 2.2: Most popular AI algorithms used in islanding detection literature

| AI algorithm              | Detection time (s) | Detection accuracy | Number of extracted features | Literature study                 |
|---------------------------|--------------------|--------------------|------------------------------|----------------------------------|
| Decision Tree             | [0.045 - 0.3]      | [95% - 99%]        | [11 - 21]                    | [47] [153] [103] [69] [58] [157] |
| Fuzzy Logic               | Not Reported       | [97% - 100%]       | [2 - 3]                      | [140] [95] [16]                  |
| Artificial Neural Network | [0.2 - 2.75]       | [97% - 99%]        | [21 - 35]                    | [48] [58] [42] [112]             |
| Support Vector Machine    | [0.05 - 0.3]       | [88% - 98%]        | [21 - 62]                    | [111] [57] [58] [103]            |



The performance of all the different techniques used to tackle the islanding detection problem are summarized in Table. 2.3.

Table 2.3: Comparison of different islanding detection techniques [91] [66]

| <b>Technique</b>    | <b>NDZ</b> | <b>Implementation cost</b> | <b>Detection time</b> |
|---------------------|------------|----------------------------|-----------------------|
| Passive             | Very large | Low                        | Short                 |
| Active              | Small      | Low                        | Average               |
| Hybrid              | Small      | Low                        | Average               |
| Communication-based | None       | Very High                  | Very short            |
| AI                  | Small      | Low                        | Short                 |

## 2.2 Enabling Communication Infrastructures and Technologies for Smart Microgrids

Smart grids employ different communication technologies to provide various services. Based on the coverage area, communication technologies in smart grids can be grouped into three main categories: (i) Wide Area Network (WAN), (ii) Local Area Network (LAN), and (iii) Personal Area Network (PAN). WAN is the largest computer network that covers a big geographical area. It is a private network used to interconnect multiple distributive LANs [97]. There are many examples of smart grids communication technologies in WAN such as WiMAX technology, cellular networks, and satellite communication. A LAN, on the other hand, connects different devices together within a small geographical area such as school, office building and residence. The most common two examples for LAN in smart grids communication are: Ethernet and WiFi. In general, routers and gateways are used to link a LAN with a WAN. A smaller area can be covered by a PAN which is used mainly for low power and short-distance networks. ZigBee, Bluetooth, and Z-Wave are examples of smart grids communication technologies in PAN.

Smart microgrid applications require a communication component to provide their services as desired. It is also an essential criterion when assuring the QoS, especially for mission critical applications such as safe and security applications [121]. Smart grids can exchange information between its entities using wire or wireless communication systems. In wire-based systems, the data can be transmitted using various methods such as telephone networks, fiber-optic networks and power line communication (PLC) [82].

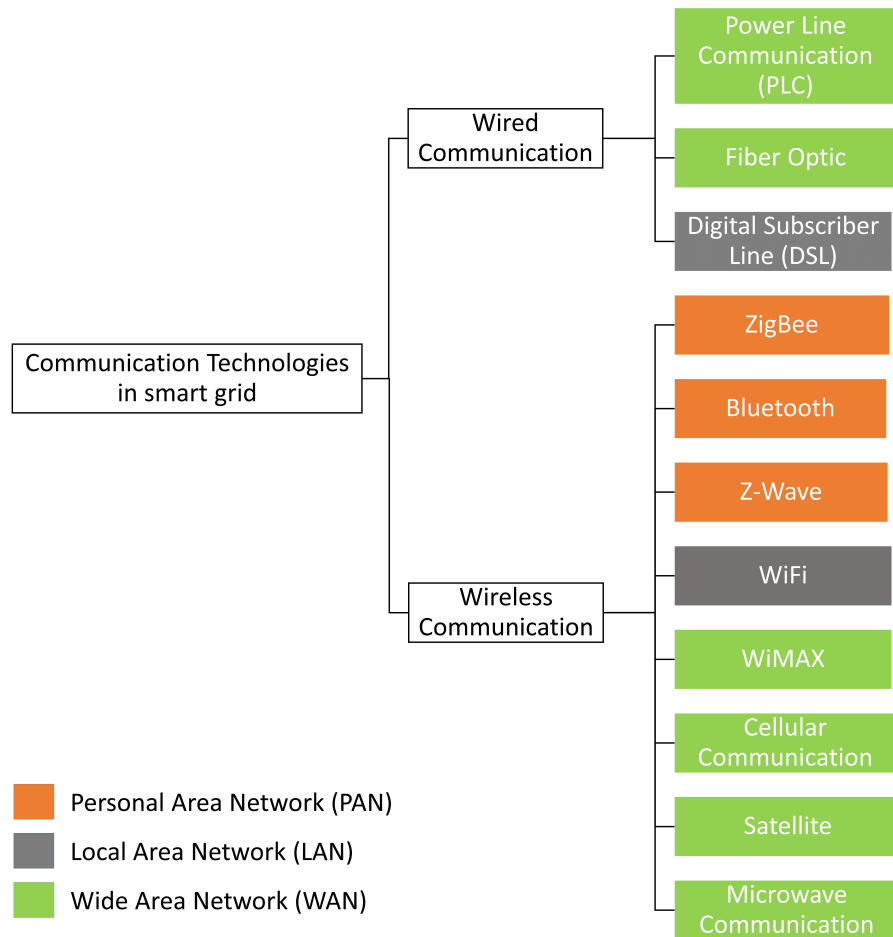


Figure 2.2: Communication classification in smart grids

On the other hand, in wireless communication systems, the data is transferred wirelessly using different technologies such as Wireless Personal Area Network (WPAN), Wireless Local Area Network (WLAN), and Wireless Wide Area Network (WWAN). In this section, we

will explain the wired and wireless communication technologies used in the smart grid. The communication technologies used in smart grid communication are shown in Figure 2.2. At the end we will discuss in a high level the Vehicular Ad-hoc Network (VANET) technology as a fundamental component in V2G integration.

### 2.2.1 Wired Communication Technologies

Service suppliers in smart grids prefer wired communication technologies to exchange data using wired networks as the name implies [162] [18]. The wired communication has many advantages, mainly connection reliability and security. Fiber optic and digital subscriber line (DSL) are two examples of the wired communication used in the smart grid. However, the PLC technology is the most wired communication that is widely used in the smart grid [105]. DSL and fiber optic can support data transmission up to 10 Gbps and 150 Gbps, respectively.

#### Power Line Communication

Electromagnetic environments (e.g. transformers) cause interference and disruptive effects to the PLC, resulting in abrupt propagation behaviour [99]. To overcome that technical challenge, the PLC can operate in two different bandwidths, namely BroadBand PLC (BB-PLC) and NarrowBand PLC (NB-PLC) [142]. The BB-PLC has a maximum data rate of 200 Mbps (on very short distance); it operates at frequency between 2 MHz and 30 MHz, covering a range up to 1.5 km. On the other hand, the NB-PLC is used for low data rate applications, such as smart metering, and it operates at 500 MHz frequency. It can reach a coverage area up to 150 km with two voltage line modes: low voltage line and high voltage line [62]. In addition to the disruptive effects, the PLC suffers from low data rate transmission for long distances as the signals experience more channel interference and higher losses [35]. Another drawback is bandwidth limitations that makes PLC technique inadequate for high bandwidth applications [147]. On the other hand, the PLC technology has low operation and maintenance cost [18].

#### Fiber Optic Communication

Another wired communication system used in smart grid is fiber optic. It provides higher data rate comparing to the PLC. In addition, fiber optic technology can cover several kilometers area with a data rate in range of gigabits [72]. There are various types of fiber

optic standards such as AON (IEEE 802.3ah), BPON (ITU-T G.983), and EPON (IEEE 802.3ah) [176]. The Active Optical Network (AON) can transmit data up to 100 Mbps on both up and down streams with a maximum distance of 100 km. Furthermore, the two standards of the Passive Optical Networks (PON) have different data rate and distance range. For instance, the Broadband PON (BPON) can achieve a data rate of 622 Mbps and covering an area range up to 60 km, whereas the Ethernet PON (EPON) can reach a maximum data rate of 1 Gbps with a distance of 20 km [29].

Fiber optic brings many advantages to the smart grid applications and services. For example, it can deliver data in diverse transmission rates from different distances ranges while preserving the signals strength and robustness. However, the fiber optic suffers from high implementation cost [71].

## Digital Subscriber Line

DSL is a digital data transmission technology that uses telephone lines to exchange information over the smart grid. Hence, it can be cheaper to implement [50]. However, it suffers from low data rate and signal interference [18]. Table. 2.4 summarizes some of the common used standards in the smart grid.

Table 2.4: Comparison of different DSL standards used in smart grids

| Name                       | Standard    | Data rate in (Mbps)                       | Distance in (km) |
|----------------------------|-------------|-------------------------------------------|------------------|
| Asymmetric DSL (ADSL)      | ITU G.992.1 | 8 downstream / 1.3 upstream               | up to 5          |
| ADSL2                      | ITU G.992.2 | 12 downstream / 3.5 upstream              | up to 7          |
| ADSL2+                     | ITU G.992.5 | 24 downstream / 3.3 upstream              | up to 7          |
| Very high speed DSL (VDSL) | ITU G.993.1 | [52 - 85] downstream / [16 - 85] upstream | up to 1.2        |
| VDSL2                      | ITU G.993.2 | 200 downstream/upstream                   | [0.3 - 1.5]      |

## 2.2.2 Wireless Communication Technologies

Wireless communication technologies can be categorized based on their transmission ranges as mentioned previously. In the following, we will explain the most important wireless communication technologies which are suitable to smart microgrids, ordered by the coverage range from the smallest to the largest.

### Wireless Personal Area Network

The WPAN is based on IEEE 802.15 family and it includes several standards such as ZigBee (IEEE 802.15.4) and Bluetooth (IEEE 802.15.1). The ZigBee technology is used for low data rate transmission in smart grids, specifically 256 kbps [175]. It is considered as a power efficient technology with a low range communication coverage [61]. The ZigBee technology can cover an area up to 100 m and it operates at frequency band of 2.4 GHz, except for Europe and the USA, where ZigBee operates at 864 MHz and 915 MHz, respectively [173]. The drawbacks of the ZigBee technology, such as slow processing, limited memory storage, and short battery life, makes it more suitable for home automation systems [12]; its various applications include smart meter reading, load control, and security systems [72].

Bluetooth is also a power efficient communication technology for short range coverage. It can support a data rate up to 721 kbps within a 100 m range. Similar to the 802.15.4 technology, the IEEE 802.15.1 standard (Bluetooth) operates in the 2.4 GHz frequency band, which makes it more susceptible to interference from other communication technologies that operate at the same frequency band, such as WiFi [127]. One of the Bluetooth application areas in a smart grid is online monitoring of local substations [138].

Another technology used in the WPAN is Z-wave communication which was developed by Z-wave Alliance. Since it operates on a lower frequency band (900 MHz), the Z-wave technology can penetrate obstacles while preserving its signal strength [173]. Although it has a low data rate transmission (100 kbps), the Z-wave is the leading technology in home automation applications, compared to Bluetooth and ZigBee technologies. The reason is the low cost and the simple implementation of the Z-wave technology [109].

### Wireless Local Area Network

WLAN is based on the IEEE 802.11 family that enables mobile devices to connect wirelessly. The market name of the 802.11 standard is known as WiFi. Although the 802.11 standard can operate on a wide range of frequencies, the 2.4 GHz and the 5.0 GHz frequency

bands are the most popular operating frequencies that are used in the smart grid [126]. There are different versions of the 802.11 standard that vary in terms of two main components: the maximum data rate, the coverage area, and the bandwidth [51]. In the following, we discuss some of the commonly used standards under the IEEE 802.11 family [115] [90] [5]. Some of these standards are used in smart grids communication according to [18], [82], [87], [94], and [135].

- 802.11a: this standard was released in 1999 and it operates at a frequency of 5 GHz with a maximum data rate transmission of 54 Mbps. It uses the orthogonal frequency division multiplexing (OFDM) as a modulation scheme, and it can operate indoors and outdoors with range up to 35 m and 120 m, respectively. The main disadvantage of this standard is the small coverage area which makes it more suitable for indoor areas. However, the presence of indoor obstacles may cause difficulties in the data transmission.

- 802.11b: similar to the 802.11a standard, the 802.11b was ratified in 1999. It operates at frequency of 2.4 GHz with maximum data rate of 11 Mbps. It can cover outdoor areas up to 140 m and indoor range of 38 m. The 802.11b standard uses a modulation technique known as Direct Sequence Spread Spectrum (DSSS). As many of the IEEE 802.11 standards operate at 2.4GHz frequency, the 802.11b standard is more likely to experience high interference. However, the low operating frequency compared to the 802.11a makes it signal more immutable to the obstacles.

- 802.11g: this standard was released in 2003. Similar to the 802.11b standard, it operates at a frequency of 2.4 GHz. However, the data transmission rate is greater than the 802.11b as it can reach a data rate up to 54 Mbps. It can use two modulation schemes, either the OFDM modulation or the DSSS modulation, and it can cover a similar range as in the 802.11b (i.e. 38 and 140 for indoor and outdoor respectively). This standard outperforms the 802.11a and 802.11b since it combines the advantages of the maximum data rate and the obstacle penetration.

- 802.11n: this standard was released in 2009 and it operates at two different frequency bands, 2.4 GHz and 5 GHz. It has a higher maximum data rate of 600 Mbps, when compared to the 802.11a/b/g standards. It uses the OFDM modulation scheme, and Multi-Input, Multi-Output (MIMO) antenna. It reaches a wide range up to 70 m and 250 m for indoor and outdoor areas, respectively. This standard has the highest coverage range among the others mentioned standard.

- 802.11ac: the 802.11ac only uses one frequency band of 5 GHz, and it was released in 2013. It can achieve a data rate up to 6900 Mbps, but it can operate indoor only with a range up to 35 m. It uses OFDM modulation with multi-user MIMO (MU-MIMO) technique in the down-link [40].

- 802.11ax: this standard was released in September 2019 and it operates on the both frequency bands, 2.4 GHz and 5.0 GHz. It can reach a transmission data rate up to 10000 Mbps, which makes it the highest achievable data rate when compared to the 802.11a/b/g/n/ac standards. Contrary to the 802.11ac, the 802.11ax standard can cover indoor and outdoor areas with ranges up to 35 m and 120 m, respectively. It uses the orthogonal frequency division multiple access (OFDMA) modulation with multi-user MIMO (MU-MIMO) technique in both up-link and down-link [41]. This standard is a promising solution for IoT and smart grid applications [172].

The WiFi protocol standards (802.11a/b/g/n/ac/ax) are used to enable a two-way communication for the smart grid applications and services. However, since wireless communication suffers from lack of security, many changes and improvements were adopted in the smart grid. For instance, the IEEE 802.11i standard was ratified in 2004 to provide security improvements [3]. In addition, IEEE 802.11w and IEEE 802.11e provided protected frame management [6], and enhanced QoS (e.g, traffic prioritization, scheduling and admission control [4]) for wireless LAN applications, respectively. The 802.11 standards discussed previously are summarized in Table 2.5.

Table 2.5: Comparison of different versions of IEEE 802.11 standard used in smart grids communication [18] [82] [87] [94] [135]

| IEEE standard | Frequency in (GHz) | Data Rate in (Mbps) | Outdoor Transmission range (m) |
|---------------|--------------------|---------------------|--------------------------------|
| 802.11a       | 5.0                | 54                  | 120                            |
| 802.11b       | 2.4                | 11                  | 140                            |
| 802.11g       | 2.4                | 54                  | 140                            |
| 802.11n       | 2.4/5.0            | 600                 | 250                            |
| 802.11ac      | 5.0                | 6900                | NA                             |

## Wireless Wide Area Network

WWAN includes various technologies to provide wireless communication to smart micro-grids. It covers the largest geographical area among our list. In the following, we will discuss four examples of WWAN technologies, namely WiMAX (IEEE 802.16), cellular communication, satellite communication, and microwave communication.

- WiMAX: IEEE 802.16 standard was first released in 2001 under a commercial name known as Worldwide Interoperability for Microwave Access (WiMAX). The 802.16 standard is considered a good solution for wireless networks as it offers low cost implementation, a high data rate, and long distance coverage [160]. Typically, the 802.16 standard can cover an area range up to 10 km with a maximum data rate of 128 Mbps and 28 Mbps for down-link and up-link, respectively [46]. The smart grid distribution domain is one of the application areas that suits the WiMAX technology when compared to the GSM solution [133].

To improve the 802.16 standard, different versions were released over the past decade. For instance, the 802.16j standard brings many features such as supporting OFDMA modulation along with other types of coding and modulation schemes, better handover techniques, and multi-cast and broad-cast services [7]. Moreover, 802.16j defines different types to multi-hop relaying techniques [8]. Another version of the WiMAX is 802.16m, which can support high mobility speed (350 km/h) while providing at least a data rate of 100 Mbps and 1 Gbps for lower speeds (i.e. fixed users) [10]. It can provide a coverage area of [30 - 100] km with reduced performance. An acceptable performance can be reached with a distance between 5 km and 30 km, whereas the optimum performance can be archived within 5 km range.

- Cellular communication: includes a wide range of network technologies such as 2G, 2.5G, 2.75G, 3G, 4G (LTE and LTE-A), and 5G; however, smart grids use 3G and beyond for wireless communication. The Universal Mobile Telecommunications System (UMTS), which is the most commonly known standard of 3G, provides a maximum data rate of 168 Mbps and 22 Mbps, offered by the Evolved High-Speed Packet Access standard (HSPA+), in the down-link and the up-link, respectively [88]. The 3rd Generation Partnership Project (3GPP) developed another cellular technology known as Long Term Evolution Advanced (LTE-A) standard which is an enhanced version of the LTE. The implementation of cellular technologies in a smart grid is expensive and may suffer from network congestion (due to the spectrum sharing [128]); however, the LTE-A brings various advantages to cellular technology such as flexible bandwidth, better handover between the cells, and more support for heterogeneous Network (HetNets) [177].

Heterogeneous Networks are composed of multiple tiers of wireless network cells. The



main advantage of HetNets is to support wireless networks with coverage in different environments (e.g., offices, tunnels, and city centers). Macro-cells, pico-cells, and femto-cells are some examples of HetNets. From an architectural point of view, HetNets are built on top of the functionalities offered by conventional macro Radio Access Network (RAN), RAN transport capability, small cells, and WiFi.

The role of (HetNets) in microgrid control and management has been considered in the last few years by several researchers. In [102], 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 [134], the authors tackle the automation problem in microgrids; they 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.

The authors in [122], proposed a framework to process smart microgrid data in HetNet using unsupervised machine learning algorithm. A multi-class queuing system in the pico-cell tier was introduced to prioritize the data based on time-sensitivity. A real-time dataset was collected from 443 microgrids for one day. The authors used the k-means algorithm to cluster the data into three categories: delay-tolerant, delay-medium, and delay-sensitive. The results showed that the proposed approach significantly reduces the delivery delay of messages carrying time sensitive events from the microgrid. In addition, the results demonstrated that the framework is able to process the time sensitive events faster and more accurately in comparison to a single-tier network infrastructure where the messages are served on First In, First Out (FIFO) basis.

