Using Embedded Systems and Artificial Intelligence for Power Control and Forecasting in Multiple Microgrid Networks

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Introduction

The climate crisis requires major changes in the electrical grid through transitioning from centralized fossil fuel sources of generation to renewable energy. According to the Intergovernmental Panel on Climate Change's 6th Assessment Report, solar photovoltaics (PV) and wind energy are among the most effective and low cost solutions to reducing greenhouse gas emissions [1]. However, these renewables introduce new challenges due to their intermittency in generation [2]. Moreover, many of these sources are commonly integrated with the distribution grid to supply power locally, such as with rooftop solar and lithium battery energy storage. These locally deployed technologies are known as distributed energy resources (DERs), and they further complicate renewable integration due to their vast number which is incompatible with the conventional notion of centralized power plants. At present, grids with high DERs either overproduce energy or must still rely on fossil fuels to meet demand. To address intermittency and decentralization of renewable energy, DERs must be controlled (e.g., predicting load, generation, scheduling energy storage). A smart grid aims to achieve this task, and thus effectively integrate renewable energy.

A microgrid is one form of a smart grid. It consists of a localized combination of DERs, energy storage, and loads. For example, a college campus with PV and battery storage could be a microgrid [3]. A microgrid behaves as a single system from the main grid perspective, and it can exist isolated (e.g., in remote locations) or have a utility connection to the rest of the grid. During a failure scenario, grid connected microgrids are capable of disconnecting power and "islanding" from the main grid while still providing power for some loads [4]. The islanding operation enables the overall grid to be modularized and resilient to outages.

To reliably manage the operation of a microgrid and integrate DERs, it also requires a control system [5]. The control of a microgrid consists of a sensing layer and computing later. The sensing layer uses embedded systems to collect data from the environment and operation of the microgrid, including power generation, load, and weather [5]. The computing layer uses artificial intelligence (AI) to analyze this data and provide relevant outputs to automate the control of the microgrid and optimize its operation.

A combination of neighboring microgrids can be joined to form a multi-microgrid network (MMG). MMGs assist in shared usage of individual microgrids' distributed energy resources. MMGs can reduce operation cost by transferring power to each other when needed [6].

Literature Review

Current literature regarding microgrid infrastructure can be categorized into simulation, embedded systems in the sensing layer, AI in the computing layer, and communication between MMGs. Microgrid management is split into three forms of control [3]. Primary control uses local voltage and current measurements to handle real-time power control. Secondary control deals with energy management, reliability and economics of an individual microgrid. Tertiary control coordinates MMGs and a host grid. Centralization for MMGs entails a central controller provided with relevant information about the microgrids, forecasting data to optimize distribution of resources according to objectives for the entire grid [3]. Distributed individual microgrids communicate to a central MMG's data collection cloud used to minimize MMG operational cost. Disrupted communication links mean individual microgrids run their own respective optimizations [6].
Hardware-in-the-loop simulation (HILS) uses electrical emulations of sensors and actuators to test real-time embedded systems, as opposed to real-time-digital simulation. HILS can accurately model electromagnetic transient phenomena in real time. Jeon et al. used HILS to test and verify the results of how AI and the microgrid management system communicate [7].

Diefenderfer *et al.* demonstrate use of embedded systems in the sensing and control layers of a single-home residential microgrid [8]. Sensors included "AcuRev2020" voltage and current meter to monitor circuit breakers and appliances (which sends data over HTTP protocol), "Belkin-WeMo" IoT connected power relay and meter, "Enphase-Enlighten" power meter for PV installation, smart IoT connected thermostat, and weather station consisting of an anemometer, rain gauge, wind vane, thermometer, barometer, and humidity sensor. Single-home microgrids are currently feasible and their sensor technology should be expanded for use in larger microgrids. As of 2016, the US already had 77 million smart meters installed for residential use [5]. For microgrids based on renewable energy, the sensing and forecasting aspect of control is crucial, because the power generated by renewables is very weather dependent [8].

Gaps exist in the application of HILS to MMG networks, lack of alternative optimization techniques for forecasting load and generation, and power allocation based on these forecasts. This issue emphasizes the implementation of AI for control of MMGs as a better alternative. In particular, machine learning and deep learning are subsets of AI which could forecast more accurately through the use of mass amounts of data collected by embedded systems.

