Artificial Intelligence Framework for Smart City Microgrids: State of the art, Challenges and Opportunities

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***Abstract*—Smart city concepts have attracted substantial attention over the last few years. Smart cities utilize the advancements in Information and Communication Technology (ICT) to enhance the quality and performance of services, costs and efficiency. Microgrids has been viewed as a potentially powerful building block in the development of smart cities. Motivated by the opportunity for the deployment of microgrids in smart cities, this article surveys the factors leadings to the gradual adoption of microgrids into mainstream electrical utilities grids, enumerates the benefits that drive this growth, identifies the challenges that are hindering the benefit-capture of distributed energy generation inside microgrids and provides a framework for the application of Artificial Intelligence (AI) to overcome these challenges. We also provide a simulation framework scenario and list some useful data sources that can help to build up AI capabilities within utilities. A brief description is also provided of the scalable BluWave-ai framework that leverages deep learning in the data center, AI inference at edge computing nodes and IoT sensors to optimize the benefits from microgrids at the residential neighbourhood, campus, enterprise, and community level.**

***Keywords*—Microgrid, smart grid, smart city, net zero, solar and wind energy, artificial intelligence.**

I. Introduction

The maturity and increasing availability of renewable energy is moving power generation geographically proximate to the locations where it is consumed. This has led to the rise of microgrids, which can be defined as small-scale power grid that operate independently or in conjunction with the area's main electrical grid [1][2]. Microgrids typically have their own power resources, generation, metering and loads and can employ definable boundaries to be viewed as a small-scale localized station, which is separated from, and yet interconnected with the main electrical grid.

Smart cities exploit the most advanced technological developments to add value to the existing services and its dwellers. Vehicular cloud, IoT, smart grid, Edge computing, and any smart system are an important player in smart cities evolving [3]. Having microgrids involved in the smart city process through renewables, efficient generation, smart metering and loads augments the capabilities of the platform without enquiring additional costs. Microgrids facilitates a number of key operations including resiliency, distributed generation, efficient use of resources, and dependability which will ultimately shape the future of electricity usage and trading [4].

The ever-increasing demand for clean, sustainable, reliable, secure, efficient, and stable sources of energy requires the integration of more renewable resources into the existing power system. These goals, many of which operate at cross-purposes, can only be accomplished through improvements in technology, such as smarter power grids (i.e. microgrids). However, such integration poses several obstacles and challenges including complex, end-to-end control strategies and consumer participation [5].

The researcher in [5] highlighted the fact that siting transmission has become more challenging than before and microgrids are expected to become the norm. Consequently, both utilities and consumers will experience a metamorphosis involving localized generation, storage and power consumption, and we anticipate that this evolution will require new smart grid control infrastructure for this vision to be fully realized.

The conventional electric power systems is going through a radical change because of increasing demand for electric power worldwide, and a new urgency to reduce carbon emission. Both these goals can be achieved by incorporating more renewable power generation into the grid, and by leveraging innovative smart grid information and communication technologies.

Microgrids are experiencing major technology development, and we are witnessing more adoption as enhanced smart grid technologies emerge [6]. Microgrids are unlike smart grids as they are still in the early stage of developments and require more research and experimental deployments to refine them. Microgrid technologies benefit from existing R&D on smart grids and smart city sub-systems. This paper focuses on the hurdles to the benefit-capture of distributed energy generation inside microgrids and provides a framework for the application of Artificial Intelligence (AI) to overcome these challenges. Moreover, real-world simulation scenarios and a list of useful data sources required to build up AI capabilities within utilities using scalable BluWave-ai

[7] framework that leverages deep learning in the data center, AI inference at edge computing nodes and IoT sensors have been presented.

The rest of the paper is organized as follows: Section II provides a summary on microgrids enabling tech trends. Section III introduces the sensor data analytics module. Section IV provides AI applicability and tasks. Section V discuss in details the simulation scenario and BluWave-ai architecture implementation. Finally, Section VI concludes the paper and provides further research directions and limitations.