The authors extended their work to include different HetNet tiers such as pico-cell, micro-cell, and macro-cell [121]. The work tested the proposed technique under different number of users with two communication scenarios. TCP and UDP protocols were employed with different time sensitive data to improve the delay while keeping the packet loss rate at low level. Through simulations, the authors showed that the proposed technique reduced the queuing delay by 93% for the packets of delay-sensitive (urgent) messages and the packet loss rate by 7% when compared to the benchmark where no aggregation mechanism exists prior to the small cell base stations.

The massive number of wireless devices produces large amounts of data that need to be processed and transmitted over the network [182]. That said, communication networks need to provide higher QoS performance in terms of communication delay, reliability, and

security. To this end, 5G cellular networks are introduced to meet the mentioned QoS requirements and as well as other requirements. The features implemented in 5G include massive MIMO, optimal utilization of network resources, and the usage of higher frequency (i.e. millimetre-Wave (mmWave) frequency band), which will increase the maximum data rate, reduce the network delay and provide better throughput performance. For instance, the 5G wireless HetNet challenges in using massive MIMO and mmWave technologies were discussed and analyzed [26]. Furthermore, there are different issues in HetNet that need to be resolved by the network operators, e.g., cells interference, implementation cost, and data flow management between the different cells. Hence, this will help the HetNet technology to grow faster with a reliable and robust services while providing a better performance in terms of delay and throughput as discussed in [178].

- **Satellite:** it can be expensive and difficult to provide rural areas with communication services through traditional systems. Hence, smart grid applications such as the SCADA system uses satellite communication technology to provide services for remote areas and substations [183]. Satellite communication systems offer various communication performance in terms of latency and bandwidth based on the orbit altitude of the satellite [144]. There are three main orbit altitudes: (i) Low Earth Orbits (LEO) (ii) Medium Earth Orbit (MEO) (iii) Geostationary Earth Orbit (GEO) [74]. It can be relatively cheap to implement a smaller satellite stations in a high altitude orbit [184], however, this might degrade the communication performance by increasing the delay.

- **Microwave:** microwave technology is widely used for line of sight communication (i.e., point to point). More than 50% of the base-stations in the world communicate through microwave technology [45]. It can provide a long distance coverage up to 80 km with a maximum data rate of [310 - 360] Mbps. The configuration of the line of sight has to be precise and accurate to avoid transmission loss and/or service interruptions. In addition, microwave technology suffers from channel fading due multipath interference and precipitation [63]. Transfer trips between smart grid units is one application of microwave technology [145].

### 2.2.3 Vehicular Ad Hoc Networks

Another communication technology that facilitates the integration of EVs to smart grids in general and smart microgrids in particular, is Vehicular Ad Hoc Network (VANET). VANET is a mobile network formed by connecting moving vehicles on the road. The Roadside Units (RSU) enable the data exchange between the VANET and communication infrastructure. The VANET technology brings many advantages such as covering wide

area, providing necessary information to assist drivers, and enhancing drivers' safety [65]. The VANET technology offers various methods of communication based on the coverage distance. For instance, Vehicle-to-everything (V2X) can be considered as WWLAN [168], whereas Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communication are considered as WLAN. The various coverage distances can help to spread the information (e.g., traffic congestion) on different levels to improve the driving experience [76]. Moreover, sharing the vehicle's information such as acceleration, direction and vehicle's size among the surrounding vehicles can assist in avoiding car accidents and improve the drivers' safety [68].

In addition, the VANET technology can help reducing the overhead power in smart grids, particularly at the peak-hours [52]. One solution is to use the Electrical Vehicles (EVs) as mobile battery units to supply the grid with power. The VANET technology is used to notify the EVs with the high demanding hours and the location where the EVs can discharge their batteries. The EVs contribute to the power supply process with part of their batteries.

The EVs can also help to mitigate the unavailability of the power grid that can happen as a result of islanding formation. Moreover, the extreme weather events can damage the utility grid and block the electrical power flow to the smart microgrids when they operate at the grid-connected mode. The EVs use the VANET technology to get the information (e.g., location and the required power) about the smart microgrids with power shortage to provide electrical power until the utility grid is recovered [100]. While V2V, V2I and V2X are used to share information among the EVs, the Vehicle-to-Grid (V2G) technology defines the discharging process [143].

In order of the vehicles to be part of the VANET, each vehicle has to be equipped with a transceiver. The transceiver enables the information to be shared among the network by forwarding the data from one vehicle to the others. The vehicles receive the information from the RSUs that serve as nodes between the vehicles and the infrastructure (i.e. V2I) [119]. In addition, the RSUs can store the information sent by one VANET and forward it to the other VANETs when they become in the range of the RSUs. There are different communication technologies such as WiFi and cellular networks that enable the VANET technology.

Two main technologies are used in V2X network communication, namely Dedicated Short Range Communication (DSRC) and cellular networks [60]. Several V2X applications for many vehicles should support both technologies to provide better network infrastructure. Thus, DSRC and cellular network technologies should be able to work together to support efficient V2X communication. To address this issue, the authors in [14] have proposed different methods to integrate DSRC and cellular network solutions interchangeably.

In the next sub-subsections, we will discuss two of the common communication technologies that are integrated with the VANET technology.

### **Dedicated Short Range Communication**

Dedicated Short Range Communication is an approved version of the WiFi standard (IEEE 802.11) to provide Wireless Access in Vehicular Environments (WAVE). The DSRC (IEEE 802.11p) was released in 2010 [9]; and it offers data exchange between high-speed vehicles (V2V). It also allows the vehicles to communicate to the infrastructure through the RSDs (V2I). The DSRC operates in the frequency band of 5.9 GHz in Japan and Europe, and 5.8 GHz in the US [81]. It provides a distance coverage up to 1 km using data transmission rate between 3 Mbps to 27 Mbps; and it uses the OFDM as a modulation scheme [15]. In addition, it can support data transmission with moving vehicle speed up to 260 km/h [101]. The DSRC brings many advantages to the V2X technology such as low latency, high data transmission with moving vehicles, data security, and fast handovers; while preserving its robustness under various weather conditions. Therefore, the DSRC is a desirable communication technology in VANET, since it can meet latency requirement for safety applications in VANET [101].

### **Cellular Networks (LTE-based)**

Cellular networks are another method to enable V2X communication, specially with the advancement of the HeTNet in LTE. The V2V communication, as a part of the V2X, can be employed by using the LTE-based cellular network to serve as an interface between the vehicle (i.e., User Equipment (UE)) and the eNodeB (using the up-link) or vice versa (using the down-link). The LTE-based can also provide a direct radio interface between the vehicles and each others using LTE device-to-device or sidelink. This powerful and rich capability of LTE network offers support for a wide range of V2X applications with different distinctive requirements on data rates, communication delay, reliability, wide coverage distance.

A performance comparison in terms of V2V communication between different LTE communication options (uni-cast, multi-cast and side-link) and the DSRC technology was proposed in [161]. The authors observed the following: i) the LTE multi-cast is more efficient than the LTE uni-cast, ii) LTE sidelink provided better reliability than LTE multi-cast for small coverage ranges in high system load whereas multi-cast outperformed the sidelink in large converge ranges, iii) LTE sidelink and multi-cast offered higher reliability performance when compared to the DSRC. A similar conclusion was reported by the authors

in [24], where the LTE sidelink communication option outperformed the DSRC for V2V communication.

The DSRC and LTE standards provide different performance in terms of scalability, latency and reliability. According to [113], LTE networks are more reliable and scale better when compared to the DSRC standard. In addition, LTE networks offer better QoS in terms of latency as it meets the latency requirements of various VANET applications. Hence, LTE networks are suitable for a very wide range of applications that are sensitive to latency and require higher communication reliability. However, increasing the traffic load and/or the number of vehicles has a negative impact on the latency as the authors reported in [113]. On the other hand, the DSRC standard has lower beacon latencies and higher throughput in scenarios where there are few number of vehicles. Furthermore, it offers an acceptable performance for scarce network topologies. However, the performance is extremely sensitive to larger vehicle densities, traffic load, and vehicle velocity.

## 2.3 Data Scheduling and Traffic Management in Smart Microgrid Network

Different previous studies have focused on the traffic management as a solution for congestion control and to improve the QoS. There are different QoS objectives defined and studied in literature such as delay, jitter, packet loss rate (PLR), and throughput. In the following, we will discuss some of the works that focused on studying the optimal methods to resolve the data traffic congestion issue, and the different data schedulers to improve the QoS in various types of networks.

The authors in [146] proposed a traffic scheduling mechanism based on interference avoidance for meter data collection in Building Area Network (BAN) to solve the communication interference due to the large number of meter data collection devices. In order to overcome communication interference, schemes for single-channel time unit assignment and for wireless multi-channel selection are presented. Besides the communication interference, the schemes handled network congestion due to intense data traffic by introducing a traffic scheduling algorithm called TSA-IA. The authors concluded that their approach can effectively avoid interference between meter data collection devices, achieving efficient traffic scheduling and accomplishing efficient data transmission.

Furthermore, cognitive radio (CR) networks have been used to improve smart grid heterogeneous networks [75]. A new traffic scheduling scheme based on data priority was proposed to support different traffic types in the network. The authors utilized the CR

concept as a promising solution for the high QoS requirements in heterogeneous networks. The results have demonstrated a significant improvement in the resources utilization and low packet loss rate of the high priority data. Another similar work considered the Dynamic Spectrum Management (DSM) technique to allocate network resources to the smart grid applications based on their data priority [59]. The authors studied the demand response management application as a typical high priority application since it uses real-time data. DSM uses opportunistically the vacant Digital TV (DTV) frequency bands to support heterogeneous networks and satisfy the QoS requirements of smart grid applications. Further, the results showed that the DSM technique provides a reliable network for critical time-sensitive applications.

Moreover, some studies have focused on the smart grid communication architecture to meet the smart grid communication requirements in terms of low latency and high reliability and sustainability. In [78], the authors presented a novel approach for monitoring and controlling the power distribution over heterogeneous networks. The work mainly introduced inner and outer control loops for communication network control and energy distribution control. Also, the Internet of Things (IoT) technology was introduced in [130] as a communication infrastructure to transmit the sensing massive information. The collected data was employed to build up the Internet of Energy to monitor, control and estimate the microgrid states in real-time. The authors proposed H-infinity-based Minimax filter as a different algorithm for state estimations and monitoring the microgrid conditions.

The authors in [27] investigated the NarrowBand Internet of Things (NB-IoT) down-link scheduling structure as a potential solution for Lower Power Wide Area Networks (LP-WAN). The study discussed the essential requirements for a NB-IoT down-link scheduling design. The proposed design showed high performance results in terms of network's resources utilization, specifically 100%. However, the authors considered their design as a best fit for only delay tolerant applications.

An earlier work, proposed by Rasool et al. [131], formulated an optimization model to find the optimal scheduling algorithm that provides the maximum throughput guarantees to the users in a wireless network. The authors considered the results in [30] to built their model, assuming that the user's Carrier-to-Noise Ratio (CNR) distribution are known. To further improve the obtained results from the model, the authors developed two Time Domain (TD) versions of the optimal algorithm. The TD technique allows the scheduling algorithm to allocate all the resources in the Transmission Time Interval (TTI) to one User Equipment (UE). The authors simulated their model under HetNet scenarios in two different throughput guarantees cases: (1) all users have the same throughput guarantees, and (2) users have different throughput guarantees. The results showed that the proposed

algorithms have archived better performance in terms of the Throughput Guarantee Violation Probability (TGVP) when compared to the common used scheduling algorithms. In a later work [37], the authors improved their work by proposing a new Frequency Domain (FD) algorithm that provides a long-term throughput guarantees to users under UDP and TCP traffic sources. The performance results showed an improvement in terms of the cell capacity, the time window of the guaranteed throughput and the packet time delay. The authors implemented their work and compared the proposed FD algorithm to different scheduling algorithms that were developed earlier in ns-3 [180] [181].

The authors in [83] studied the delay and throughput performance using opportunistic scheduling algorithms in wireless networks. The work focused on suitable scheduling algorithms for real-time services as well as non real time services. The quality-of-service (QoS) requirement, in terms of delay, for real-time services and non real-time services are different, delay sensitive (i.e. short-time) and delay tolerant, respectively. Three different algorithms were considered in the work: MAX, Proportional Fair (PR) and Relatively Best (RB). The authors concluded that the small-time delay required for the real-time applications has affected the throughput of non real-time applications, resulting in overall throughput degradation.

Xin Liu et al. focused on opportunistic scheduling algorithms as solution to enhance the efficiency of the spectrum [107]. The work presented an opportunistic scheduling framework to increase the wireless network performance, regarding the overall throughput and the network resources, fulfilling different QoS requirements. The authors tested their framework under different number of users, different SNIR values, and different scheduling algorithms. The work also considered two different fairness guarantees cases. The first fairness case is temporal fairness where users are provided with same portion of the network resources, whereas in the second case (i.e., utilitarian fairness) the users are guaranteed the same throughput performance. The results showed that opportunistic scheduling algorithms outperformed non-opportunistic (i.e., round robin) algorithm.

In another work, the throughput and the round trip delay of different packet sizes were analyzed in [148]. The authors studied different scheduling algorithms with focusing on Max Weight (MW) schedulers under UDP and TCP traffics. A TCP-aware scheduling algorithm, known as queue max weight (Q-MW), was designed to give high priority to TCP flows that has very small queue at the eNodeB. The authors compared their proposed algorithm to different variations of MW schedulers, e.g. Max Rate (MR) and Max Queue (MQ), in LTE network implemented in ns-3. Different number of UEs were considered: 5, 10, and 20 in a cell radius of [0.5-5] km under two packet sizes, particularly 512 and 1024 bytes. The simulation results showed that Q-MW algorithm performs better than the classic PF and MW algorithms in terms of throughput and delay.



A survey presented by A.Asadi and V.Mancuso reviewed the different works that focused on enhancing the QoS using opportunistic scheduling techniques [19]. The authors categorized the proposed schedulers in literature into two groups: (i) single QoS objective (i.e., one QoS metric is considered in the scheduler algorithm) and (ii) Multiple QoS objectives (i.e., more than one QoS metric is considered in the scheduler algorithm). The proposed scheduler algorithm in [92] is an example of single QoS metric to avoid the performance anomaly due to the traffic integration. Communication delay improvement was the scope for other works in literature [79]. For instance, the authors in [139] introduced a delay optimally algorithm using log rule-based scheduler. The throughput performance was also considered among the single QoS objective schedulers. In [117], the authors proposed an optimal throughput scheduler while guaranteeing the delay in unknown channel condition, using Lyapunov drift and optimization techniques. On the other hand, the works that studied multiple QoS objectives included [38] and [23]. The authors in [38] solved a real-time problem by proposing a scheduler for OFDMA systems with multimedia support. The problem was formulated and solved as an optimization model with two objectives, namely average transmission rate and the Average Absolute Deviation of Transmission Rate (AADTR). In the study in [23], the authors considered three QoS metrics for the scheduler as following: throughput, delay and packet loss rate. The proposed scheduler operates based on the position of the flow in the QoS unity cube or based on the QoS residual time.



## Chapter 3

# Prediction of Time-Sensitive Events in Smart Microgrid

### 3.1 Introduction

A smart grid is an electric power system comprised of sensors, communication technologies, and control units to improve customer experience with cost-efficient power services [56]. A smart microgrid is defined as a small scale of the smart grid [70]. Cost efficiency relies on the reliability and sustainability of power systems, which are the two major concerns in smart microgrids that call for proactive emergency preparedness and self-recovery solutions [129]. With the increasing the penetration of Distributed Generators (DGs), these concerns have become more essential to investigate since DGs aim at generation through renewable/stored energy resources, particularly for Community Resilience Microgrids [164]. Therefore, one cannot expect the exact power generated out of the DGs, which has a direct impact on system reliability and sustainability. In addition, with their negative environmental impact, natural gas, oil and coal usage in electricity generation can be costly due to the limited nature of non-renewable resources. Hence, utilization of renewable energy resources to generate electricity and forming microgrids to stay disconnected from the utility grid is a promising idea [54]. Due to these reasons, novel solutions to ensure resiliency, reliability and sustainability of smart microgrids are emergent.

Smart microgrids operational modes are classified into two categories: islanded mode and grid-connected mode. Islanding occurs when DGs continue to supply power to the loads even after a portion of the power network is disconnected from the utility grid. Under these conditions, the utility grid is unable to supply or control the newly formed

DG island. On one hand, according to the IEEE 1547 standard, the grid must detect islanding within 2 seconds [11]. That is, islanding, from the grid perspective, is a critical issue that must be detected as soon as possible so that remedial actions can be quickly called to resolve potential system issues. On the other hand, in the presence of renewable and/or sustainable resources, generating power from environmental friendly and low-cost energy resources, instead of importing electricity from the utility grid, could be more preferable for the majority of the consumers [124]. To this end, consumers would aim at taking the highest possible benefit from the microgrid by utilizing DGs to sustain demands [22]. However, it is worth mentioning that the motivation to produce renewable energy does not conflict with the conventional operation of the power grid, which aims to detect and avoid any islanding formation. As a matter of fact, the main concern is the sudden and unexpected transition from the islanded mode to the grid-connected mode [156]. However, this requires an accurate prediction of upcoming grid-connected modes for the sake of preparedness and sustainability in microgrids.

Indeed, smart microgrids generate, distribute, and regulate locally the flow of electricity to consumers, and they have significantly increased the penetration of distributed generators (DGs). However, DGs introduce substantial uncertainty to the microgrid operation if they rely on renewable energy sources, such as cells, wind turbines, bioenergy, and energy storage. Therefore, the availability of the generated power remains variable and uncertain, which makes it difficult to accurately predict its behaviour, resulting in a vital request to intelligent grid-connected detection.

The objective of our feasibility study primarily lies in assisting community microgrids to prolong the duration of sustaining with their reliable energy resources, instead of importing power from the grid. To this end, we employ machine learning techniques over microgrid scenarios, which can predict grid-connected transitions of a smart microgrid under different time window requirements. We simulate a smart microgrid operation, introducing a radial distribution system with two DGs, one diesel generator, and one photovoltaic (PV) panels. The machine learning models used in this study include a decision tree model with different leaf sizes, a linear regression model, Gaussian Process Regression (GPR), and Support Vector Machines (SVMs). The results show that the decision tree model has the best average performance regarding the prediction accuracy, speed, and time, which makes it a good candidate for further studies.

## 3.2 System Overview

The system under study consists of two layers, namely the power generation layer and the data analytics layer, as shown in Figure 3.1. The former denotes a smart microgrid that is aimed to be sustained by renewable resources, whereas the latter consists of a data analytics framework running machine learning models to predict upcoming grid-connected events. Moreover, output data of the power layer (power generation and consumption data) are used with weather information as input features to the regression module. The idea behind using weather data is to mitigate uncertainties of renewable energy sources that are used in the power generation module, by providing additional information about the expected power generation level and increasing the prediction accuracy of the grid-connected transition time. The weather data is mainly used to obtain the irradiance data for the PV panel. Irradiance is an instantaneous measurement of solar power over some area. The unit of irradiance is watts per square meter ( $W/m^2$ ). The product of the efficiency, the area covered by the PV panel and the irradiance give the power generated by the PV panel [149]. Although in this chapter we modeled one single smart microgrid user, it is possible to apply the same settings on multiple users as we will explain in the next chapter.