Research Question

This study aims to answer the following research question: how can using embedded systems and AI in tertiary control of power allocation, load and generation forecasting of a PV-based MMG network be improved in terms of forecast accuracy and energy loss? In the context of this question, forecast accuracy refers to the minimization of root-means-squared error (RMSE) between predicted and actual data for load and generation. This will be achieved through the mass collection of data, focusing on factors causing trends in fluctuating energy demands and supply. Effective power allocation in the tertiary layer between microgrids aims to minimize load curtailment and maximize the time loads receive power. Energy losses include efficiency loss, generation curtailment, and loss from battery charge, which is to be minimized. The pilot study aims to build the preliminary infrastructure for the embedded system and HILS, develop the precursory programs for the simulation and use of AI, and generate initial graphs to describe how the metric of prediction accuracy works.

Social Relevance

To facilitate transition to stronger reliance on solar energy, PV-based grids must be optimized in a way that lets us modularize grid systems. Microgrids aim to effectively integrate DERs, which comprise a major source of renewable energy. According to the US Department of Energy, residential rooftop solar alone could supply up to 650 GW of power which is equivalent to the electricity usage of 531.4 million homes annually [9],[10]. This study will analyze a dataset called the SMART* Trace Repository, which analyzes house and apartment microgrid data for varying homes across western Massachusetts from the years 2014-2017 [11]. The results of this study could be applied to a microgrid for UMass or for statewide expansion of renewable energy infrastructure in accordance with the Massachusetts Clean Energy and Climate Plan for 2025 and 2030 [12].

Introduction to Hardware-In-The-Loop Simulation

This study uses hardware in the loop simulation (HILS) as its primary methodology. It consists of emulation of hardware such as that of a microgrid to test a system in real time. Two Raspberry Pi 4s will be portable and easily mutable devices to be used to simulate a multiple microgrid (MMG) network, as shown in figure 1. One represents tertiary control as mentioned in the research question (coordination of MMGs with respect to power allocation), and the other abstractifies the microgrids (forecasting of load and generation for each individual microgrid on the network). An embedded system will be used to collect weather data and estimate solar generation for a microgrid. This helps test various models and algorithms for the MMG network without needing to heavily change the physical architecture of an MMG network. It also enables estimation of system efficacy before full implementation.