II. MICROGRIDS ENABLING TECH TRENDS

Microgrids can reduce carbon emissions through integration of renewables, reduce long distance transmission line losses, decrease the cost of the power mix, and enhance resilience of strategic loads against extreme weather and other threats; and boost reliability for customers. These technologies accrue benefits to both utilities and end users alike.

Two other trends that have opened new opportunities for AI are the penetration of smart meters at residences and other community buildings in the electric grids, and the availability of massive new computing capabilities in the cloud. Edge computing hardware nodes are also available in the microgrid as well as in private and public cloud data centers. AI application can significantly leverage the new computing infrastructure and the large amount of data sets that are newly available, to develop and train AI models and deploy them inside the microgrid.

According to the *US Energy Information Administration*, there are over 77 million residential smart meters installed in the US by 2016 and this is expected to hit 90 million by 2020 [8].

The decentralization of power generation also requires local computing capabilities that do not need to be as powerful as the central predictive systems. However, the edge computing nodes need to be able to execute pre-generated machine learning models and filter through and make sense of local signals to pass on upstream t the central microgrid controller.

Edge computing supports the efficacious deployment cloud computing systems by performing data processing near the source of the data (i.e. within the microgrid, or one hop away from it) [9]. Moreover, the advent of AI inference at edge computing nodes also allows for the sampling of data at much higher intervals than the typical 15 to 60-minute time frame in many utilities in North American and Europe. Such improvement (Sub 1-minute level), overcome the limitations of data network congestion, cloud storage, and offline computing. Real time inference at the edge, allows for the early reduction of the overall data size by the fast edge-based AI operations.

The early stage AI inference at the edge reduces the communications bandwidth required between sensors and the central datacentre, enables effective decentralization and scalability and makes the system able to react in a timely manner by performing analytics and knowledge generation at or near the source of the data. By assuming that continuous network connection is not available, the entire system becomes more resilient and cost effective as bandwidth and connectivity requirements are minimized. Data that is produced at the edge of the network can processed locally. Edge computing is discussed in greater detail by Shi et al in [10].

The high CPU and storage servers that would traditionally require to be installed on site at the microgrids to support AI and ML were a prohibitive expense, not only due to the cost of the hardware and the software required to make use of it, but also due to expensive server management experts who would be required throughout the lifecycle of these machines.

The advent of cloud computing means that ML-capable machines are now a commodity, and the chief bottleneck is no longer cost, but rather bandwidth. Cloud computing in the energy service industry is discussed further in [11], however, the rapid expansion of cloud computing facilities has made localized servers obsolete and allows for remote processing of the heavy number crunching required. Indeed, edge computing is a necessary requirement to leverage cloud computing, as it reduces the bandwidth required, which is the key constraint for accessing cloud computing infrastructure.

There are other factors that make smart city microgrids a compelling proposition. For one, renewables are dependent on climate and weather, which are hard to predict in the short term, and yet relatively predictable over the medium and long term. New technologies for energy storage are now available, and maturing at a rapid rate, which make it possible to smooth out the demand-production gap between the energy delivered by renewable energy source, and the energy requirements of the local microgrid. These storage technologies also make it possible to leverage power from the main grid, by purchasing more than the microgrid's requirements during cheap (off-peak) times, consuming by discharging batteries during higher hourly energy price periods and furthermore have the option of selling back excess energy produced from its own renewable energy panels during expensive (peak-usage) times or discharging from its storage into the main grid during these periods.

This buffering of energy requires it to be purchased or generated during lower energy cost periods and stored locally. This stored energy is then released during higher pricing periods. This benefit the energy users in the microgrid, while also helping city scale of national scale utilities by smoothing out daily production over the very variable daily user loads.

III. SENSOR DATA ANALYTICS

Distributed AI edge-based inference allows for utilizing all available data at high bandwidth to make better localized decisions to move towards carbon neutral smart city goals. This is based on both the AI edge inference and machine learning on a subset of the data at central data centre. Hence, there are some assumptions that we can make about the nature of the data, which is a critical enabling factor for injecting intelligence into the microgrid.