### 3.2.1 Power Layer

A radial distributed system containing two DGs is studied in this chapter for the sake of discussion. The first DG is a diesel generator which is the base power of the microgrid, with the capacity of 10 kW to compensate uncertain power output of the PV panel when needed. The second DG is a PV panel with an area of  $236 m^2$  and an efficiency of 16%, based on the average efficiency of the current 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 [36] Eq.(3.1):

$$E_{out} = A_e E_e G \quad (3.1)$$

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 panel; and  $G$  the total solar irradiation in  $kW/m^2$ .

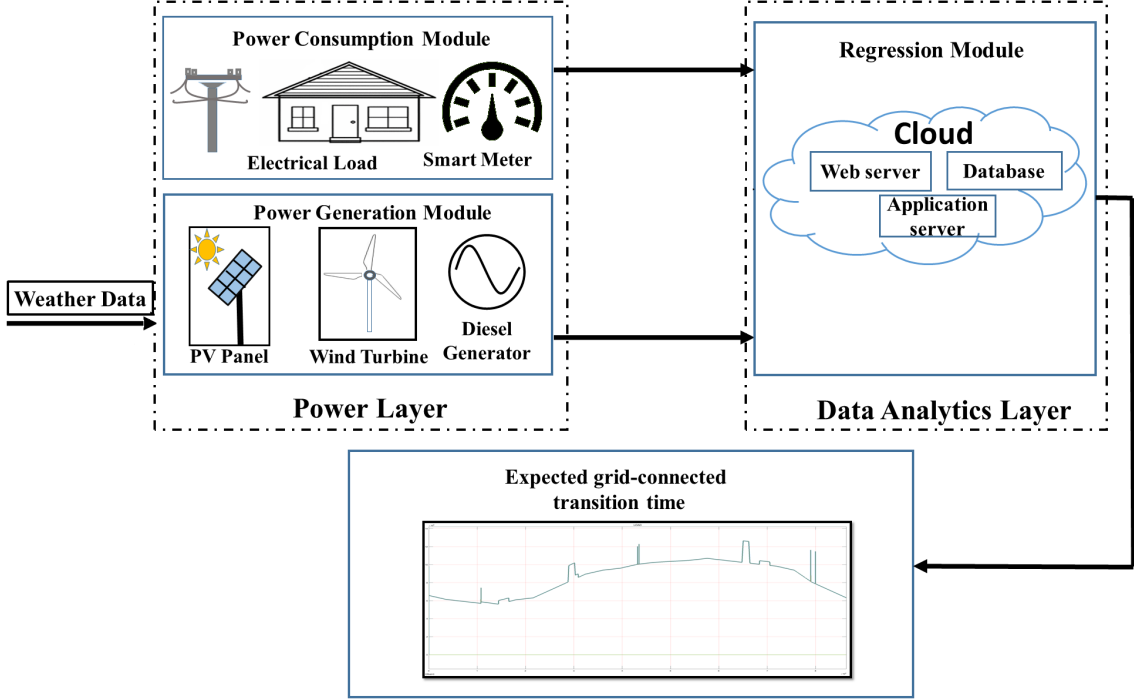


Figure 3.1: An overview of our proposed framework for predicting grid-connected transition in a smart microgrid

Moreover, Figure 3.2 illustrates the studied system which has a circuit breaker to switch the microgrid to the grid-connected mode when the generated power from the diesel generator and the PV panel is no longer sufficient to sustain the microgrid, and transition to the grid-connected mode is inevitable. Table. 3.1 presents system parameters that are used as the basis for our comparative study.

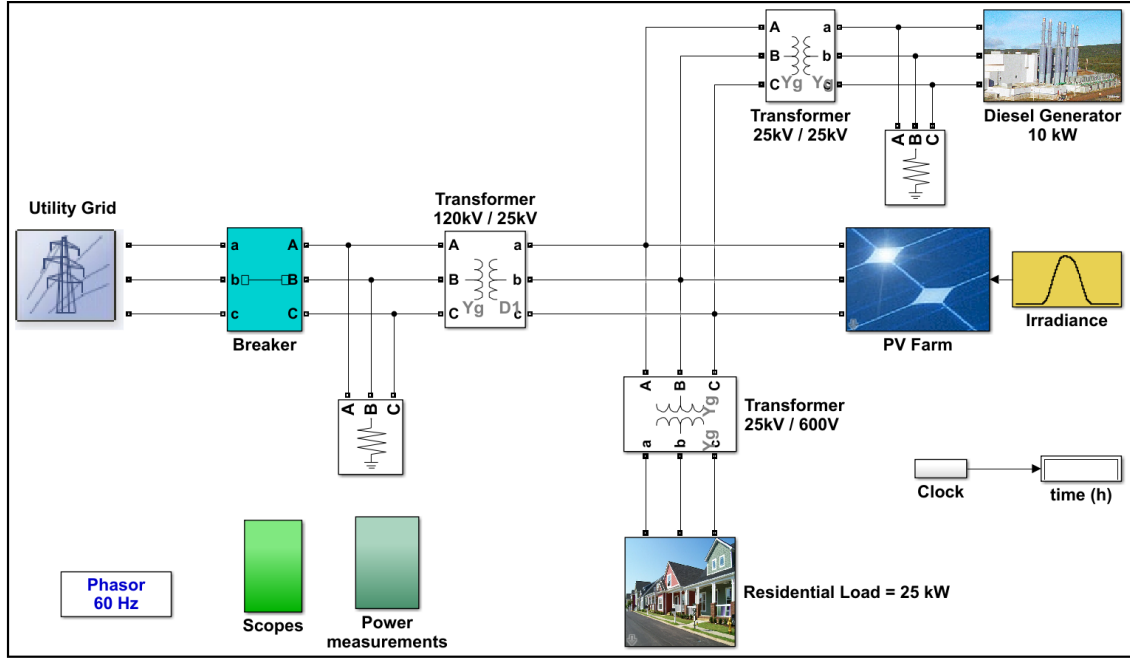


Figure 3.2: The microgrid under study. Two distributed DGs make up the tested microgrid network. The first DG is a diesel generator whereas the second DG is a PV panel. Circuit breaker enables switching on/off the grid-connected mode. Table. 3.1 summarizes the system specifications of the smart microgrid under study.

Table 3.1: Smart microgrid operational parameters

| PARAMETER           | DESCRIPTION                 |
|---------------------|-----------------------------|
| Utility grid        | 120 kV, 1000 MVA source     |
| Diesel generator    | 10kW dc                     |
| Transformer         | 120/25 kV                   |
| Transformer         | 25/25 kV                    |
| Transformer         | 25/0.6 kV                   |
| Residential Load    | 25 kW and power factor=0.95 |
| PV panel area       | 236 $m^2$                   |
| PV panel efficiency | 16%                         |

### 3.2.2 Data analytics layer

The data analytics layer aims to predict the transition from the islanded mode to the grid-connected mode using several machine learning models, and observing the performance in terms of the prediction accuracy, prediction speed, and training time. In our setup, this layer employs the Regression Learner application to predict the microgrid transition to the grid-connected mode for different sample frequencies, since cloud providers are expected to provide a variety of machine learning models. For the sake of feasibility study, we employ different machine learning models. Our feasibility study focuses on using the decision tree model with different sizes of leaves, linear regression model Gaussian Process Regression (GPR) and Support Vector Machines (SVMs) with various kernel functions. Linear regression model is also used with different types such as interactions, robust and stepwise.

## 3.3 Performance Evaluation

In this section we discuss the implementation of the machine learning models to predict the next grid-connected transition within different time windows under the presented smart microgrid model.

### 3.3.1 Simulation settings

We employ the Simscape Power Systems toolbox in MATLAB/Simulink software to simulate the microgrid and generate the test and training data [1], whereas the power consumption component is simulated based on residential loads, which is a function of time. The power output of the PV panel, which represents the renewable energy part in the microgrid, is also a function of time since it primarily depends on the light intensity. The irradiance data pattern of the PV panel is calculated by the PVWatts Calculator, created by the National Renewable Energy Laboratory (NREL) [43], in which the irradiance data is based on Ottawa’s local weather data source. In addition, the load pattern is adapted from a real residential user’s (i.e. B. Kantarci) profile for 24 hours in a winter season. The data is collected every 15 seconds for a total duration of 3 minutes, and different window sizes are considered in the simulations. Various comparison results are conducted between groups of the selected machine learning models, as described in the next subsection.

In decision trees model, we test various sizes of leaves, specifically 4, 12, and 36, to explore their impacts on the prediction performance. Decision trees with a leaf size of 4,

12, and 36 are respectively identified as a fine tree, medium tree, and coarse tree in the results. Similarly, different kernel functions are selected for GPR and SVM models. The kernel function represents the input data in a higher dimension, which make it easier to find similarity among data and solve highly complex data. It is worth noting that various kernel functions can present a different performance for the same model [167]. Hence, for the GPR kernel functions, we use exponential, Matérn 5/2, and rational quadratic functions, while our SVM models include linear, quadratic, and fine Gaussian kernel functions.

k-fold cross validation is used in the preparation process for the dataset, and the dataset is split into two distinct groups for training and validation. In k-fold cross-validation, the data set is broken down into k folds, the classifier is then learned using k1 folds, and the prediction error is calculated by testing the classifier in the last fold. In 10-fold cross-validation process, we break the data into 10 sets; 9 of which are used to train the model and the remaining 1 is used for validation. This process is repeated 15 times and the average of each process is recorded. Simulation settings are given in Table. 5.1

Table 3.2: The description of the used parameters in the feasibility study

| Parameter                              | Description                                                         |
|----------------------------------------|---------------------------------------------------------------------|
| Machine learning models                | SVM, GPR, Decision Tree, and linear regression                      |
| Decision Tree leaf sizes               | {4, 12, 36}                                                         |
| GPR kernel functions                   | Exponential, matérn 5/2, and rational quadratic                     |
| SVM kernel functions                   | Linear, quadratic, and fine Gaussian kernel                         |
| Linear regression types                | Interactions, robust and stepwise                                   |
| Grid-connected prediction time         | {15, 30, 45, 60, 75, 90, 105, 120, 135, 150, 165, 300, 600} seconds |
| Season of power consumption data       | Winter season for 24 hours                                          |
| Smart microgrid modeling tool          | MATLAB (Simscape Power Systems toolbox)                             |
| PV irradiance data source and location | PVWatts Calculator, Ottawa                                          |

### 3.3.2 Numerical results

In this section, the grid-connected prediction performance for the window sizes of 15 to 180 seconds are compared for every 15 seconds under different types of machine learning models in terms of prediction accuracy, prediction speed and training time. The prediction accuracy is evaluated using a statistical measure, namely Root Mean Square Error (RMSE) which is defined as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (P_t - A_t)^2} \quad (3.2)$$

where  $P_t$  and  $A_t$  represent the predicted and the actual values, respectively. The prediction accuracy metric used in the performance comparison is defined as the percentage accuracy as follows:

$$Accuracy(\%) = (1 - RMSE) * 100 \quad (3.3)$$

The prediction speed is measured in observation per second and it allows our methodology to be deployed for online (real-time) condition monitoring in smart microgrids [158]. Moreover, the training time criterion is another indication of the suitability of the model in real-time applications. A higher prediction speed combined with a lower training time are good indication that the model is a good fit for real-time applications. Table 3.3 presents the results of prediction accuracy which achieves more than 95% accuracy for window size interval between 15 and 75 seconds. In that interval, it is observed that GPR model under different kernel functions achieves the highest accuracy of 96%. on the other hand, decision tree model with different leaf sizes (i.e. fine, medium and coarse) has lower accuracy than GPR model by 1%. Beyond that interval, the accuracy becomes lower than 95% as the window size increases, but are still higher than 90% for all machine learning model up to a window size of 180 seconds. Thus, to ensure the highest possible accuracy, a window size less than 90 seconds is needed. Two extreme situations, i.e., window sizes of 300 and 600 seconds, are further considered in the simulation. The 300-second window achieves the highest accuracy using GPR model with accuracy of 93% and 92% for exponential and rational quadratic kernel functions, and above 85% for all others. Furthermore, all the machine learning models are able to offer over 80% accuracy for a 600-second (10 minutes) window, Decision tree with leaf size of 36 (i.e. coarse tree) archives the highest prediction accuracy of 85% similar to GPR model under exponential kernel. As the prediction accuracy changes with different window size, it is hard to choose one model to be the best



model under all window sizes. It is worth noting that there is not a significant difference among the used models as the window size changes. The reason behind that is because the difference between two consecutive windows is very small (i.e., 15 seconds). Therefore, the change in accuracy is not remarkable, however, changing the window size every 15 seconds help us to decide on how often we should send the data. Moreover, some of the used kernel functions achieved the same accuracy which means that we have a wide range of kernel functions to choose among them.

Table 3.3: Prediction accuracy of the top six models

| <b>Time<br/>(s)</b> | <b>Fine Tree<br/>accuracy<br/>(%)</b> | <b>Medium<br/>Tree ac-<br/>curacy<br/>(%)</b> | <b>Coarse<br/>Tree ac-<br/>curacy<br/>(%)</b> | <b>Matern<br/>5/2<br/>GPR<br/>(%)</b> | <b>Exponential<br/>GPR ac-<br/>curacy<br/>(%)</b> | <b>Rational<br/>Quadratic<br/>GPR ac-<br/>curacy<br/>(%)</b> |
|---------------------|---------------------------------------|-----------------------------------------------|-----------------------------------------------|---------------------------------------|---------------------------------------------------|--------------------------------------------------------------|
| 15                  | 97                                    | 97                                            | 97                                            | 99                                    | 99                                                | 98                                                           |
| 30                  | 96                                    | 94                                            | 94                                            | 97                                    | 97                                                | 97                                                           |
| 45                  | 95                                    | 94                                            | 93                                            | 98                                    | 98                                                | 98                                                           |
| 60                  | 95                                    | 94                                            | 94                                            | 97                                    | 97                                                | 97                                                           |
| 75                  | 95                                    | 95                                            | 95                                            | 96                                    | 96                                                | 96                                                           |
| 90                  | 93                                    | 94                                            | 94                                            | 94                                    | 94                                                | 94                                                           |
| 105                 | 93                                    | 94                                            | 93                                            | 94                                    | 94                                                | 95                                                           |
| 120                 | 92                                    | 92                                            | 93                                            | 94                                    | 94                                                | 94                                                           |
| 135                 | 92                                    | 92                                            | 92                                            | 94                                    | 94                                                | 95                                                           |
| 150                 | 92                                    | 91                                            | 92                                            | 93                                    | 94                                                | 94                                                           |
| 165                 | 91                                    | 91                                            | 91                                            | 93                                    | 94                                                | 94                                                           |
| 180                 | 91                                    | 91                                            | 91                                            | 91                                    | 93                                                | 94                                                           |
| 300                 | 88                                    | 88                                            | 89                                            | 87                                    | 92                                                | 92                                                           |
| 600                 | 83                                    | 83                                            | 85                                            | 83                                    | 85                                                | 84                                                           |

Table 3.4: Prediction speed of the top six models

| <b>Time<br/>(s)</b> | <b>Fine<br/>Tree pre-<br/>diction<br/>speed<br/>(obs/s)</b> | <b>Medium<br/>Tree pre-<br/>diction<br/>speed<br/>(obs/s)</b> | <b>Coarse<br/>Tree pre-<br/>diction<br/>speed<br/>(obs/s)</b> | <b>Linear<br/>SVM pre-<br/>diction<br/>speed<br/>(obs/s)</b> | <b>Quadratic<br/>SVM pre-<br/>diction<br/>speed<br/>(obs/s)</b> | <b>Fine<br/>Gaus-<br/>sian SVM<br/>predic-<br/>tion speed<br/>(obs/s)</b> |
|---------------------|-------------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|--------------------------------------------------------------|-----------------------------------------------------------------|---------------------------------------------------------------------------|
| 15                  | 880000                                                      | 420000                                                        | 890000                                                        | 190000                                                       | 180000                                                          | 210000                                                                    |
| 30                  | 420000                                                      | 360000                                                        | 410000                                                        | 150000                                                       | 130000                                                          | 190000                                                                    |
| 45                  | 220000                                                      | 250000                                                        | 260000                                                        | 140000                                                       | 120000                                                          | 170000                                                                    |
| 60                  | 180000                                                      | 210000                                                        | 180000                                                        | 140000                                                       | 115000                                                          | 170000                                                                    |
| 75                  | 140000                                                      | 150000                                                        | 160000                                                        | 140000                                                       | 108000                                                          | 110000                                                                    |
| 90                  | 130000                                                      | 150000                                                        | 150000                                                        | 130000                                                       | 10200                                                           | 105000                                                                    |
| 105                 | 110000                                                      | 100000                                                        | 120000                                                        | 120000                                                       | 85000                                                           | 83000                                                                     |
| 120                 | 100000                                                      | 85000                                                         | 101000                                                        | 91000                                                        | 76000                                                           | 74000                                                                     |
| 135                 | 80000                                                       | 81000                                                         | 80000                                                         | 89000                                                        | 69000                                                           | 65000                                                                     |
| 150                 | 76000                                                       | 71000                                                         | 87000                                                         | 80000                                                        | 65000                                                           | 60000                                                                     |
| 165                 | 65000                                                       | 60000                                                         | 76000                                                         | 70000                                                        | 63000                                                           | 55000                                                                     |
| 180                 | 57000                                                       | 55000                                                         | 61000                                                         | 61000                                                        | 62000                                                           | 50000                                                                     |

The second performance criterion is prediction speed. The prediction speed for a window size starting with 15 seconds to 90 seconds is over 100,000 obs/s (observations per second). Beyond 90 seconds, the prediction speed dramatically drops down to reach around 57,000 obs/s at 180 seconds as shown in Table 3.4. It is worth noting that the fine tree and coarse tree models reach significantly higher speed as compared to SVM models with

small the window size while all models operate approximately at the same speed when the window size reaches to about 135 seconds. In addition, coarse tree achieves the highest prediction speed at all window sizes. Table 3.5 shows that slightly better training time is achieved as the window size increases. Additionally, all the compared models experience less than 1 second training time for the entire window. Coarse tree in particular achieves the lowest training time of approximately 0.5 seconds. The last two tables reveal the high performance of decision tree models in terms of prediction speed and training time.