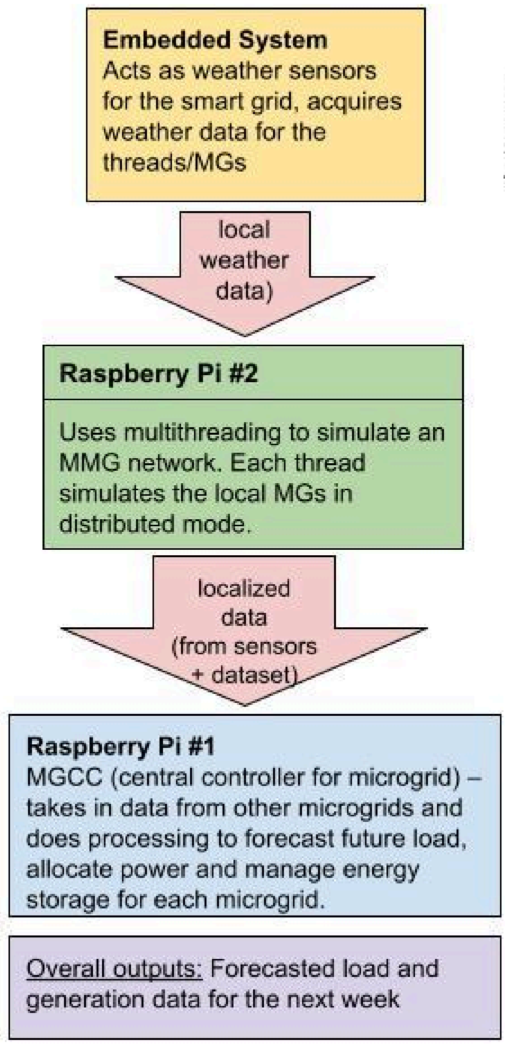


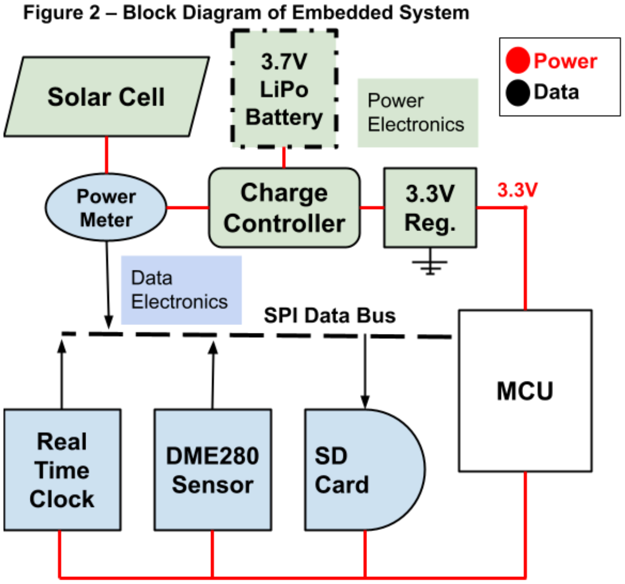
Figure 1 – Description of HILS setup with respect to hardware

For the full study, four microgrids will be simulated (microgrid no. 1-4) corresponding to the location of the following universities: UMass Amherst, Smith, Amherst College, and Mt. Holyoke. Three MMG network scenarios will be tested; scenario one will test microgrids 1 and 2; scenario two will test microgrids 2, 3, and 4; and scenario three will test all four microgrids. Each scenario will run five cases, the first four cases will use AI tertiary control and in the last case each microgrid will operate individually using an abstracted primary-secondary controller with no AI. The four AI controller cases will test combinations of two different types of classifiers and two different types of regression models. The five-case system will be included in the full study, and the pilot study will solely compare the two types of regression models, as later described in the *Data Analysis with Artificial Intelligence* section.

Data Collection with Embedded System

To improve the study's accuracy, the HILS will use weather and solar data collected in Western Massachusetts using an embedded system device (figure 2). A voltage and current sensor will monitor the power output (W) of the device's PV solar cell and a BME280 weather sensor will measure temperature (°C), relative humidity (%), and atmospheric pressure (hPa). The power output of the solar cell can be converted to irradiance (W/m^2) by dividing by the panel area and factoring in PV cell efficiency. To log data, a real time clock and SD card module are employed which will record data to a CSV (comma separated value) file with timestamps for the minute/hour/day. An ATmega328p microcontroller is the computer used to control the sensors, SD card, and clock via a serial peripheral interface (SPI) data bus that connects the secondary devices. Data will be collected for 30 days, with collection every five minutes (to be averaged later to an hourly rate).

Figure 2 – Block Diagram of Embedded System



For each university, relevant authorities will be contacted for data collection in the full study. One embedded device will be placed on each campus situated free from disturbances and with access to large solar irradiance (away from trees and buildings). The data collected will be made publicly available with the consent of each university. The pilot study will involve analysis of an online dataset (described in the next section) rather than the device sensor data.