- There are two types of sensor data sources those from generation and from consumption nodes in a community.
- The other two type of relevant data that are real-time are micro weather pattern data, as well as minute by minute, hour by hour, day over day electricity market pricing data.
- Effectively real time intervals for electrical grids is ~1 min. Unfortunately, there is insufficient storage and computing resource at edge aggregation points to ingest the complete data available at these intervals from the multiplicity of sensors of both the consumption and generation side. Today, in most jurisdictions, data is only polled every 15-60 minutes, leaving large gaps in optimized network level energy management optimizations.
- In essence, the prediction window for 1 day ahead, 5 hours ahead and 1 hour ahead for electrical dispatch is not optimized which leads to over usage of fossil fuels vs renewables.
- Because of the heterogeneity of data sources there is a further complication at aggregation points at edge nodes to ingest and utilize the data before using it in the AI pipeline to make better decisions.
- Given the diverse conditions of uncertainty under which predictions are being made, the system has to predict based on past patterns and self-learn based on current patterns to optimize future decisions with robustness.

It is worth noting also that as microgrid telemetry data arrives up to a minutes later than when it is generated (under the lowest latency scenario), there are interesting edge cases where power provisioning may exceed or fall under the actual power required and so the AI system needs to take into account inertia and momentum associated with generation, load and storage availability levels.

IV. AI Applicability and Tasks

A) *AI Applicability*

A robust evaluation of AI for microgrids in smart cities should take into consideration whether the following benefits are captured; (1) can renewable energy production capacity for a microgrid be predicted based on local weather information in close to real-time; (2) can battery storage and discharge management be optimized to take advantage of cheaper (off-peak) energy prices available from the grid; (3) can the energy generation being provided by renewables be blocked when the battery storage banks are fully charged and the energy load is less than the generation; and (4) can load elements be managed based on AI predictive to reduce consumption of energy in real time to smooth out the demand side curves.

The failure scenarios that the AI system must seek to avoid include the following:

1. *Under-provisioning of power.*

This occurs when the power available is less than the load. In most circumstances, power should be available from the main grid to fill in the supply gap; however, in real-life scenarios where this is not possible, it can lead to brownouts or blackouts.

2. *Overprovisioning of power.*

When the battery storage banks are fully charged, and there is more energy generated than is being used due to potential overprovisioning of local fossil generation inside the microgrid due to poor predictive on load and renewable generation. This scenario has a poor economic outcome for the microgrid and it may in some cases overload the main grid to which the microgrid is connected.

3. *Virtual stored charge value.*

When the battery storage contains charge, and the main-grid is supplying power at off-peak prices, there exists an opportunity to reserve the battery charge for when the peak-price power period begins for main grid supplied energy. Discharging the batteries early can result in opportunity cost. Conversely, charging batteries using grid power prior to the lowest pricing may result in storing energy at an average market cost. The AI needs to optimally discharge and store batteries based on community needs while reserving capacity to charge batteries with either renewable energy or cheap off-peak grid power.

B) *AI Tasks*

To test the efficacy of AI methods, we have identified the following tasks as being critical for an effective smart microgrid system:

1. *Energy Usage*

Prediction of energy usage (demand side) based on a holistic set of metrics associated with time of day, vehicle traffic patterns, human presence density, weather, commercial and industrial activity and historical energy usage information.

2. *Energy Production*

Prediction of energy generation based on a holistic set of metrics associated with installed generation capacity, salient weather signals and historical generation information.

3. *Savings*

Estimation of net savings or loss associated with discharging available charge in batteries based on price of energy stored originally, and compared with future energy generation and usage predictions, in the light of the prices of the energy mix available. In addition, estimation of net savings or loss associated with charging available battery capacity based on current prices and future energy generation and usage predictions, in the light of the prices of the energy mix available.

V. Simulation Scenario and Architecture

A) Simulation Scenario

A minimal microgrid model, for simulation or testing purposes would require a connection with the main grid, one or more sources of renewable power (ex: solar, wind, hydro, biomass, and biogas power system), storage, and multiple power consuming entities. The model also describes minimal configurations for a residential (Figure 1), neighbourhood (Figure 2) and campus/community (Figure 3) simulation. These configurations provide realistic simulations that can be used to theoretically test AI algorithms, which can draw real-life data on consumption, local generation and external factors (i.e. weather, market pricing and traffic) to simulate microgrids, prior to constructing them.