Table 3.5: Training time of the top six models

| <b>Time<br/>(s)</b> | <b>Fine Tree<br/>training<br/>time (s)</b> | <b>Medium<br/>Tree<br/>training<br/>time (s)</b> | <b>Coarse<br/>Tree<br/>training<br/>time (s)</b> | <b>Interactions<br/>LR train-<br/>ing time<br/>(s)</b> | <b>Robust<br/>LR<br/>training<br/>time (s)</b> | <b>Stepwise<br/>LR train-<br/>ing time<br/>(s)</b> |
|---------------------|--------------------------------------------|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------------|------------------------------------------------|----------------------------------------------------|
| 15                  | 0.71                                       | 0.62                                             | 0.52                                             | 0.96721                                                | 0.89                                           | 0.8                                                |
| 30                  | 0.69                                       | 0.61                                             | 0.53                                             | 0.95                                                   | 0.86                                           | 0.77                                               |
| 45                  | 0.65                                       | 0.58                                             | 0.57                                             | 0.93                                                   | 0.83                                           | 0.75                                               |
| 60                  | 0.62                                       | 0.57                                             | 0.51                                             | 0.92                                                   | 0.82                                           | 0.72                                               |
| 75                  | 0.61                                       | 0.55                                             | 0.51                                             | 0.89                                                   | 0.77                                           | 0.69                                               |
| 90                  | 0.58                                       | 0.54                                             | 0.50                                             | 0.87                                                   | 0.75                                           | 0.66                                               |
| 105                 | 0.56                                       | 0.53                                             | 0.47                                             | 0.85                                                   | 0.73                                           | 0.65                                               |
| 120                 | 0.54                                       | 0.5                                              | 0.45                                             | 0.83                                                   | 0.71                                           | 0.64                                               |
| 135                 | 0.50                                       | 0.48                                             | 0.49                                             | 0.8                                                    | 0.69                                           | 0.62                                               |
| 150                 | 0.53                                       | 0.45                                             | 0.5                                              | 0.78                                                   | 0.69                                           | 0.58                                               |
| 165                 | 0.49                                       | 0.42                                             | 0.48                                             | 0.74                                                   | 0.66                                           | 0.58                                               |
| 180                 | 0.46                                       | 0.39                                             | 0.48                                             | 0.71                                                   | 0.65                                           | 0.54                                               |

Furthermore, while fine tree and coarse tree are approximately equivalent in terms of prediction performance, the coarse tree model is considered as a better candidate as it

presents a better performance with higher window sizes. Table 3.6 illustrates the accuracy comparison between linear regression and SVM models.

Table 3.6: Prediction accuracy (excluding decision tree models)

| <b>Time<br/>(s)</b> | <b>Interactions<br/>LR accu-<br/>racy (%)</b> | <b>Robust<br/>LR ac-<br/>curacy<br/>(%)</b> | <b>Stepwise<br/>LR ac-<br/>curacy<br/>(%)</b> | <b>Linear<br/>SVM<br/>accu-<br/>racy<br/>(%)</b> | <b>Quadratic<br/>SVM ac-<br/>curacy<br/>(%)</b> | <b>Fine Gaus-<br/>sian SVM<br/>accuracy<br/>(%)</b> |
|---------------------|-----------------------------------------------|---------------------------------------------|-----------------------------------------------|--------------------------------------------------|-------------------------------------------------|-----------------------------------------------------|
| 15                  | 84                                            | 65                                          | 84                                            | 73                                               | 85                                              | 93                                                  |
| 30                  | 85                                            | 64                                          | 85                                            | 74                                               | 85                                              | 93                                                  |
| 45                  | 85                                            | 63                                          | 85                                            | 73                                               | 83                                              | 92                                                  |
| 60                  | 84                                            | 63                                          | 84                                            | 74                                               | 84                                              | 92                                                  |
| 75                  | 83                                            | 63                                          | 83                                            | 73                                               | 84                                              | 91                                                  |
| 90                  | 83                                            | 63                                          | 83                                            | 71                                               | 83                                              | 91                                                  |
| 105                 | 82                                            | 62                                          | 82                                            | 71                                               | 82                                              | 91                                                  |
| 120                 | 82                                            | 66                                          | 82                                            | 71                                               | 82                                              | 91                                                  |
| 135                 | 85                                            | 65                                          | 83                                            | 74                                               | 85                                              | 91                                                  |
| 150                 | 82                                            | 63                                          | 83                                            | 73                                               | 84                                              | 90                                                  |
| 165                 | 84                                            | 64                                          | 83                                            | 75                                               | 86                                              | 91                                                  |
| 180                 | 85                                            | 63                                          | 82                                            | 73                                               | 85                                              | 91                                                  |
| 300                 | 80                                            | 58                                          | 79                                            | 70                                               | 83                                              | 91                                                  |
| 600                 | 73                                            | 50                                          | 74                                            | 66                                               | 79                                              | 91                                                  |

The accuracy of linear regression models does not exceed 85% under any window size. However, SVM models, especially the fine Gaussian SVM model, demonstrate better ac-

curacy performance compared to the linear regression model. In addition, it is noted that fine Gaussian SVM model achieves 91% accuracy under 600 seconds when compared to coarse tree model that achieves 85% under the same window sizes. Thus, fine Gaussian SVM model is considered the best candidate to predict grid-connected transitions under a window size of 10 minutes.

Table 3.7: Prediction speed (excluding decision tree models)

| <b>Time<br/>(s)</b> | <b>Interactions<br/>LR predic-<br/>tion speed<br/>(obs/s)</b> | <b>Robust<br/>LR pre-<br/>diction<br/>speed<br/>(obs/s)</b> | <b>Stepwise<br/>LR pre-<br/>diction<br/>speed<br/>(obs/s)</b> | <b>Matern<br/>5/2<br/>GPR<br/>pre-<br/>diction<br/>speed<br/>(obs/s)</b> | <b>Exponential<br/>GPR pre-<br/>diction<br/>speed<br/>(obs/s)</b> | <b>Rational<br/>Quadratic<br/>GPR pre-<br/>diction<br/>speed<br/>(obs/s)</b> |
|---------------------|---------------------------------------------------------------|-------------------------------------------------------------|---------------------------------------------------------------|--------------------------------------------------------------------------|-------------------------------------------------------------------|------------------------------------------------------------------------------|
| 15                  | 270000                                                        | 350000                                                      | 390000                                                        | 5500                                                                     | 6300                                                              | 3700                                                                         |
| 30                  | 160000                                                        | 120000                                                      | 160000                                                        | 11000                                                                    | 11000                                                             | 8600                                                                         |
| 45                  | 97000                                                         | 100000                                                      | 99000                                                         | 15000                                                                    | 17000                                                             | 11000                                                                        |
| 60                  | 68000                                                         | 85000                                                       | 81000                                                         | 22000                                                                    | 24000                                                             | 15000                                                                        |
| 75                  | 73000                                                         | 65000                                                       | 71000                                                         | 27000                                                                    | 30000                                                             | 15000                                                                        |
| 90                  | 56000                                                         | 60000                                                       | 53000                                                         | 33000                                                                    | 34000                                                             | 20000                                                                        |
| 105                 | 51000                                                         | 52000                                                       | 49000                                                         | 41000                                                                    | 43000                                                             | 23000                                                                        |
| 120                 | 44000                                                         | 41000                                                       | 46000                                                         | 42000                                                                    | 46000                                                             | 23000                                                                        |
| 135                 | 32000                                                         | 37000                                                       | 36000                                                         | 42000                                                                    | 46000                                                             | 28000                                                                        |
| 150                 | 30000                                                         | 35000                                                       | 33000                                                         | 41000                                                                    | 50000                                                             | 31000                                                                        |
| 165                 | 28000                                                         | 31000                                                       | 31000                                                         | 39000                                                                    | 44000                                                             | 30000                                                                        |
| 180                 | 23000                                                         | 30000                                                       | 24000                                                         | 35000                                                                    | 37000                                                             | 29000                                                                        |

Prediction speeds of the linear regression models and GPR models are compared in Table 3.7. The linear regression models operate at higher prediction speed with a smaller window size, then they slow down and approach to the speed of the GPR models. Specifically, the linear regression model reaches a higher speed when compared to the SVM models under a window size interval of [15-135] seconds, and beyond that SVM slightly outperforms the linear regression. Given these results, the decision tree model is considered to perform better than SVM, linear regression, and GPR models in terms of prediction speed. Hence, the final comparison is conducted between the SVM and GPR models. Table 3.8 shows that SVM models perform worse than the GPR models in terms of training time. On the other hand, the training time of decision tree models is better as they are capable of accomplishing a training time around one second in the worst case.

Table 3.8: Training time (excluding decision tree models)

| <b>Time<br/>(s)</b> | <b>Linear<br/>SVM<br/>training<br/>time (s)</b> | <b>Quadratic<br/>SVM<br/>training<br/>time (s)</b> | <b>Fine<br/>Gaussian<br/>SVM<br/>training<br/>time (s)</b> | <b>Matern<br/>5/2<br/>GPR<br/>training<br/>time (s)</b> | <b>Exponential<br/>GPR<br/>training<br/>time (s)</b> | <b>Rational<br/>Quadratic<br/>GPR<br/>training<br/>time (s)</b> |
|---------------------|-------------------------------------------------|----------------------------------------------------|------------------------------------------------------------|---------------------------------------------------------|------------------------------------------------------|-----------------------------------------------------------------|
| 15                  | 41.7                                            | 204.4                                              | 1.4                                                        | 200.7                                                   | 185.9                                                | 307.5                                                           |
| 30                  | 11.0                                            | 100.5                                              | 1.3                                                        | 72.0                                                    | 111.2                                                | 214.6                                                           |
| 45                  | 10.1                                            | 69.0                                               | 1.4                                                        | 41.1                                                    | 68.5                                                 | 159.6                                                           |
| 60                  | 9.8                                             | 56.3                                               | 1.4                                                        | 22.6                                                    | 38.3                                                 | 84.7                                                            |
| 75                  | 9.4                                             | 42.0                                               | 1.2                                                        | 14.9                                                    | 24.3                                                 | 50.2                                                            |
| 90                  | 5.2                                             | 35.4                                               | 0.93                                                       | 11.0                                                    | 17.4                                                 | 36.3                                                            |
| 105                 | 1.8                                             | 21.8                                               | 0.55                                                       | 6.1                                                     | 8.5                                                  | 20.9                                                            |
| 120                 | 1.5                                             | 23.3                                               | 0.37                                                       | 5.7                                                     | 9.4                                                  | 17.2                                                            |
| 135                 | 1.3                                             | 12.9                                               | 0.33                                                       | 4.0                                                     | 9.4                                                  | 14.5                                                            |
| 150                 | 0.69                                            | 5.0                                                | 0.22                                                       | 3.9                                                     | 5.1                                                  | 10.1                                                            |
| 165                 | 0.67                                            | 3.3                                                | 0.12                                                       | 3.9                                                     | 4.2                                                  | 8.9                                                             |
| 180                 | 0.71                                            | 4.0                                                | 0.75                                                       | 3.0                                                     | 3.9                                                  | 7.6                                                             |

## 3.4 Summary

The diversity in distributed renewable energy generators and load distribution in microgrids requires robust techniques to detect upcoming transitions to the grid-connected mode. We presented a comparative study on four of the most popular machine learning models by considering their distinct options in the prediction of upcoming grid-connected events for the sake of resilience and sustainability. The presented methods have been evaluated on a radial distribution system with one diesel generator and one PV panel for a period of 24 hours. Performance is assessed in terms of prediction accuracy, prediction speed, and training time against different window sizes.

An interesting observation resulted from the analyses lies in the fact that no model stands out against all criteria. Indeed, each model tends to focus on a specified criterion, which in general makes it preferable to be used for a particular situation. For instance, GPR models performed better in terms of accuracy with average of 95% at window sizes between 15 and 300 seconds. In addition, decision tree models has obtained a good accuracy of 93% at window sizes between 15 and 300 seconds. On the other hand, fine Gaussian SVM model archived better accuracy of 91% whereas GPR models achieved around 84%. Thus, GPR models are better accuracy candidates for small window sizes and fine Gaussian SVM model is a favorable option for larger window sizes.

In addition, the prediction speed and training time were evaluated as both parameters are critical in real application. The prediction speed criterion is important for real-time applications in smart microgrids. Results showed that decision tree models, particularly coarse tree model, obtained the highest prediction speed when compared to the GPR and linear regression models. Coarse tree model achieved prediction speed between 890k (obs/s) and 61k (obs/s) for window sizes of 15 and 180 seconds, respectively. In terms of training time, results showed that decision tree models outperformed the other models. Specifically, coarse tree model obtained the best training time when compared to the rest of the models. Coarse tree model has the best average performance regarding the prediction accuracy, speed, and training time, which makes it a good candidate for predicting grid-connected transitions. It is also suitable to be deployed online since it meets the real-time applications requirements in smart microgrids which are: high prediction speed and low training time.

# Chapter 4

## Time-Sensitive Data aggregation for Wireless Heterogeneous Networks in Smart Microgrids

### 4.1 Introduction

Smart grids allow bi-directional exchange of electricity and information among different parties in the grid, i.e. generation, distribution, transmission, and consumption subsystems [55]. Similarly, smart microgrids employ communication technologies to exchange the information between the consumers and the grid to improve the reliability, sustainability and efficiency of electricity services [54]. A microgrid is a relatively small-scale, self-contained, medium/low voltage electric power system that houses various distributed energy resources (DERs) and loads, and can island, if needed [98]. With the increasing penetration of DERs, the smart microgrid owner becomes not only a power consumer but also can act as a energy producer named as *prosumer* [163], where multiple smart microgrids can be controlled together to form a community microgrid [164].

Smart microgrids have various applications, such as Demand Response Management (DRM), the Supervisory Control and Data Acquisition (SCADA) system, Advanced Metering Infrastructure (AMI), and emergency response. Those applications have different Quality of Service (QoS) requirements regarding reliability and latency [97]. SCADA systems, for instance, monitor, gather, and process real-time data from the transmission lines. They require high reliability and low latency for data delivery [152]. Furthermore, there can be some electrical issues, such as transmission line failure, circuit-breaker failure and



large variations in system frequency that need to be reported in the order of  $\mu s$  to  $ms$  for the sake of preparedness and sustainability in microgrids [104]. For the AMI application, Automated Meter Reading (AMR) data can be delayed by minutes before being delivered to the base station [171]. Besides, this can be critical in case of catastrophic weather events when network congestion occurs due to the sudden traffic of the subsystems and applications that try to report and send the data to the central station. Hence, there are high possibilities to lose packets, which can be carrying essential data [59]. Traffic management allows congestion control by specifying the order in which the traffic is sent out at an interface based on priorities assigned to those packets [141]. It entails the creation of queues, packet assignment to those queues based on a classification, and transmission packet scheduling. Well-known queuing algorithms include first in first out (FIFO), priority queuing (PQ), custom queuing (CQ), and weighted fair queuing (WFQ).

In the previous chapter we used Gaussian process regression algorithm to predict the grid-connected transitions. The packets that carry the time of the next grid-connected transition are considered urgent packets. This requires reliable communication links between the smart microgrids and the base stations while ensuring minimum queuing delay. In this chapter, we extend our previous work that exploited a new traffic scheduling approach using a multi-class queuing system based on data priority [122]. Our previous work gives an introduction about using a multi-queuing system that takes advantage of unsupervised machine learning-based data aggregation at the edge of the network. We perform an extensive study of the smart data aggregation approach, and compare it to urgency-unaware scheme which does not pursue pre-assessment-based aggregation of the microgrid messages, a.k.a. traditional LTE. Data is categorized into different priority classes using an unsupervised machine learning algorithm namely, k-means algorithm. Based on the priority class, data is fed to the scheduler of the small-cell base station, after which channels are allocated based on 3rd Generation Partnership Project (3GPP) LTE standard [13] at each Transmission Time Interval (TTI). We compare the results to a baseline solution that works without the priority queuing mechanism, i.e. traditional LTE with no pre-assessment/aggregation.

## 4.2 Proposed Framework

The communication network infrastructure followed in this chapter consists of two tiers, namely the macro-cell and small-cell tiers that form a heterogeneous network for the smart grid as shown in Figure 4.1. Our proposed framework consists of three main subsystems: 1) Data acquisition 4.2.1, 2) Data analytics 4.2.2, and 3) Data aggregation 4.2.3. These

subsystems are co-located with the eNodeB and small-cell base stations and they collectively perform priority queuing of the microgrid packets before they are handled by the base stations. The acquired data from the smart grid applications and systems undergo the data analytics framework that employs machine learning algorithms to cluster the data based on the time-criticality feature. The data processing subsystem is responsible for processing the data rapidly based on their clusters/priorities. It is worth noting that all the subsystems are located and operate at the small-cell tier.

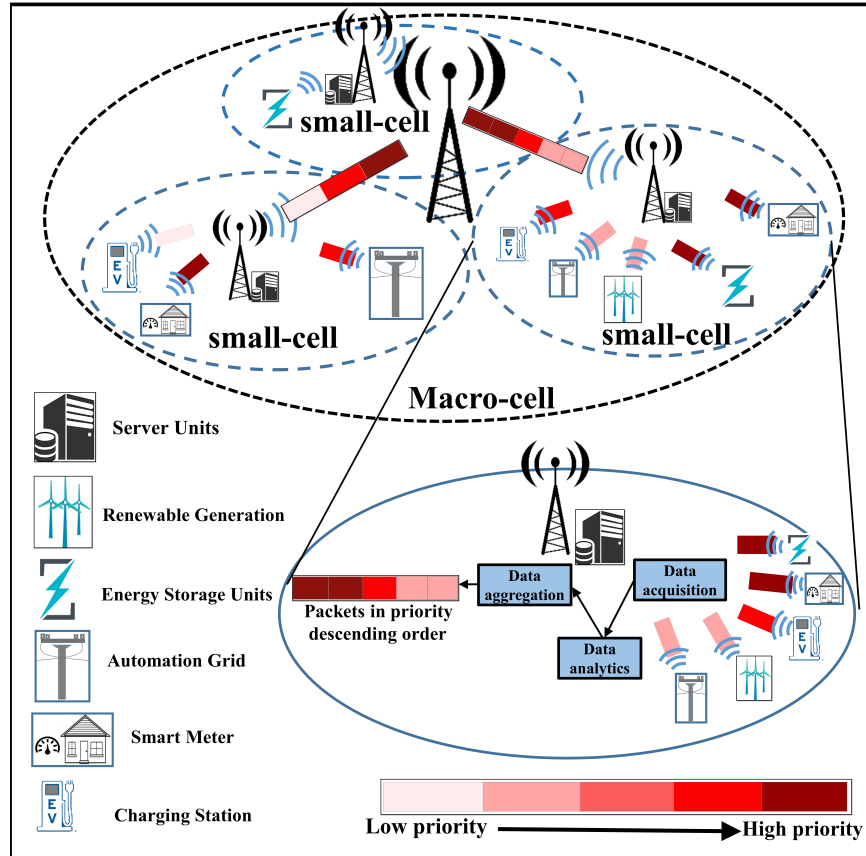


Figure 4.1: Traffic management using priority-based technique. Proposed framework consists of three sub-systems: 1) Data acquisition, 2) Data analytics, and 3) Data aggregation.