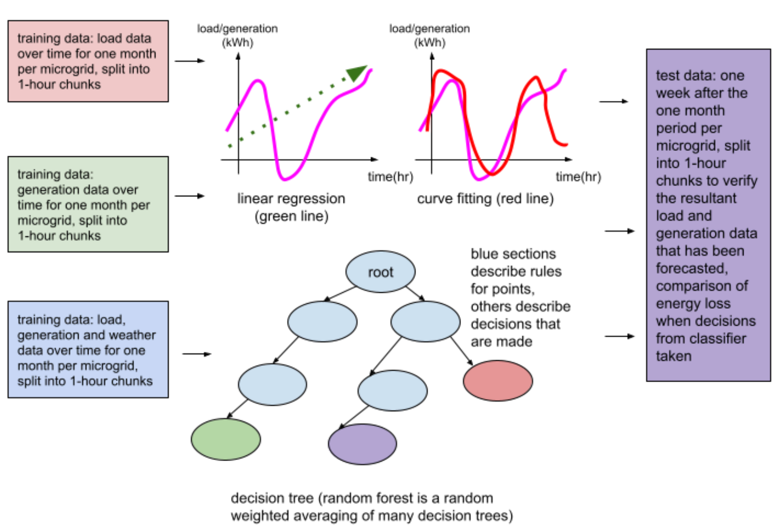
Data Organization

The hardware simulation's communication and analysis relies on load, generation, and weather data to inform decision making for power management. This study will use the SMART* dataset, an online collection of home, apartment, microgrid and solar data (in CSV format) from varying locations within western Massachusetts. The data being analyzed is load (kWh), generation (kWh), temperature (ºC), wind speed (mph), relative humidity (%) and atmospheric pressure (Hg) data from the dataset for the pilot study, cross referencing with collected embedded system data in the full study. It is publicly available but for privacy reasons the locations are not specified to us. To simulate each microgrid, processed files representing month-long samples of the data taken at hourly intervals will be stored on the Raspberry Pis. Python will be used to extract the data from the CSV files and send the data between the microgrids via TCP/IP, a protocol used to communicate via Wi-Fi, likely writing the server and client side code in C to be called by the Python code as needed. Models for regression and classification, as described later, will be created using the SciPy library in Python and results plotted with Matplotlib.

Data Analysis with Artificial Intelligence

The simulation's use of artificial intelligence (AI) is divided into three tasks: forecasting load, forecasting generation, and classifying actions to take for power management. Power management involves shifting load and power between microgrids, dissipating excess power, scheduling discharge and charge of batteries, shutting off loads, and using the host grid's power to supplement unfulfilled load. Forecasting of load and generation can be done using regression analysis, because load and generation can be described as functions over time. The study uses two different kinds of models in order to do the regression analysis on the data. The first is linear regression, a supervised machine learning model that finds the line of best fit between independent (load/generation in kWh) and dependent (time) variables. The second is curve fitting, which is the use of non-linear functions for extrapolation. To describe the power management tertiary control system, there is a set of action items, and a classifier creates a model that extracts features from load, generation and weather data (e.g., mean temperature and mean and standard deviation of difference between load and generation). These features will be used to classify what action the controller should take according to the action items, based on typical decisions for power control during a month interval. Two

Figure 3 – data and resultant AI models used



types of models will be used for the power control classifier algorithms. The first is a decision tree classifier, which is a tree that defines decisions at its leaf nodes, and a series of tests to select decisions, made by analyzing the features in the data from load, generation, temperature, pressure, and humidity over time. The second is a random forest classifier, which is a supervised machine learning algorithm that aggregates multiple decision trees and randomly merges them to optimize accuracy in fitting the training dataset.

Outputs of The Simulation

To characterize efficacy of the AI controller, energy loss, power allocation, and forecast accuracy will be outputs of the simulation. These will be compared with and without the AI controller for a week of MMG network operation. Power loss (kW) will be plotted vs time and used to generate a table of total energy loss for each microgrid. Power allocation will involve plots of solar generation (kW), generation curtailed (kW), microgrid interchange (kW), battery energy storage system (BESS) power output (kW), storage energy (kWh), load of each microgrid (kW), and load curtailed (kW). In addition, a table will show total energy of load and generation curtailed for each microgrid, maximum load curtailed at any time, and mean percentage of loads powered over all time. Finally, forecast accuracy will be shown with plots of forecasted load and generation (kW) over time alongside the actual load and generation for each microgrid in the simulation. A table of root mean squared error will show the accuracy of the AI in the forecasts.

Hypothesis

This study aims to improve load and generation forecasting, reduce power loss, and mitigate curtailment of load and generation using AI as a controller for power management in a MMG network. When using the optimal AI method as a controller for power management in a MMG network compared to no AI, it is hypothesized that energy loss will reduce by at least 10%, demand and generation curtailment will reduce by 20%, and the optimal AI will have a forecast root mean square error of less than 5kW for load and generation in the week interval. It is expected that random forest and curve fitting will be the most effective classification and forecasting AI.