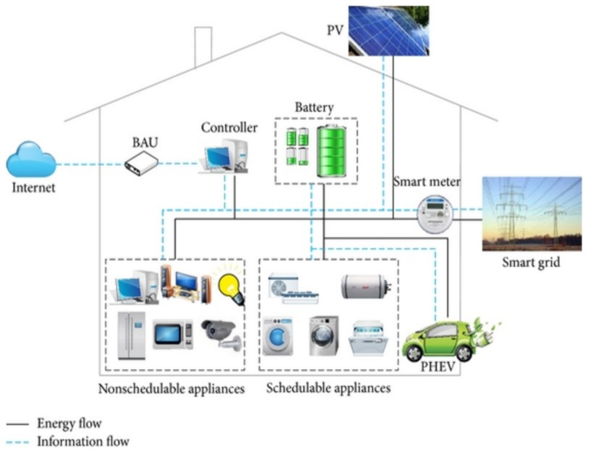

Fig.1: Residential microgrid model

In this research, we focus on a neighbourhood model as that is the fastest growing, and most commonly found configuration in real-life communities that take advantage of renewable power sources. The neighbourhood model can be adequately represented by a simulation that supports the following configuration: 500 houses neighbour, 200 houses with 5kW solar installation each, and 125 houses with battery capacity of 5kWh.

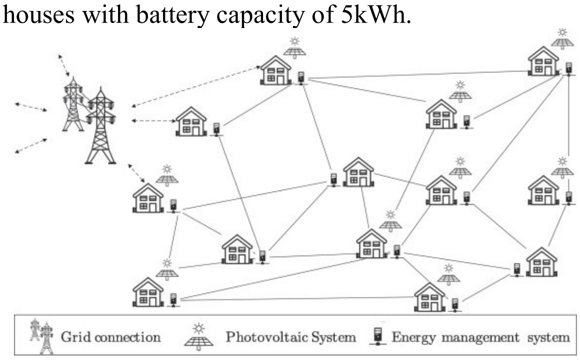

Fig. 2: Neighbourhood microgrid model

The primary hard constraints are the power generation capability and the storage capacity. The simulation also has a simplifying assumption that sufficient power is available from the adjacent main power-grid on an "as needed" basis to more than cover all microgrid needs during periods of zero renewable generation and all storage being depleted. However, this assumption may not hold in all circumstance, and may require further capacity modelling capabilities to adequately support scenarios involving remote communities, or those with more limited external power connections. This is a typical soft constraint that microgrid managers may need to work with; however, this is out of the scope of the current paper.

Most localities also have hourly (or more granular) pricing fluctuations based on predicted demand and available supply which generally follows the demand side peak and off-peak consumption, but can substantially vary hour over hour, day over day, season over season. With the increasing penetration of electric vehicles into the automobile marketplace, there is also the opportunity for households to employ their cars as a storage repository for energy at appropriate times. This energy may be used locally within the microgrid or it may be moved such that stored energy in the car is made available to dense downtown locations where that storage can assist the local substation with suitable quantities of discharge to support both the needs of the consumer and utility.

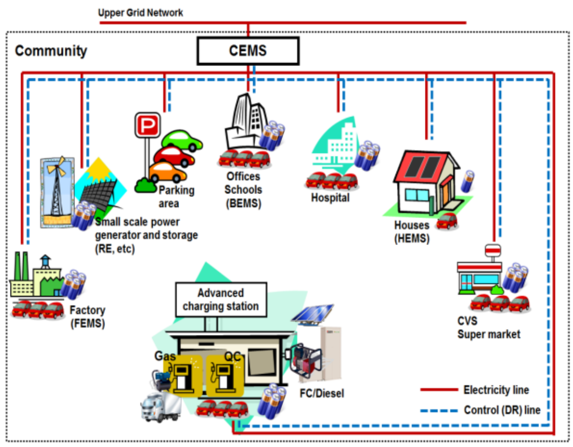

Fig.3: Community microgrid overview model

We are recommending that this be taken into consideration in the pricing model to provide an intermediate price-level for households using in community microgrid storage or generation (could belong to private citizens or the microgrid operator) when compared to the higher cost of the main grid, and the lower cost of renewable energy that they product themselves.