### 4.2.1 Data Acquisition

The data acquisition subsystem works as the first recipient of the data sent by the smart grid applications, concerning devices such as smart meters, DGs and/or the SCADA system. The subsystem receives the data with various delay requirements to be passed to the data analytics subsystem for further processing. In other words, the data acquisition subsystem acts as an intermediate component between the data transmitters and data analytics subsystem to help prepare the data for clustering. We can identify the sensitivity of the collected electrical data from the different units in the smart microgrid, by calculating the difference in electrical costs between every two consecutive minutes over 24 hours [122], and the data is collected every minute. The main reason of using the power consumption cost, as an indication of the urgency of the packets, is because the transition from an islanded (i.e., stand-alone) mode to a grid-connected mode can be noticed clearly from the variation of the cost. A high variation of the cost means that the smart microgrid has switched from generating its own power (stand-alone) to importing power from the utility grid (grid-connected). Therefore, the packets with high cost variations message are identified as highly time-sensitive packets. In addition, the k-means algorithm is implemented because the cost variations can vary from one smart home to another, and thus rule-based methods cannot be applied and clustering technique is inevitable.

### 4.2.2 Data analytics at the edge

The data analytics at the edge is the major component in the priority-based microgrid data aggregation. Indeed, analysis of microgrid data and possibly triggering necessary actions are done at the macro-cell base station and/or in the Cloud. However, analytics at the small-cell serves for the pre-assessment of the microgrid data from the standpoint of delay sensitivity. Without data analytics at the edge, each packet would be treated identically at the small-cell scheduler. As the data analytics component at the edge is a pre-assessment module, it is expected to run efficiently; hence it utilizes unsupervised machine learning to cluster the data based on specific features. The unsupervised machine learning module aims to detect the hidden patterns and special features in the data structure. As the algorithm does not aim at detecting anomalies but instead clustering microgrid data under different time sensitivity categories, k-means is sufficient to determine the number of clusters. Initially, k-means assigns all data points  $\delta^{(i)}$ , sent by the data aggregation subsystem, into random clusters (cluster  $j$  denoted by  $\phi_j$ ) and compute the centroids ( $C_j$  is the centroid of  $\phi_j$ ) of those clusters. In each iteration, the algorithm proceeds with computing the Euclidean distance between each data point and the centroids as in

Eq.(4.1). The data points are assigned to the closest centroid. Eq.(4.2) formulates the final step where the centroids are re-computed by taking the average of the points in the cluster.

$$\phi_j = \operatorname{argmin} \|\delta^{(i)} - C_j\|^2, j \in J \quad (4.1)$$

$$C_j = \frac{\sum_{i=1}^m \delta^{(i)}}{m}, \delta^{(i)} \in \phi_j \quad (4.2)$$

The electricity cost is translated into different priority levels based on the cost variation between two consecutive payload packets  $x^{(i)}(t)$  [122]. The variation between the cost values indicates the transition between the microgrid operation modes (i.e the islanding mode and the grid-connected mode). For instance, in the islanding mode, a microgrid has to generate electrical power to sustain its power demand, whereas in the grid-connected mode, the microgrid owners can receive power through the power grid. Moreover, the transition between the operation modes is time-critical information that requires low latency and high reliability communication. Thus, the higher the variation value, the more urgent the packets tend to be. Equations 4.3-4.4 formulate the overall delay at the aggregator in small-cell  $n$ . Eq.(4.3), as the highest delay sensitive category, comprised of three delay terms; the delay of the packets dequeue, the delay of the packets transmission, and an additional summation term to denote the delay due to dropped and re-transmitted packets by TCP. Here, we assume three delay sensitivity levels for microgrid packets; however Equations 4.3-4.4 can be generalized for further granularity for  $J$  levels of delay sensitivity as formulated in Eq.(4.4), where the last delay term in the equation denotes the delay due to the packets of higher priority in the queue. The average delay per delay sensitivity class at the macro-cell level can be calculated by summing the delay of the small-cells under the macro-cell coverage as shown in Eq.(4.5).

$$D_n^{\phi_j} = d_{\text{dequeue}} \cdot Z_1 + \frac{\sum_{s=1}^{Z_1} (L_s/R)}{Z_1} + \frac{\sum_{k=1}^K (P_k/R)}{K}, \forall n \in F, j = 1 \quad (4.3)$$

$$D_n^{\phi_j} = d_{\text{dequeue}} \cdot Z_j + \frac{\sum_{s=1}^{Z_2} (L_s/R)}{Z_2} + D_n^{\phi_{j-1}}, \forall n \in F, j > 1 \quad (4.4)$$

$$D_{\text{avg}}^j = \frac{\sum_{n=1}^N D_n^{\phi_j}}{F}, \forall j \in J \quad (4.5)$$

### 4.2.3 Data aggregation

Upon clustering the data packets into their corresponding priority queues, the packets are sent to the data aggregation subsystem for further management. In the data aggregation subsystem, the packets are sent to fill up a queue based on their priority cluster. Since our proposed scheme groups packets into three different types of time-sensitivity clusters (i.e., highly time-sensitive, moderately time-sensitive, and delay-tolerant), packets are handled by the data aggregation subsystem such that their processing times start according to the level of urgency. Hence, aggregation of microgrid packets, prior to transmission to the small-cell base station scheduler, is vital in the analysis of the microgrid data in a timely manner. Multi-class queuing system emerges when the traffic data in the network require different QoS in terms of the latency and reliability. For instance, real-time data are considered as time-sensitive data, and packets carrying time-sensitive messages should be treated as highest priority class with respect to the QoS requirements. On the other hand, ambient sensory data can tolerate delays up to several minutes [78]. At the transport layer, TCP is employed to ensure reliable delivery of the messages that are clustered as time-sensitive. As re-transmission of dropped packets would decrease the throughput while increasing the delay for the lower priority packets, moderately and low sensitive packets are transported via UDP ports in order to compromise the throughput as well as the delay. On the other hand, traditional LTE packet scheduling algorithms such as First In, First Out (FIFO), lack of meeting delay requirements for urgent messages. In FIFO queuing, all packets are treated equally by placing them into a single queue, then servicing them in the same order they were placed in the queue. FIFO queuing is also referred to as First Come First Serve (FCFS) queuing.

## 4.3 Performance Evaluation

### 4.3.1 Simulation Settings

To evaluate our proposed traffic scheduling technique, we have employed the UMass Smart\* Dataset 2013 release, which is a microgrid dataset providing electricity usage data from 443 anonymous microgrids over a single 24-hour period [21]. The electrical data is collected in a time sequence order per minute using timestamps with respect to the Unix time. The simulation environment is built on OMNeT++ development platform [2]. Due to memory limitation, the platform can only employ data of 48 microgrids out of the 443 microgrids. Simulation settings are summarized in Table. 4.1. The simulated wireless network consists

of one macro-cell and four small-cells. Similar to the preliminary study in [122], in order to compare the performance of various cases, two types of user distributions are simulated, namely *uniform network* and *non-uniform network*.

Table 4.1: Simulation parameters used to test the proposed data aggregation framework

| PARAMETER                                                               | VALUE                              |
|-------------------------------------------------------------------------|------------------------------------|
| Number of small-cells                                                   | 4                                  |
| Number of macro cells                                                   | 1                                  |
| Number of priority classes                                              | 3                                  |
| User distribution on small-cell network                                 | Uniform (UN) and Non-Uniform (NUN) |
| Number of microgrids per small-cell (UN)                                | 12                                 |
| Number of microgrids per small-cell 1, 2, 3 and 4, respectively (NUN).  | {5, 10, 15, 18}                    |
| Average propagation delay                                               | {1, 5} $\mu$ s                     |
| Bit error rate (BER)                                                    | $10^{-5}$                          |
| Average transmission rate                                               | {100, 200} Mb/s                    |
| Range of a small-cell BS                                                | {300, 1500} meter                  |
| Number of packets received at a small-cell 1, 2, 3 and 4, respectively. | {5, 10, 12, 15, 18}                |
| Number of microgrids per small-cell 1, 2, 3 and 4, respectively.        | {5, 10, 15, 18}                    |

In the uniform network, the microgrids are distributed over the small-cells uniformly (i.e. 12 microgrids per small-cell), whereas the non-uniform network considers certain small-cells as hot spots. In the non-uniform network, the microgrids are distributed over the small-cells 1, 2, 3 and 4 as 5, 10, 15 and 18 users, respectively. Each microgrid owner (i.e. user) sends a packet of their microgrid energy cost information every 10 minutes over the entire 24 hours. However, the packet length may vary based on the changes of the electricity usage. The number of distributed microgrids over a small-cell is responsible for the number of the packets received at the cell. For example, a small-cell with 5 microgrid users will have 5 packets every 10 minutes. Similarly, a cell with 18 users will have 18 packets every 10 minutes.

An average propagation delay of  $1\mu$ s and  $5\mu$ s were considered in both network scenarios. To be precise, the propagation delay represents the time needed to send a packet from the transmitter to the receiver (i.e. from the microgrid to the small-cell tower). However, since the speed of the propagation wave is constant (speed of light), the delay values of  $1\mu$ s and

$5\mu\text{s}$  represent the distance between the microgrid and the small-cell tower as 300 and 1500 meters, respectively. These ranges correspond to two types of small-cells namely, pico-cells and microcells. In addition, the average data rate used for the communication link between the microgrid and the small-cell are 100 Mb/s and 200 Mb/s with bit error rate (BER) of  $10^{-5}$ . Two simulation settings are studied UN and NUN<sup>1</sup> using different combinations of the mentioned values [151], as follows:

- *Scenario-1*: Data rate of 200 Mb/s, propagation delay of  $1\mu\text{s}$  and  $10^{-5}$  BER are considered as the first simulation scenario.
- *Scenario-2*: The second scenario sets the data rate at 100 Mb/s, propagation delay at  $5\mu\text{s}$  and BER at  $10^{-5}$ .

In order to group the received packets in the small-cell, k-means clustering algorithm is used. Three centroids are selected randomly in the simulations and hence the three clusters are considered to denote highly time-sensitive, moderately time-sensitive and delay-tolerant queues. Highly time-sensitive messages are also considered to require reliable delivery as the content of the message denotes urgency such as raising of an alert for an upcoming mode switching event. To this end, TCP is employed at the transport layer to handle the re-transmission of the dropped packets. However, re-transmission of any dropped packet can cause further network congestion. Therefore, we introduce a slight modification in the transport layer and only trigger re-transmission of the packets of the highest priority class (i.e. the highly time-sensitive class) to keep the data traffic low and preserve the most important messages while UDP is adopted as the transport layer protocol for messages of the other categories so that the throughput and delay can slightly be compensated for moderately and low sensitive packets. In the simulation results, every point is the average of 10 runs with a confidence level of 95%. The calculation of the confidence interval can be found in the appendix (6).

### 4.3.2 Numerical Results

We evaluate the performance of our proposed technique for both scenarios under the uniformly and non-uniformly user distribution in terms of queuing delay and packet loss rate. We compare the results of the proposed solution to the baseline data aggregation approach that works on first come, first serve basis as opposed to multi-class priority queue-driven aggregation.

---

<sup>1</sup>NUN and UN denote non-uniform and uniform distribution of microgrid owners (i.e. users) in a small-cell network, respectively.

## Numerical results under *Scenario-1*

Under scenario-1 settings, Figure 4.2 shows the average number of the queued packets in each small-cell, i.e. pico-cell in the first scenario. Regarding pico-cell 1 the uniform network (UN), 9.49% of the received packets are considered highly time-sensitive packets, whereas the moderately time-sensitive and the delay-tolerant contribute to 26.62% and 62.44% of all microgrid messages, respectively. Under the traditional LTE context (i.e. no pre-assessment/aggregation), the number of packets represents the total number of received packets without clustering. As the number of microgrids is equally distributed over the (UN), the time-sensitive packets in all small-cells have approximately the same percentages.

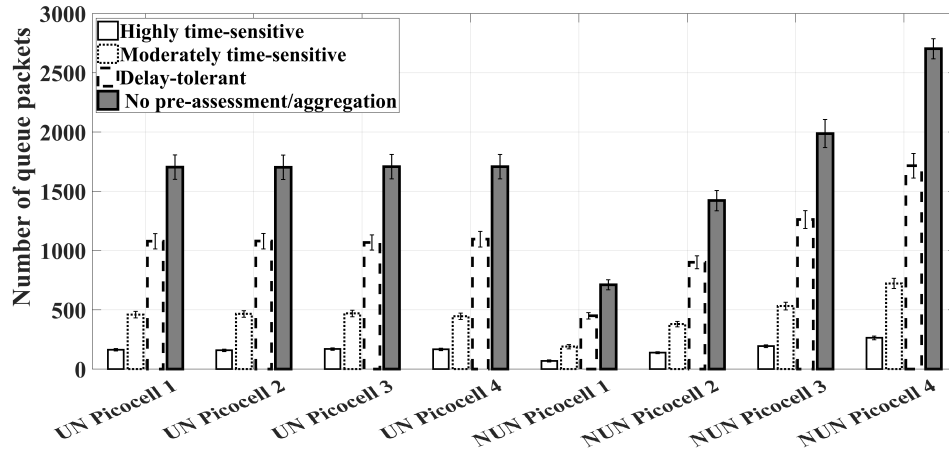


Figure 4.2: Number of queue packets at the pico-cell level under scenario-1 settings. NUN and UN are the non-uniform and uniform user distribution network, respectively. No pre-assessment/aggregation denotes the benchmark, i.e. traditional LTE scheduler.

Figure 4.3 illustrates the queuing delay regarding the three time-sensitive clusters (highly time-sensitive, moderately time-sensitive and the delay-tolerant). It is observed that the queuing delay, under both uniform and non-uniform networks, follows the same behavior as the number of queue packets. Thus, when the users are uniformly distributed among the small-cells, the queuing delay is approximately the same for the four pico-cells. However, under the non-uniform distribution of user equipment, the queuing delay increases with the number of microgrid users per pico-cell. It is worth noting that in spite of the queuing delay increment per pico-cell, the proposed urgency-aware queuing mechanism does not experience rapid changes in the queuing delay. In pico-cell 1 under the uniform network, the average queuing delay of highly time-sensitive and the moderately time-sensitive packets has improved by at least 78.3%, whereas the delay-tolerant



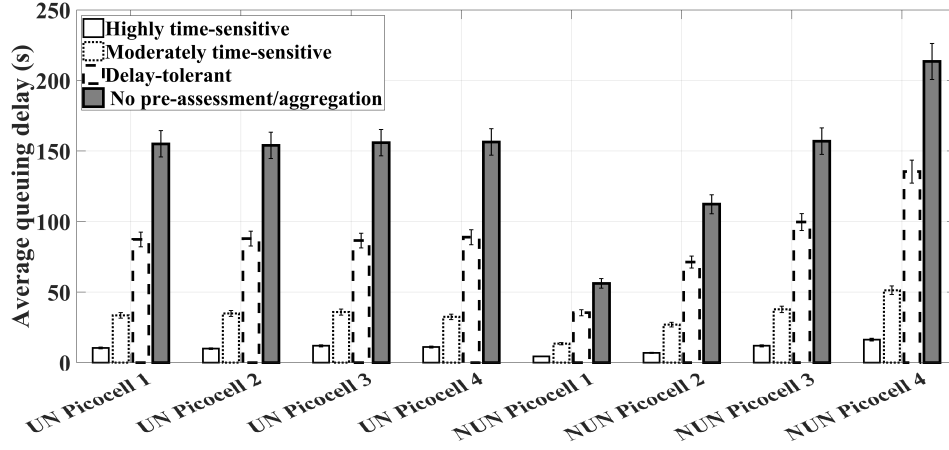


Figure 4.3: Delivery time of queue packets at the pico-cell level under scenario-1 settings where *no pre-assessment/aggregation* stands for the benchmark, i.e. traditional LTE scheduler.

packets have only improved by 43.6% when compared with the benchmark with no pre-assessment/aggregation. Similar to the previous results, the pico-cells under the uniform network have the same values. However, the average queuing delay in pico-cell 1 under the non-uniform network regarding the highly time-sensitive, moderately time-sensitive and the delay-tolerant packets has improved by 92%, 76% and 36.8%, respectively. The previous results have shown the impact of the distribution of microgrid owners per pico-cell on the queuing delay. Moreover, the queuing delay of the highly time-sensitive packets has reduced significantly, under both user distributions when compared to the other categories of packets. The same pattern holds for the rest of the small-cells, where the packets of highly time-sensitive class experience the lowest queuing delay followed by the moderately time-sensitive and delay-tolerant packets. In addition, the packets under the benchmark (i.e. no pre-assessment/aggregation) have the highest queuing delay as expected.

In Figure 4.4, the results present the packet loss rate (PLR) at the pico-cell level under the two different user distribution networks. The introduced TCP protocol for packet re-transmission improves the PLR. Under the non-uniform user distribution network, the PLR for the packets that undergo delay sensitivity-driven data aggregation is always better than the packets under the benchmark (i.e. no pre-assessment/aggregation). Over the four pico-cells, the PLR is relatively the same even though the number of microgrids is different among them. The reason is that the TCP protocol re-transmit the packets of the highly time-sensitive messages. However, this comes at the expense of reduced throughput as the packets need additional time for the re-transmission process.

In order to transmit the packets (under the setting where users are uniformly dis-

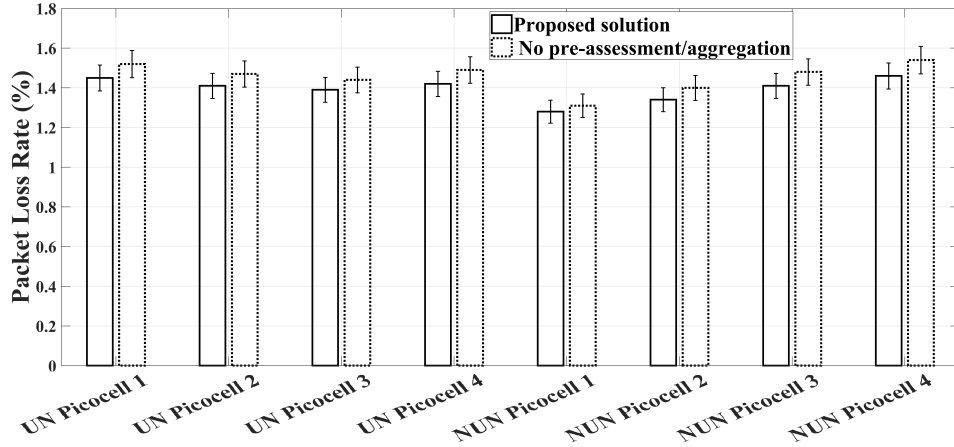


Figure 4.4: Packet loss rate of the transmitted packets at the pico-cell level under scenario-1 settings where *no pre-assessment/aggregation* stands for the benchmark, i.e. traditional LTE scheduler.

tributed among the small-cells), the packets on average experience less queuing delay when compared to benchmark where there exists no pre-assessment/aggregation. The improvement of the benchmark by highly time-sensitive packets is at the order of 93% as shown in Figure 4.5; whereas, the moderately time-sensitive and delay-tolerant packets improve the benchmark by 78.7%, and 44.4%, respectively. Under the non-uniform distribution of microgrid owners, delay of the highly time-sensitive, moderately time-sensitive, and delay-tolerant packets can be reduced by 93.76%, 79.1%, and 44.88% as compared to the benchmark.