Based on the dynamics articulated above, each microgrid will have six levels of theoretical energy pricing (at a minimum), as follow:

1. Own-residence renewable power (cheapest).
2. Own-residence battery storage.
3. Community grid power.
4. Community battery storage.
5. Off-peak main grid power.
6. Peak main grid power.

The difference between the utilization of power directly, and the power stored in the battery is due to the degradation that the batter suffers from due to repeated charging and discharging cycles. These simulation configurations have the following conditions in common:

- To move towards the goal of carbon-neutral communities, ideally all power consumption and generation are done locally in a confined geographical space, which is generally similarly affected by local weather that impacts generation of local power be it from solar or wind.
- Typically baseline sources of power in a state-wide or province wide grid, tend to have a base layer, provided by nuclear, coal or hydro power, with a fluctuating overlay that is built up from renewable sources as well as peaking fossil fuel local sources to deal with peak loads.

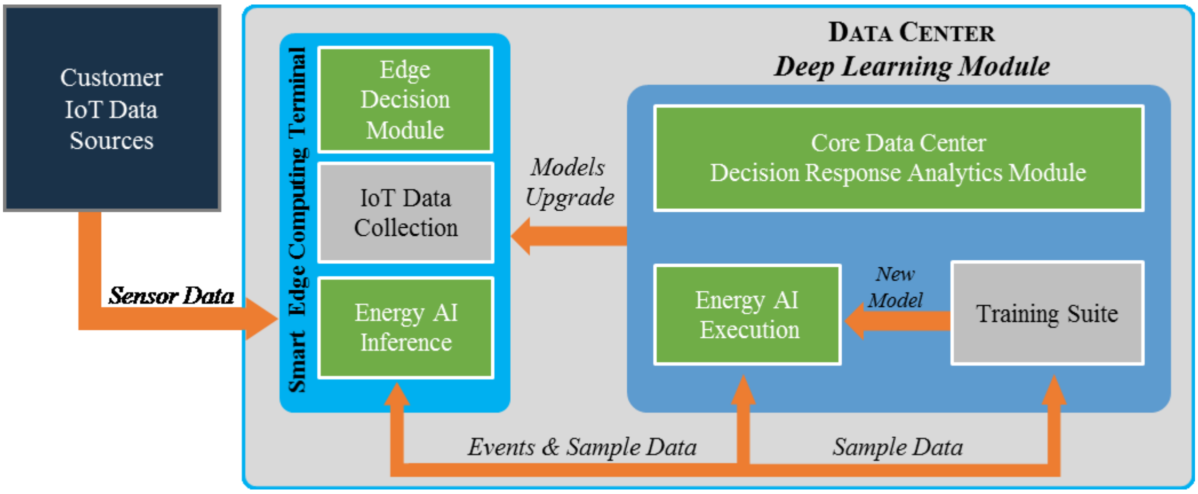

Fig. 4: BluWave-ai Edge and Data Simulation architecture

B) Simulation Architecture and Implementation

We assume that the telemetry data from the individual residences are collected in a central control room and instructions to the renewable energy systems, and storage systems are processed directly. We anticipated also that all communication can only take place once a minute, and that communication can happen bidirectional. An overview of BluWave-ai Edge and Data Simulation architecture is shown in Figure 4.

Our implementation of the Smart Microgrid Controller (SMC) is based on a framework that utilizes best-of-breed open source tools for data capture and aggregation, off-line analytics and real-time control shown in Figure 5. Our reference implementation consistent of: (1) sensor data capture from MQTT and REST sources, (2) aggregation of sensor data into Apache Cassandra, (3) Apache Spark for large scale data processing, (4) Custom ML models for price optimization on the microgrid, and (5) Real-time smart system to orchestrate microgrid generation and storage elements.