## Numerical results under *Scenario-2*

The average number of the queued packets based on the time-criticality is relatively the same as in *Scenario-1*. The decrease of the data rate from 200 Mb/s to 100 Mb/s has no impact on the number of clustered packets. The increase of propagation delay value from  $1\mu\text{s}$  to  $5\mu\text{s}$  does not affect the performance behavior in Figure 4.6. For different microcells, the average number of queue packets is insignificant when users are uniformly distributed among the small-cells. When the users are non-uniformly distributed among the small-cells, the number of packets increase as the number of microgrids per microcell increases. On the other hand, Figure 4.7 shows that the queuing delay is 10% higher than that obtained under *Scenario-1*. This phenomenon is due to the following reason: Data rate in *Scenario-2* has been reduced by 50%. Thus, the queuing delay increases as expected according to equations (4.3)-(4.4). In microcell 1, when microgrid owners are uniformly

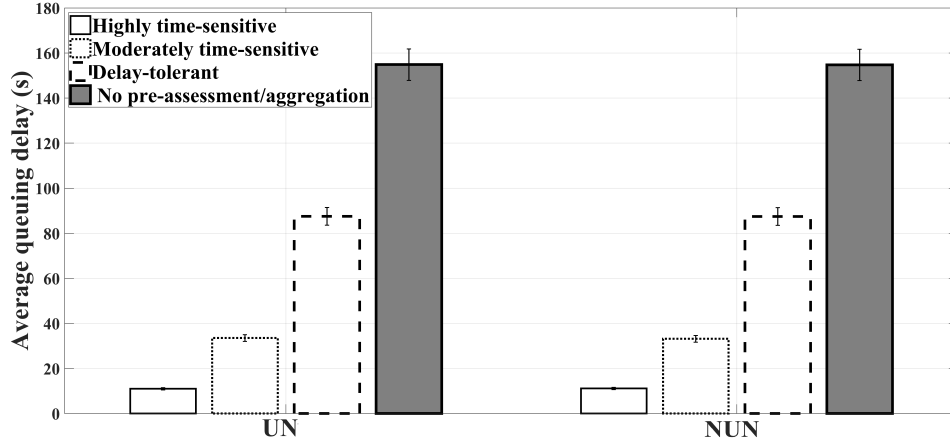


Figure 4.5: Delivery time of queue packets at the macro-cell level under scenario-1 settings. NUN and UN are the non-uniform and uniform user distribution network, respectively. No pre-assessment/aggregation denotes the benchmark, i.e. traditional LTE scheduler.

distributed, the average delivery of the enqueued packets for the highly time-sensitive and moderately time-sensitive categories can be expedited by 91.5%, 76.3%, respectively when compared to the delivery ratio of packets under the benchmark where there exists no pre-assessment/aggregation. However, as the delay-tolerant packets considered as the least urgent messages, such a drastic improvement is cannot be observed.

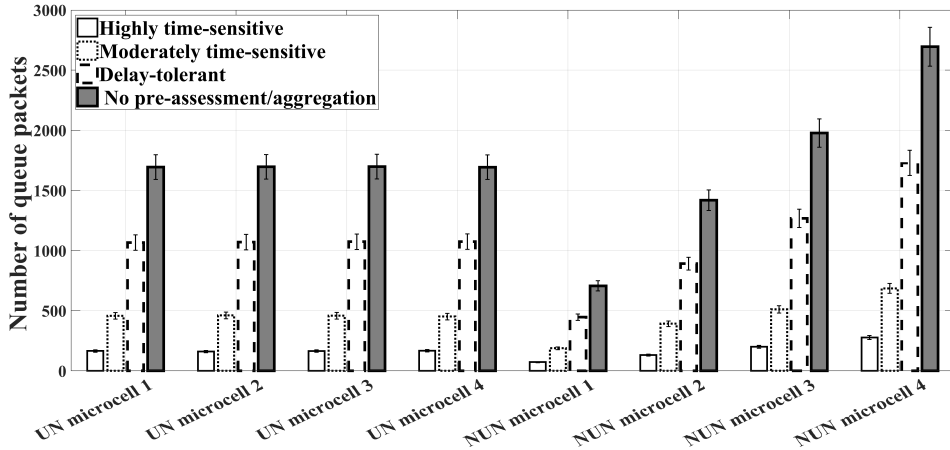


Figure 4.6: Number of queue packets at the microcell level under scenario-2 settings where *no pre-assessment/aggregation* stands for the benchmark, i.e. traditional LTE scheduler.

At the macro-cell tier, the queuing delay increases by 11.5% compared to the first

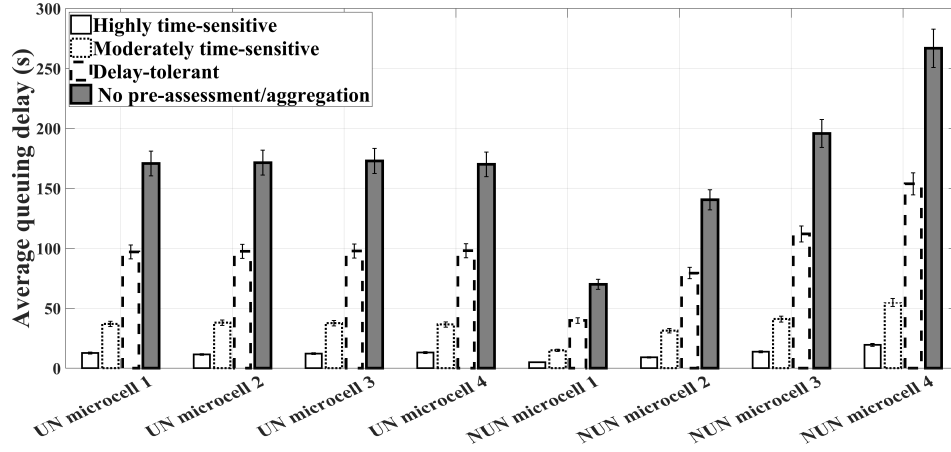


Figure 4.7: Delivery time of queue packets at the microcell level under scenario-2 settings where *no pre-assessment/aggregation* stands for the benchmark, i.e. traditional LTE scheduler.

scenario as shown in Figure 4.8. As in all queuing delay figures, the higher the urgency of messages, the lower the time needed to deliver the packets. Besides, when compared to the benchmark (i.e. no pre-assessment/aggregation), the average queuing delay of the packets for highly time-sensitive, moderately time-sensitive and delay-tolerant categories is reduced by 91%, 76.1%, and 41%, respectively. Similar to the case of uniformly distributed microgrid owners, the non-uniform user distribution follows the same pattern in terms of the queuing delay with respect to the delay sensitivity.

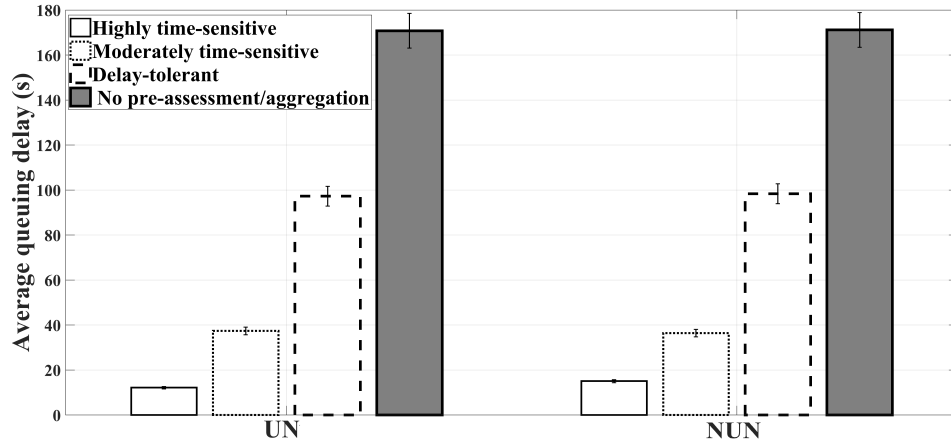


Figure 4.8: Delivery time of queue packets at the macro-cell level under scenario-2 settings where *no pre-assessment/aggregation* stands for the benchmark, i.e. traditional LTE scheduler.

It is observed that the number of packets- at the data aggregator- that carry highly time-sensitive data always has the least number of packets when compared to the moderately time-sensitive and delay-tolerant packets. Hence, we can infer that not all of the acquired data from the microgrid users will be considered as time-critical data, which brings more advantages to our proposed solution. For instance, the proposed pre-assessment-based and multi-class queue-driven microgrid aggregation system would experience less blocking probability and PLR for the packets that are delay tolerant. However, in the case of significant number of highly time-sensitive packets to be aggregated, the aggregator's capacity will be filled by the packets of that category while other packets with lower delay sensitivity levels will be dropped/blocked.

## 4.4 Summary

To process different types of microgrid packets asynchronously according to their levels of urgency, a data aggregation scheme based on a priority queuing mechanism has been integrated into the smart microgrid communication network. Packets carrying microgrid packets are pre-assessed at the aggregators; their delay sensitivity (i.e. urgency) is analyzed so that the overall delay for the highly time-sensitive (highly urgent) packets are minimized while buffering the delay tolerant packets in the queues. This pre-assessment is performed through using k-means algorithm, such that the packets carrying microgrid packets are clustered under three categories corresponding to delay sensitivity degrees varying from highly sensitive to delay tolerant.

We have shown that the successful integration of machine intelligence at the pre-assessment stage significantly reduces the delay of the packets that are highly delay sensitive, particularly, by 93.76% with respect to the case when there is no pre-assessment. Further, communicating through TCP and UDP ports for highly time-sensitive messages and moderately time-sensitive messages, respectively allows for re-transmission of the dropped packets, and this leads to a 7% reduction in the overall PLR when compared to no pre-assessment and/or aggregation. Moreover, even with using the TCP protocol, the average queuing delay of the highly time-sensitive cluster is less by approximately 70% when compared to the average queuing delay of the moderately time-sensitive cluster that implements the UDP protocol. However, UDP protocol is preferred for the support of time-critical protection data due to the additional delay required for TCP; thus, our proposed technique outperforms in terms of employing TCP for time-critical data that ensures the packets deliverability without requiring longer time delay.

# Chapter 5

## Communication and Operational Management Framework for EV-Microgrid Integration

### 5.1 Introduction

Cost efficiency depends on the reliability and sustainability of power systems, the two major concerns in smart microgrids that call for proactive emergency preparedness and self-recovery solutions. These concerns have attracted substantial attention given the penetration of Distributed Generators (DGs) and the advances in the smart microgrid concept. Smart microgrids utilize these local generators to produce power through renewable/stored energy resources which introduces uncertainty to the power grid operation, particularly when severe weather incidents occur.

Catastrophic weather events inflict serious social and economic impacts, where a critical issue associated with such catastrophes is the availability of electricity. These kinds of severe weather events damage the utility grid and result in 78% of the service interruptions and power outage to the grid users but also the cost of such events ranges from \$20 to \$55 billion [34]. Microgrid owners can survive such incidents; however, as the time duration of the power unavailability is expected to increase [125], some of the microgrid owners might be impacted. In addition, microgrids resiliency is another key factor to withstand rare extreme weather events with high impact on the grid. It is also defined as the ability of the microgrid to adapt and mitigate the damages of different weather cases. This requires

novel solutions to ensure the microgrid’s reliability, sustainability and resiliency.

One possible solution is peer-to-peer (P2P) energy trading [106]. This is formed as a network of microgrid owners (i.e. prosumers) to share essential resources such as renewable energy and storage room with other prosumers in the network [164]. Furthermore, the P2P energy trading benefits the prosumers by incentivizing them to achieve certain goals (e.g. maximize the usage of DGs, minimize the electricity cost and improve the network resiliency), while serving critical loads, such as pharmacies and hospitals, in the aftermath of a major weather disaster.

Another solution is to use the vehicle-to-grid (V2G) technology to improve the resilience of the microgrids. EV batteries are considered as mobile distributive energy storage resources [143]. This can be considered as a valuable opportunity to support microgrids with power on the fly, especially at severe weather events. However, this solution requires high quality-of-service (QoS) communication link between the mobile EVs and the base station, in terms of reliability and latency.

### 5.1.1 Solution Overview

We model the interaction between the microgrids and the EVs as an optimization model, where V2G cost-benefit analysis is investigated. The model finds the optimal set of EVs to provide energy to the microgrids with energy shortage, while minimizing the cost. The model performance is evaluated based on three criteria: cost, outstanding energy and average revenue/EV. To guarantee maximum communication reliability, the PDSCH throughput performance between the eNodeB and the EVs is considered as a benchmark to determine the number of participating EVs in the power supply request/process.

Through simulations, we show that increasing number of participating EVs in the power supply request can significantly help the microgrids support their electric needs; however, the total cost increases as the number of participating EVs in the cell expands. On the other hand, the average revenue per EV increases as the number EVs decreases. We extended our experiments to include more intense environment where a QoS metric (i.e., the PDSCH throughput performance) is considered to determine the qualified EVs to participate in the request. The results show the impact of the communication constraint on the total cost, outstanding energy, and the average revenue per EV. The optimization model provided the optimal set of EVs in terms of distance and throughput that can participate in the power supply process.

## 5.2 Methodology

### 5.2.1 System Description

Power supply process addressed by our model uses real time information of the microgrid power demand to find the optimal set of EVs to participate in the process considering a reliable communication between eNodeB and EVs. This problem has the following components and inputs: a set of  $M$  microgrids with a distance of  $K_{im}$  between any two microgrids, a cell tower with different number of EVs, and a set of EVs participating in the power supply request, as shown in Figure 5.1.

Each microgrid transmits the power data (i.e. generation and consumption) to the cell tower. Since microgrids rely on renewable energy resources to generate power such as solar panels and wind turbines, it is necessary to consider the weather data for an accurate prediction of the power generation. If the microgrid power generation is less than the power consumption, and the utility grid is damaged due to severe weather or transmission line failure, the microgrid owner sends a power supply request to the eNodeB. This is considered as a highly-time sensitive message and a priority queuing mechanism using machine learning algorithms was proposed in a previous work to handle this issue between the microgrids and the eNodeB [121]. The base station forwards the request to the EVs in the coverage area to participate in the service request. To guarantee a reliable power supply process, the base station selects the participating EVs based on the PDSCH throughput performance of each vehicle. If the throughput of an EV is below a certain threshold, the EV is excluded from the process.



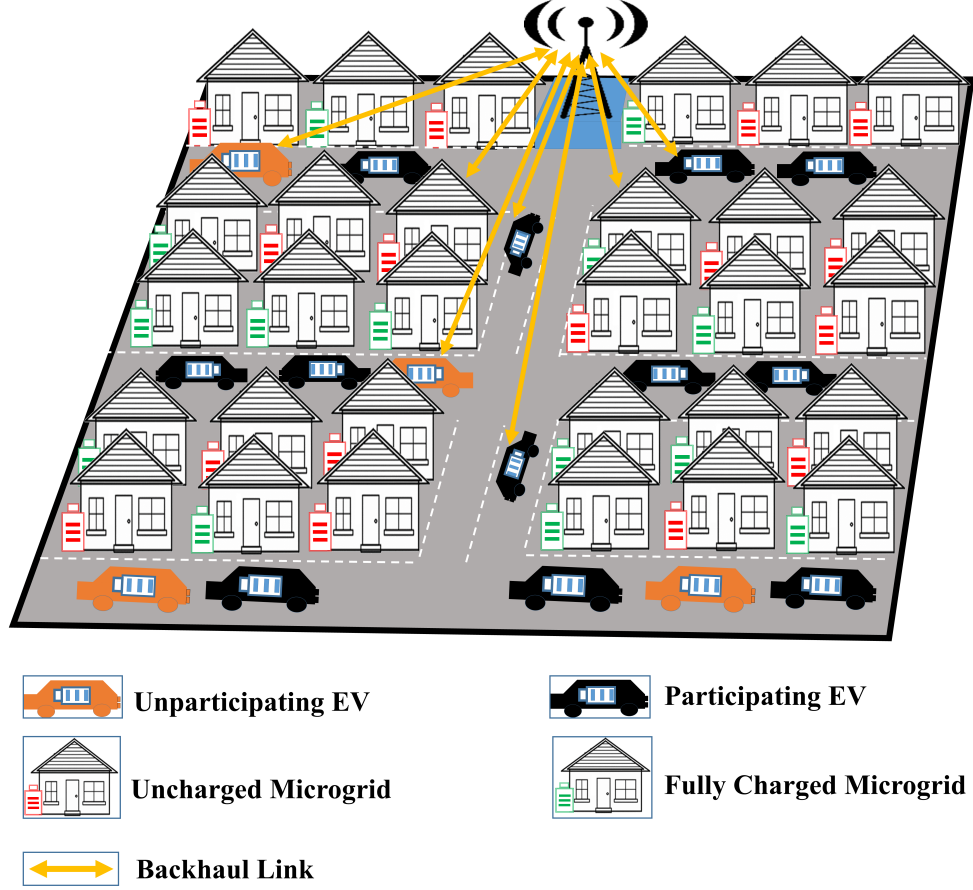


Figure 5.1: System model overview

### 5.2.2 Optimization Model

We propose a Mixed Integer Linear Programming (MILP) model to find the optimal set of EVs to supply the affected microgrids with the required power until the main grid is maintained. The principle of the introduced MILP model is adopted from our previous work [120].

The cost-based optimization model objective is to minimize the cost of the power supply process. The objective function in Eq.(5.1) is broken down into the cost components in the set of constraints starting at Eq.(5.2). The following parameters contribute to the cost

of microgrid  $m$  power supply operation: traveling distance, waiting time, amount of given energy and service request fees.

$$\text{Minimize } \sum_{m=1}^M \text{cost}_m \quad (5.1)$$

subject to

$$\begin{aligned} \text{cost}_m - \left( \sum_{n=1}^N S_m^n + \sum_{i=1}^M \sum_{n=1}^N \sum_{r=1}^M z \cdot K_{im} \cdot A_{im}^{nr} + \sum_{n=1}^N O_m^{n1} \cdot T_m \cdot z \right) \cdot P_n - \left( \sum_{n=1}^N S_m^n / H \right) \cdot W \\ - \sum_{n=1}^N \sum_{r=1}^M O_m^{nr} \cdot v = 0, \forall m \in M \end{aligned} \quad (5.2)$$

$$A_{im}^{nr} - O_m^{nr} \leq 0, \forall i \in M, \forall m \in M, \forall n \in N, \forall r \in M \quad (5.3)$$

$$A_{im}^{nr} - O_i^{nr+1} \leq 0, \forall i \in M, \forall m \in M, \forall n \in N, \forall r \in M \quad (5.4)$$

$$O_i^{nr} + O_m^{nr+1} - A_{im}^{nr} \leq 1, \forall i \in M, \forall m \in M, \forall n \in N, \forall r \in M \quad (5.5)$$

The optimization model requires formulating the conditional variable that denotes whether microgrids  $i$  and  $m$  are served by EV  $n$  at the  $r$ -th and  $(r + 1)$ -th order, respectively. This can be formulated as the multiplication of the two variables, i.e.,  $(O_i^{nr} \times O_m^{nr+1})$ . The non-linearity in  $(O_i^{nr} \times O_m^{nr+1})$  is linearized by the constraints in (5.3)-(5.5). The first two inequalities ensure that  $A_{im}^{nr}$  will be zero if either  $O_i^{nr}$  or  $O_m^{nr+1}$  is zero. The last inequality ensures that  $A_{im}^{nr}$  will be equal to one, only if both binary variables are one. Therefore, this will linearize  $A_{im}^{nr}$  without violating any of the other constraints.

$$\sum_{n=1}^N S_m^n \geq D_m, \forall m \in M \quad (5.6)$$

$$\sum_{m=1}^M S_n^m + \sum_{i=1}^M \sum_{m=1}^M \sum_{r=1}^M z \cdot K_{im} \cdot A_{im}^{nr} + \sum_{m=1}^M O_m^{n1} \cdot T_m \cdot z \leq E_n \cdot \alpha_n, \forall n \in N \quad (5.7)$$

The next two constraints define the lower bound and the upper bound of the transferred energy from EV  $n$  to microgrid  $m$ , respectively. The constraint in Eq.(5.6) ensures that the total energy  $S_m^n$  transferred to microgrid  $m$  is at least equal to the microgrid's demand  $D_m$ ; and the constraint in Eq.(5.7) guarantees that the total transferred energy from EV  $n$  and the total consumed energy in traveling is at most equal to the contribution factor  $\alpha$  of the initial energy level of the EV's battery  $E_n$ .

$$\sum_{m=1}^M \sum_{r=1}^M O_m^{nr} - \sum_{i=1}^M \sum_{m=1}^M \sum_{r=1}^M A_{im}^{nr} = 1, \forall n \in N \quad (5.8)$$

$$\sum_{m=1}^M O_m^{nr} \leq 1, \forall n \in N, \forall r \in M \quad (5.9)$$

$$\sum_{n=1}^N \sum_{r=1}^M O_m^{nr} \geq 1, \forall m \in M \quad (5.10)$$

$$U_n - \sum_{m=1}^M S_m^n \cdot P_n - (\sum_{m=1}^M S_m^n / H) \cdot W - \sum_{m=1}^M \sum_{r=1}^M O_m^{nr} \cdot v = 0, \forall n \in N \quad (5.11)$$

Eq.(5.8) defines the number of trips made by EV  $n$  between two followed microgrids. The constraint in Eq.(5.9) guarantees the following: given EV  $n$ , order  $r$  can be set to microgrid  $m$  at most once. In this paper, we assume that EVs are the only source of power; thus, Eq.(5.10) ensures that microgrid  $m$  must be served by at least one EV to provide the microgrid with the necessary power. Eq.(5.11) formulates the revenue  $U_n$  of EV  $n$  by summing three components: the sold energy, the waited time to transfer the energy to the microgrid, and the service request made by the microgrid.

## 5.3 Performance Evaluation

### 5.3.1 Simulation Settings

To evaluate our model, three MATLAB toolboxes were used, namely optimization toolbox, LTE toolbox and simscape electrical toolbox [110]. The optimization toolbox was used to

solve the MILP cost model, whereas the LTE toolbox was used to to measure the physical down-link shared channel (PDSCH) throughput performance between the eNodeB and the EVs. The simscape electrical toolbox simulated the microgrids power data (i.e. consumption and generation) to provide the microgrid's demand value [122].

Table 5.1: The values of the used parameters to evaluate the proposed optimization model

| Notations                                                              | Value        |
|------------------------------------------------------------------------|--------------|
| Number of EVs/cell for case-1, case-2 and case-3, respectively         | {4, 8, 12}   |
| Number of participating EVs ( $N$ ) in scenario-1 (Com constraint off) | {4, 8, 12}   |
| Number of participating EVs ( $N$ ) in scenario-2 (Com constraint on)  | {3, 5, 6}    |
| Number of microgrids ( $M$ )                                           | {4, 8, 12}   |
| EV energy price ( $P_n$ )                                              | 0.201 \$/kWh |
| Average energy consumption per km ( $z$ )                              | 0.18 kWh/km  |
| EV charger's power ( $H$ )                                             | 20 kW        |
| Waiting time price ( $W$ )                                             | 10 \$/h      |
| Service request price ( $v$ )                                          | 1 \$/request |
| Distance between microgrids ( $K_{im}$ )                               | [0.2-3] km   |
| Distance from EV $n$ initial location to first microgrid $m$ ( $T_m$ ) | [0.2-3] km   |
| Microgrid's demand ( $D_m$ )                                           | [5-30] kWh   |
| EV's initial battery level ( $E_n$ )                                   | [10-40] kWh  |
| EV's contribution value ( $\alpha_n$ )                                 | [0.1-0.9]    |
| Signal to noise ratio ( $SNR$ )                                        | 40 dB        |
| Number of antennas at eNodeB                                           | 4            |

Simulation settings are given in Table. 5.1. The EVs are distributed in random locations in a cell size of 3 km. The delivery cost, denoted by the sum of  $T_m$  and  $K_{im}$ , is paid by the microgrid that sends the service request. The initial location between the EVs and the first microgrid is  $T_m$ =[0.2-3] km, and the distance among the microgrids is  $K_{im}$ =[0.2-3] km. All the given distances in kilometer (km) are converted to kilowatt hour (kWh) using the average conversion rate of 12 different EV's brands  $z$ =0.18 kWh/km [33]. The cost of

a smart microgrid requesting a power supply service  $v$  is calculated considering the average base fare of the transportation apps in the market which is 1 \$/request [32].

In addition, the microgrid is charged for the waiting time spent by the EVs to transfer all the required energy  $W=10$  \$/h [32]. The waiting time price is chosen similar to the price of the transportation apps in the market. The EVs contribute to the power supply request by selling part of the energy stored in their batteries. The contribution value is determined by  $\alpha_n$ , and the kilowatt selling price is  $P_n= 0.201$ \$/kWh [85]. The contribution value determines the amount of energy each EV is willing to give in the power supply process. The contribution value vary between 0.1 and 0.9. This allows us to examine the impact of different contribution values on the total cost, outstanding energy and revenue/EV. It is worth to mention that since we assume the EVs are the only source of power, the energy selling price is not bounded by the grid prices (i.e. Ontario Hydro). However, a selling price of 50% more than the on-peak grid rate (13.4 cents/kWh) [77] is considered as a realistic assumption.

Table 5.2: The impact of the communication constraint on the number of selected EVs to participate in the power supply request

| Number of selected EVs          | Case-1 | Case-2 | Case-3 |
|---------------------------------|--------|--------|--------|
| Scenario-1 (Com constraint off) | 4      | 8      | 12     |
| Scenario-2 (Com constraint on)  | 3      | 5      | 6      |

We simulated three cases of different numbers of EVs per cell: 4 EVs/cell, 8 EVs/cell and 12 EVs/cell, respectively. However, the number of EVs participating in the power supply request is determined based on the communication constraint as shown in Table 5.2. If the communication constraint is deactivated (i.e. scenario-1), the number of EVs participating in the request is  $N=\{4, 8, 12\}$ . This means, for each case, all the EVs in the cell are included and participating in the request. On the other hand, if the communication constraint is activated (i.e. scenario-2), then the number of EVs participating in the request is  $N=\{3, 5, 6\}$ . In that case, not all the EVs in the cell are participating in the request. For example, in case-1, there are 4 EVs/cell: scenario-1 considers all 4 EVs; however, scenario-2 only considers 3 EVs. Based on the average EV's battery capacity exists in the market, the initial energy level of the EVs batteries  $E_n$  is considered in interval of [10-40] kWh.

In scenario-1, the EV's initial energy level for case-1 are  $\{10, 20, 30, 40\}$  kWh. We replicate case-1's initial values two and three times for case-2 and case-3, respectively. In scenario-2, the EV's initial energy level for case-1, case-2 and case-3 are  $\{10, 20, 30\}$  kWh,  $\{10, 20, 20, 30, 40\}$  kWh and  $\{10, 20, 30, 40, 40, 40\}$  kWh, respectively. However, the deployment of the communication constraint does not impact the number of microgrids  $M=\{4, 8, 12\}$ . The microgrid's demand covers the range between  $[5-30]$  kWh. For  $M=4$ , the microgrid's demands are  $\{5, 10, 15, 20\}$  kWh. For  $M=8$ , the demands values of  $M=4$  is replicated twice.

### 5.3.2 Numerical Results

We evaluate the performance of our model for different contribution values under different number of microgrids and different number of EVs. The results represent three performance metrics namely, cost, outstanding energy and EV's revenue. As the communication constraint directly affects the number of participated EVs in the power supply request, the impact of it is considered as shown in the results.

Before we proceed with the results of the optimization model, it is worth clarifying the functionality of the communication constraint. The PDSCH throughput is considered as

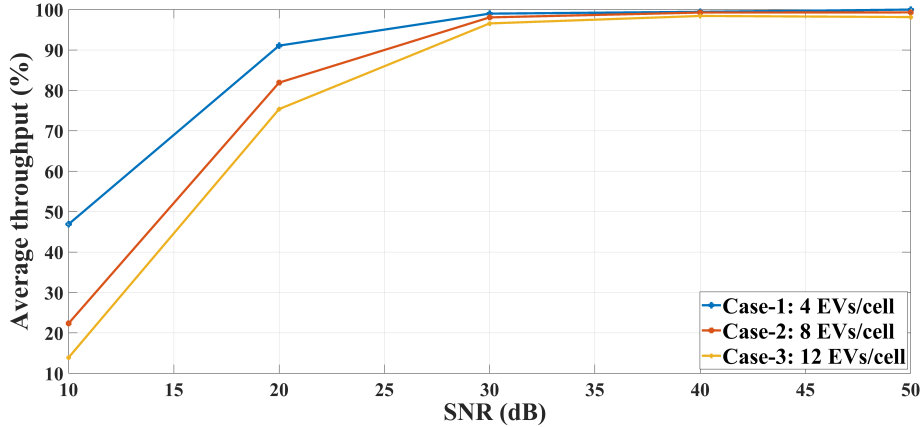


Figure 5.2: The average throughput under various SNR values for different number of EVs/cell

the main criteria to decide which EVs to participate in the power supply request. However, since the throughput changes with changing the SNR, we first experimented different SNR values  $[10-50]$  dB to get the best average throughput of each case, as shown in Figure 5.2.

The throughput percentage is the ratio between the achieved throughput (i.e. considering the packet loss) over the maximum throughput (i.e. considering no packet loss). The SNR of 40 dB is selected as it achieves the best throughput even better than SNR of 50 dB particularly, for case-3: 12 EVs/cell. The reason is that increasing the SNR value can lead to a higher inter-user interference, and thus, decrease the throughput. After selecting the SNR value, we investigate the throughput of each EV under the three cases and exclude the ones that do not meet the minimum throughput requirement.

In Figure 5.3, in scenario-1 under case-1: 4 EVs/cell, case-2: 8 EVs/cell and case-3: 12 EVs/cell, the number of participating EVs  $N$  is 4, 8 and 12 with initial energy level  $E_n$  of 100, 200 and 300 kWh, respectively. The total microgrids demand is 50 kWh. For all cases, the total cost raises as the EVs contribution value increase, however, the total cost saturates in all cases at \$41.5, because the total demand is fixed at 50 kWh for all cases.

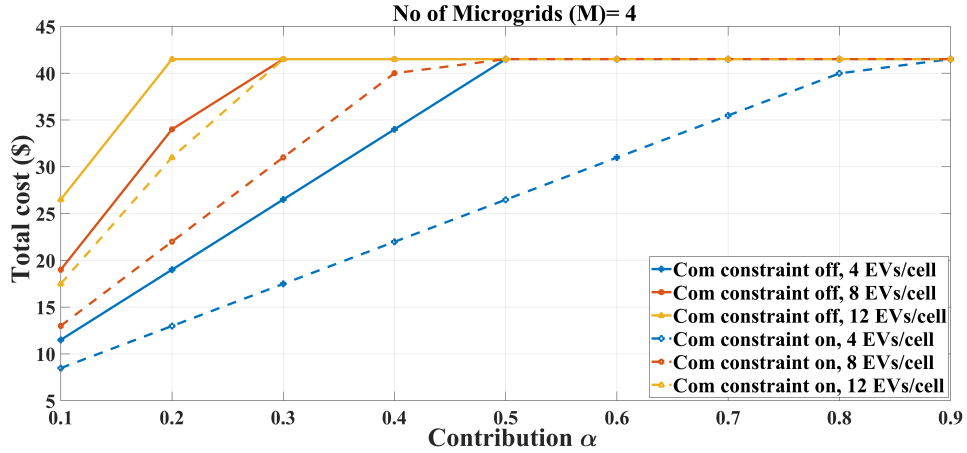


Figure 5.3: The total cost of 4 microgrids under scenario-1: Com constraint off, and scenario-2: Com constraint on, for different number of EVs/cell: 4, 8, and 12

However, each case out of the three mentioned cases converges at a different contribution value, particularly at 0.5, 0.3 and 0.2 when  $N$  is 4, 8 and 12, respectively. Under same contribution value and before saturation, the cost of  $N=12$  is the highest, and the cost of  $N=4$  is lowest.

This means that increasing the number of participating EVs leads to a higher cost. The reason behind that is observed in Figure 5.4, where the outstanding energy shrinks as the number of participating EVs increases. In other words, the total cost raises as the sold energy increases when more EVs participate in the power supply request. Thus, higher

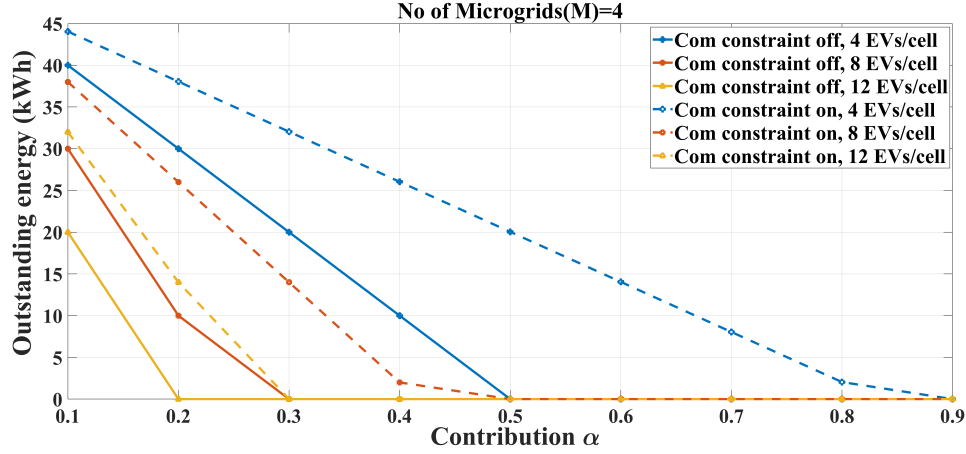


Figure 5.4: The outstanding energy of 4 microgrids under scenario-1: Com constraint off, and scenario-2: Com constraint on, for different number of EVs/cell: 4, 8, and 12

cost means that the outstanding energy vanishes. Furthermore, as the contribution value increases beyond the convergence points (i.e. 2, 0.3 and 0.5), the average revenue/EV significantly increases, as shown in Figure 5.5a. This behaviour is justified as increasing the contribution values causes the set of participating EVs to get smaller, and thus, increase the average revenue/EV. For instance, under case-1: 4 EVs/cell, the total energy given by the EVs is 100 kWh with a total demand of 50 kWh. Therefore, at  $\alpha=0.5$ , the microgrid demand is almost covered, and all the EVs in the set have participated in the process. However, at  $\alpha=0.8$ , only 3 EVs are enough to cover the microgrid demand. As a result, the average revenue/EV increases.

In scenario-2, under case-1: 4 EVs/cell, case-2: 8 EVs/cell and case-3: 12 EVs/cell, the number of participating EVs  $N$  is 3, 5 and 6 with total initial energy level  $E_n$  of 60, 120 and 180 kWh, respectively. When the communication constrain is applied (i.e. scenario-2), the total cost remains unchanged even though the number of participating EVs is less than scenario-1. This is because the total cost is determined by the total energy demand of the microgrids. However, the number of participating EVs and the contribution values determine the convergence points in each case. Furthermore, reducing the number of participating EVs changes the convergence points, and thus affect the total cost, the outstanding energy and the EVs revenue. The convergence points are moved from 0.5, 0.3, 0.2 (scenario-1) to 0.9, 0.5, 0.3 (scenario-2) when number of EVs/cell is 4, 8, and 12, respectively. For instance, the pending energy of scenario-1 under 4-microgrids reaches zero at  $\alpha=0.5$ , whereas in scenario-2 the pending energy reaches zero at  $\alpha=0.9$ . Thus,



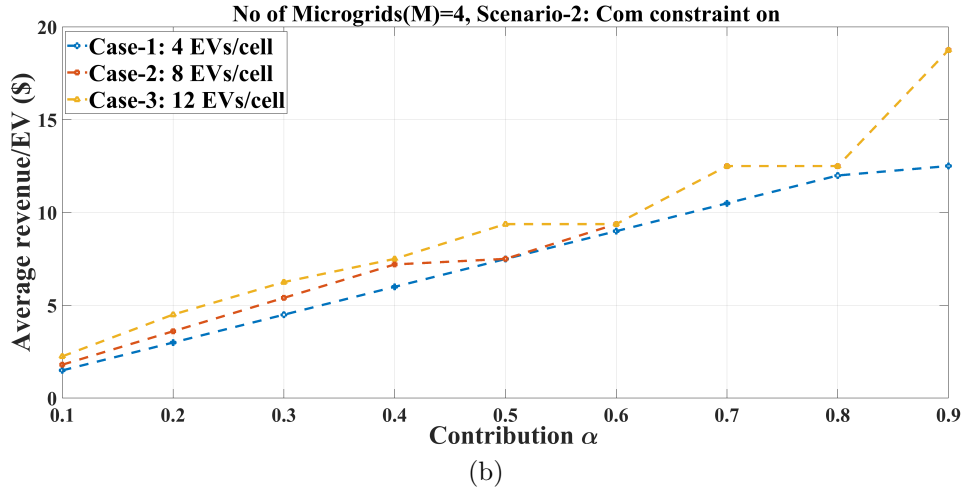
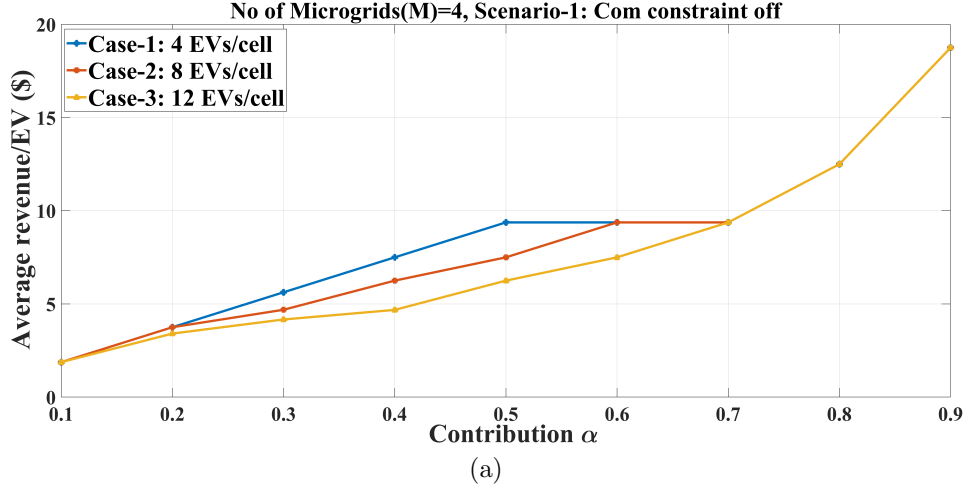


Figure 5.5: Average revenue/EV for four microgrids under different contribution values (a) The average revenue/EV under scenario-1: Com constraint off, for different number of EVs/cell, 4, 8, and 12 (b) The average revenue/EV under scenario-2: Com constraint on, for different number of EVs/cell, 4, 8, and 12

the microgrids resilience is directly affected. Similar impacts happen to the total cost and outstanding energy under case-2 and case-3. In Figure 5.5b, the same behaviour occurs again as in scenario-1, but this time under case-3. At  $\alpha=0.5$  the revenue/EV keeps the same (\$9.5/EV) until  $\alpha=0.6$ , and then increase to \$12.5/EV between 0.7 and 0.8. Finally, average revenue/EV reaches approximately \$19/EV at  $\alpha=0.9$ .