This reference implementation is designed for real-world deployment, while providing a compartmentalized workflow that can enable researchers to test out different AI and ML implementation to arrive at an optimal model configuration. These models can then be pushed down to the residential level to operate located in the same place where generation, storage and power load dispatch occurs.

C) Control Techniques

The linear–quadratic–Gaussian (LQG) [12] control problem is a fundamental optimal control problem. It captures the uncertain linear systems (load and generation capacity) disturbed by additive white Gaussian noise (i.e. weather status, especially related to sunshine and wind), having incomplete state information (i.e. not all the state variables are measured and available for feedback due to latency between the sensors and the central control machinery) and undergoing control subject to quadratic costs.

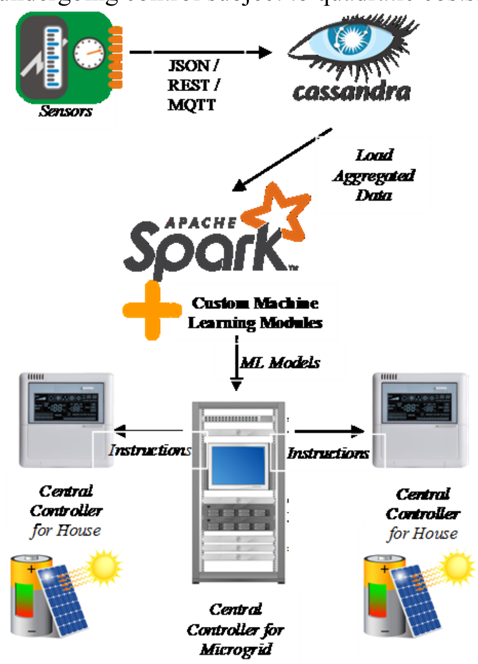

Fig. 5: Smart Microgrid Controller (SMC) implementation framework

The solution constitutes a linear dynamic feedback control law that is unique, easily computed and with a simple implementation. One limitation of this model is that although it provides an excellent solution for the provisioning problem, it does not take into consideration differential between energy pricing.

Indeed, this is a recurring characteristic of all eleven techniques that are surveyed by Mahmoud et al in [1]. We argue that an economically viable AI deployment for Smart Microgrids needs to take into consideration the differential cost of different power sources, and thus to be complete, must also represent renewables, battery storage, external factors and the temporal gap between sensor data being delivered and the instructions provided by the central controller.

We have limited ourselves to studying the factors that are salient for the application of AI to optimize the economic considerations in smart micro-grids. There are many other design and control elements that have not been touched upon, and we recommend Cañizares, et al [13] which provides a comprehensive overview of the collateral issues.

VI. Conclusion and Future Direction

In this paper, we surveyed the key issues that can support an economically viable adoption of AI enabled microgrids in smart cities. Our research has also established that given the diverse variable inputs on the generation side, demand/consumption side, weather-based variability and finally pricing impact on the instantaneous value of microgrid generated energy, microgrid stored energy and energy available from the main grid, the benefits of microgrids and AI are compelling, and worthy of further effort. By building in the pricing and temporal factors for microgrid management, we have set up our evaluation to solve economically-relevant problems that go beyond optimal provisioning of power.

The research has also provided a minimal simulation framework at the residence and community level that leverages edge computing effectively and have also created a proof of concept that is scalable and sensitive to the low bandwidth and networking-resource-poor reality associated with incumbent deployed grid networks. This proof of concept has been reified by the BluWave-ai research group and is currently in the process of being trialed in three Canadian microgrid test beds. We are currently approaching this research as a centralized control problem; however, we are also leveraging cloud computing paradigms to make the reference implementation easy to adopt for microgrid management. We have follow-on research which takes advantage of edge computing to shift the data filtering, feature aggregation and machine learning execution down to the residential level by collocating this server where the data is being generated. A plan to add more depth into inter-microgrid interactions by modelling the capacity soft-constraints presented by the grid interconnections between the microgrids is underway.

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