In Figure 5.6, in scenario-1, the total initial energy level  $E_n$  and the number of par-

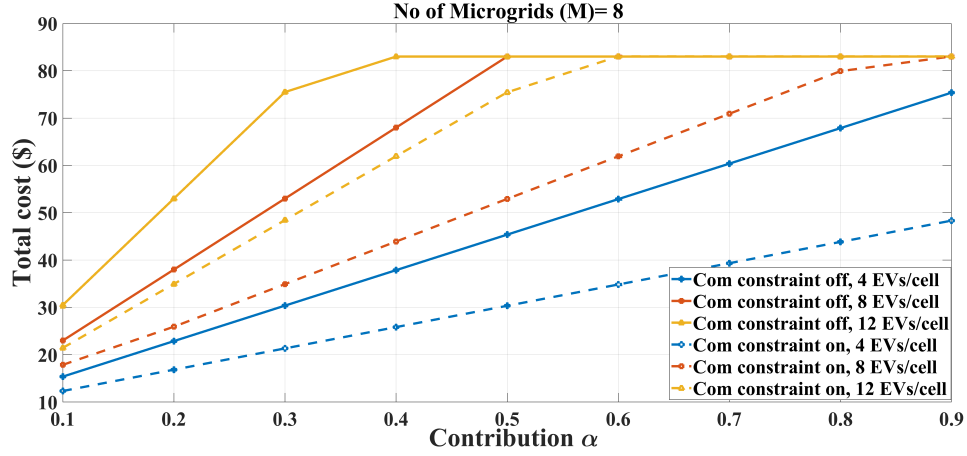


Figure 5.6: he total cost of 8 microgrids under scenario-1: Com constraint off, and scenario-2: Com constraint on, for different number of EVs/cell, 4, 8, and 12

ticipating EVs  $N$  are similar to scenario-1 when  $M=4$ . However, the total microgrids demand is changed to 100 kWh. Similarly, the total cost raises as the EVs contribution value increase, however, this time the total cost saturates at \$84. The fact that the total cost saturates at \$84 under different participating EVs is justified as the total demand is constant under all EVs cases. The change of the total microgrids demand causes the convergence points to be changes as well, particularly at 0.5 and 0.4 when  $N$  is 8 and 12, respectively. For  $N=4$ , the EVs cannot cover the total demand, as the total energy level at any contribution value is less than the total energy demand. This can be seen clearly in Figure 5.7, where the outstanding energy does not reach zero at any point. In Figure 5.8a, the average revenue/EV raises after the convergence point because the EVs can contribute to the power supply request with more energy, and thus not all the EVs are needed. However, in  $N=4$ , since all the EVs are needed and the convergence point is beyond  $\alpha=0.9$ , the revenue of case-1 becomes less than case-2 and case-3 which converges earlier.

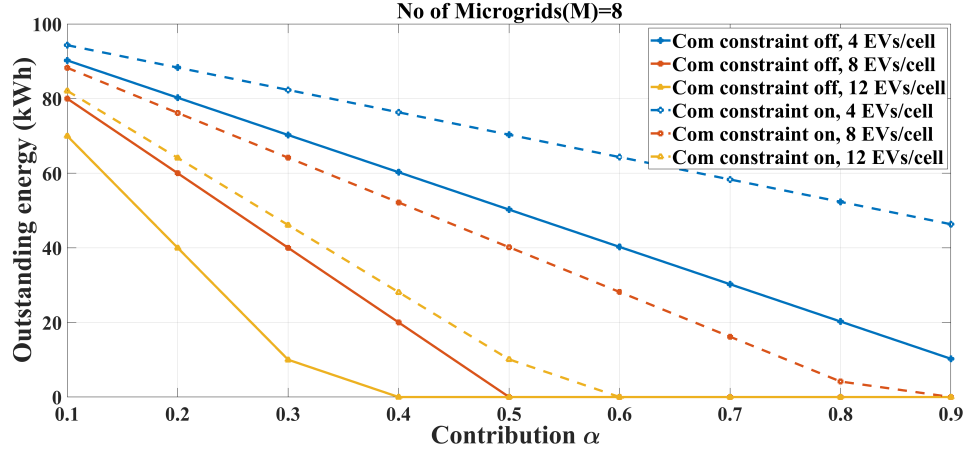


Figure 5.7: The outstanding energy of 8 microgrids under scenario-1: Com constraint off, and scenario-2: Com constraint on, for different number of EVs/cell: 4, 8, and 12

In scenario-2, under case-1: 4 EVs/cell, case-2: 8 EVs/cell and case-3: 12 EVs/cell, the number of participating EVs  $N$  is 3, 5 and 6 with total initial energy level  $E_n$  of 60, 120 and 180 kWh, respectively. When the communication constrain is applied (i.e. scenario-2), the total cost remains unchanged even though the number of participating EVs is less than scenario-1. This is because the total cost is determined by the total energy demand of the microgrids. However, the number of participating EVs and the contribution values determine the convergence points in each case. Furthermore, reducing the number of participating EVs changes the convergence points, and thus affect the total cost, the outstanding energy and the EVs revenue. The convergence points are moved from 0.4, 0.5 (scenario-1) to 0.6, 0.9, 0.3 (scenario-2) when number of EVs/cell is 12, and 8, respectively. Similarly to scenario-1, at  $N=4$ , the EVs cannot cover the total demand, since the total energy level at any contribution value is less than the total energy demand.

In Figure 5.8b, the average revenue/EV raises after the convergence point because the EVs can contribute to the power supply request with more energy, and thus not all the EVs are needed. However, for  $N=8$ , since all the EVs are needed to cover the total microgrids, demand and the convergence point is exactly at  $\alpha=0.9$ . The revenue of case-1 becomes less than case-2 and case-3 which converges earlier.

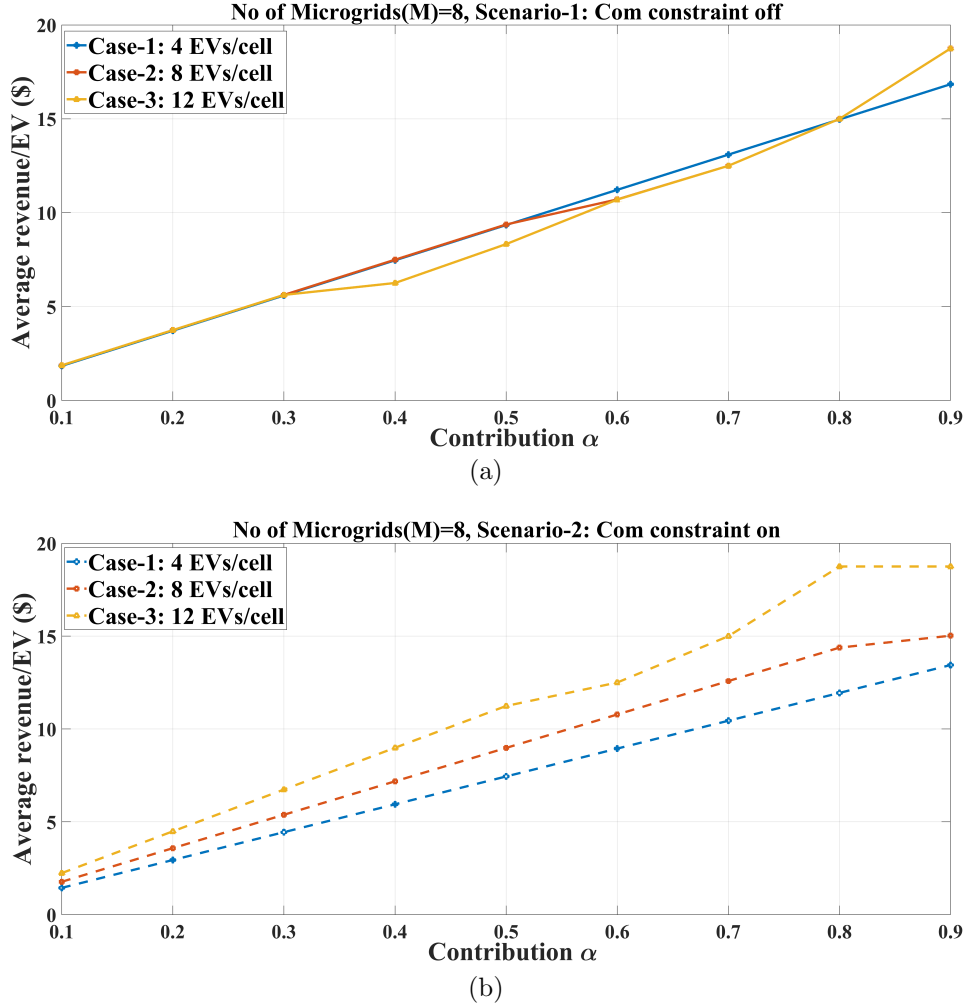


Figure 5.8: Average revenue/EV for four microgrids under different contribution values (a) The average revenue/EV under scenario-1: Com constraint off, for different number of EVs/cell, 4, 8, and 12 (b) The average revenue/EV under scenario-2: Com constraint on, for different number of EVs/cell, 4, 8, and 12

It is worth noting that the MILP execution time depends on the number of participating EVs as well as the number of smart microgrids that request power supply. As the number of EVs and/or the number of microgrids increase, the MILP execution time grows exponentially. This can result in a high execution time for larger scenarios, particularly when the MILP is used for real-time cases. However, in our case which is considered as a small/medium scenario, the execution time to solve the MILP model is around [5-7] minutes under  $N=12$  and  $M=8$ . Although this can be acceptable for our problem, we need to

further reduce the execution time. In addition, increasing the number of constraints, can raise the execution time of the model significantly. This is because adding more constraints to the model makes it harder for the optimization solver to find a feasible solution. In other words, if the optimization model constraints are too stringent, there may not be a feasible solution. On the other hand, if the constraints are too loose, the resultant EVs set may not be optimal.

## 5.4 Summary

The EV batteries are utilized as energy storage systems that can help microgrids in supplying load when the utility grid becomes unavailable due to extreme weather events. This service, which is known as V2G, requires EV participation and reliable communication. This paper has proposed a model to determine the optimal set of EVs to help microgrids in power supply request. The output of the model specifies the total cost under different demand and supplies. The microgrids total demand determines the total cost: \$41.5 and \$84 for 50 kWh (4 microgrids) and 100 kWh (8 microgrids), respectively. on the other hand, the number of participating EVs and the contribution values only determine the convergence points. Moreover, considering the contribution value between 0.1 and 0.9 emulates a real-life case where the EV owner chooses the amount of energy to contribute with. In addition, the EV owners benefit from the situation as they get paid for their services. The results showed that, beyond the convergence point of each case, the number of participating EVs decreases which result in raising the revenue of the EVs. Furthermore, the impact of the communication constraint was studied to filter the participating EVs that do not achieve the minimum required PDSCH throughput. It is noted that considering the PDSCH throughput results in less number of participating EVs when compared to the scenario where no communication constraint is applied. Indeed, that ensures reliable communication channels between the base station and the EVs. However, that increases the outstanding energy of the smart microgrids.

# Chapter 6

## Conclusion and Future Directions

The advancement in communication technology has equipped the traditional electrical grid with new developments such as IoT devices to exchange information over the network. The transferred data helps improve the electricity QoS provided by the electrical grid and transform it into a smart grid. As a micro-scale of the smart grid, smart microgrids inherit the same powerful capabilities from the smart grid. There are three requirements to define the performance of power systems in general and particularly smart microgrid, namely: reliability, sustainability, and resiliency. These major concerns require proactive emergency preparedness and self-recovery solutions. The DGs utilize the DERs to provide smart microgrids with their needed power. However, smart microgrids can suffer from technical issues such as transmission line failures and human errors that can lead to serious hazards. Islanding formation is one example that can be caused by a transmission line failure, where the DGs continue to supply the microgrid without grid supervision. In addition, smart microgrids can operate in a grid-connected mode, where the DGs cannot provide enough energy to the loads and the microgrids depend on the utility grid to obtain the required energy. One of the main problems that smart microgrids can face is transition from the islanding mode to the grid-connected mode while the power grid is unavailable to provide power to the microgrid. There are several reasons that can contribute to the power grid unavailability, such as severe weather conditions that cause serious damages to the transmission lines and distribution stations. Therefore, it is necessary to predict grid-connected events using weather-assisted data to accurately expect the microgrids' transitions when the utility grid is unavailable. This will significantly improve the smart microgrids key performance as mentioned above.

In this thesis, we have provided a three-stage solution to address a major problem that directly impacts smart microgrids reliability, sustainability, and resiliency. That is, we

predicted the transition from the islanding mode to the grid-connected mode. In order to achieve accurate and fast prediction, we implemented a comparative study based on four machine learning algorithms under window sizes up to 10 minutes. Using machine learning models with different kernel functions helped to achieve better performance in terms of prediction accuracy. We showed that GPR models with different kernel functions can predict the next grid-connected transition up to 2 minutes window size with accuracy of 95%. However, SVM model with fine Gaussian kernel predicted the next transition at 10 minutes window size with accuracy of 93% whereas GPR models had 85% accuracy at the same window size. Decision tree model with leaf size of 36 (i.e. coarse tree) had accuracy lower than the mentioned SVM and GPR models, particularly 89% and 85% for 2 minutes and 10 minutes, respectively. However, it achieved better performance in terms of prediction speed and training time than SVM and GPR models. We concluded that GPR model can be the best option to accurately predict the next transition with maximum 2 minutes window size, whereas fine Gaussian SVM model is better for time window beyond 2 minutes. However, decision tree models, particularly coarse tree, is more favorable when prediction speed and/or training time are more important than the accuracy.

The prediction data of the grid-connected transition is considered as a highly time-sensitive data, and thus it needs to be managed quickly through the communication infrastructure. This will leave enough time for the control unit to consider a mitigation response. Thus, we proposed a data aggregation mechanism using a multi-class queuing system that ordered the packets according to the packet load priority. The data was clustered based on the time-sensitivity using k-means algorithm into three clusters. We found that the number of messages clustered as highly time-sensitive were the lowest when compared to the moderately time-sensitive and delay-tolerant messages. Moreover, using the TCP protocol to transmit the highly time-sensitive messages has reduced the packet loss rate by 7% while minimizing the queuing delay by 93% when compared to the naive solution where no aggregation mechanism is considered prior to the small-cell base stations. We have observed that the smart microgrids distribution over the cells did not affect the queuing delay at the macro-cell level.

The urgent messages are received by the base station; the station is informed with the microgrids that are expected to switch to grid-connected mode during utility grid unavailability. A power supply request is broadcast to the EVs, to discharge their batteries into the microgrids, within the coverage area to participate in the request. We found that using the down-link throughput as a criterion to select the EVs has reduced the total cost and increased the revenue/EV as the number of participating EVs became smaller when compared to the situation of excluding the throughput criterion. Although considering the throughput performance provided reliable communication channels between the base

station and the EVs, it is observed that with such consideration the outstanding energy of the microgrids has increased. Thus, there is a trade-off between the reliability of the down-link channels and the outstanding energy of the microgrids.

For future works, we are considering to improve the prediction accuracy of the grid-connected events by investigating new machine learning techniques that can fit the problem under study. Moreover, using deep learning techniques such Recurrent Neural Network (RNN) can be useful since the data used for predicting grid-connected transitions is time series data. In addition, integrating local and active methods with AI techniques can be another solution for predicting grid-connected events. Furthermore, studying the loads consumption pattern of multiple smart microgrids at different time of the year can result in higher prediction accuracy and prediction speed.

There are different methods that currently being studied to reduce the delay and enhance the PLR of the urgent messages. For instance, reinforcement learning technique is investigated as a promising solution to address the reliability of the communication channels. That is, reinforcement learning method can help to choose the best communication channel to be used by learning the behaviour of each link in different settings. However, reinforcement learning method can take long time to learn the environment behavior under different settings. Therefore, using the imitation learning technique can be considered as a possible alternative to distribute and transfer the knowledge gained by the expert (i.e. reinforcement learning). Moreover, understanding the behavior of the collected data and the communication channels at different time of the day can help to choose the best packet scheduling technique to be used.

There are various methods that can be considered as mitigation responses in case of power outage due to the utility grid unavailability. For instance, the EV batteries can be utilized to carry the energy between a fully charged microgrid and another microgrid with power shortage. However, it is necessary to set policies that can clearly define the obtained benefits for both participating parties: the smart microgrids and the EVs. Execution time of MILP is another issue that need to be addressed. The execution time for the presented MILP model in chapter 5 grows exponentially as the number of EVs and smart microgrids increase. One way to resolve that can be with reducing the number of constraints and/or running the model on small scenarios. Using fewer constraints, the problem can be solved with less computation time and the MILP model can be incorporated in real-time decision making. However, that can result in non-optimal solutions that might be unsuitable for critical cases where power outages affect many microgrids and optimal solutions are needed. Genetic Algorithm (GA) approaches are suggested by recent studies as an alternative method to MILP achieve near-exact solutions that can be more suitable for real-time problem.



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# APPENDIX A

In Chapter 4, every point in the results is the average of 10 runs with a confidence interval of 95% as calculated in the following equation, where  $\bar{x}$  is mean and  $SD$  denotes standard deviation and  $N$  denotes number of samples.

$$error = \bar{x} + \frac{t * SD}{\sqrt{N}} \quad (6.1)$$

Since the total sample size is less than 30, t distribution table is used instead of z-table. We plotted the marginal error bars for crucial metrics that determine the efficiency of overall system such as the queuing delay and the packet loss rate.