Conducting the Pilot Study

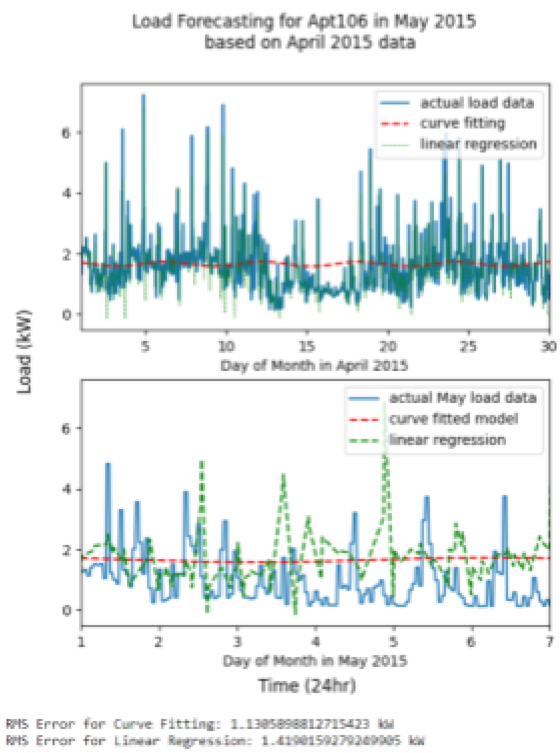
With respect to the AI, the pilot study aims to show the comparison of linear and curve fitting regression models with respect to effectiveness in forecasting the load/generation algorithms. A Jupyter Notebook with data and predictions plotted for load and generation is in the study's GitHub, https://github.com/20ramachandrana/i2estudy, to be uploaded onto the first Raspberry Pi. Linear regression is peaked at the maximum value of load within the prediction data so as to recreate the semi-periodic nature of the monthly load graph, whereas curve fitting automatically accounts for that. Comparison plots are made for the next week, resulting from the prediction data for the month of April for one of the microgrid buildings.

Anticipated Results and Limitations

The simulation outputs will be plotted over time for each microgrid, for each scenario and case tested. There are nine microgrids tested in the three MMG scenario configurations, and 5 cases for the AI (combinations of 2 types of regression, 2 classifiers, and no AI). Thus, 45 total microgrid simulations will be conducted. For each, the following figures will be generated: power and energy loss, total battery storage energy, generation & load curtailed, load & generation forecast, and load, generation, & interchange. However, forecasts will not be done for the no AI case.

The following figures are a demonstration of potential output for one case of microgrid no. 1 (UMass), with the random forest and curve fitting AI:

Figure 4: Load Forecasting Plot and RMSE [linear regression, curve fitting comparison]



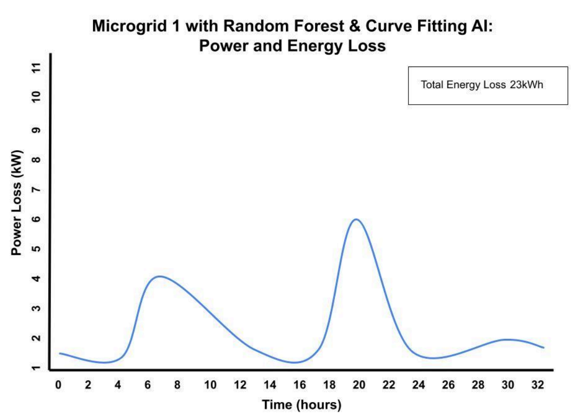


Figure 6.1

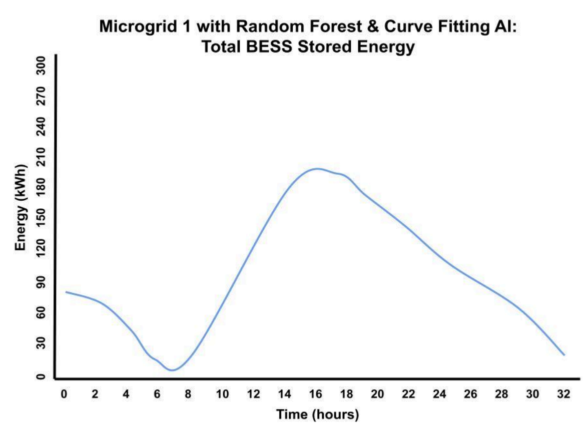


Figure 6.2

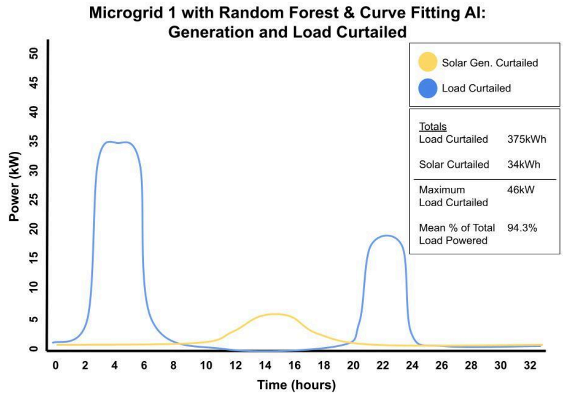


Figure 6.3

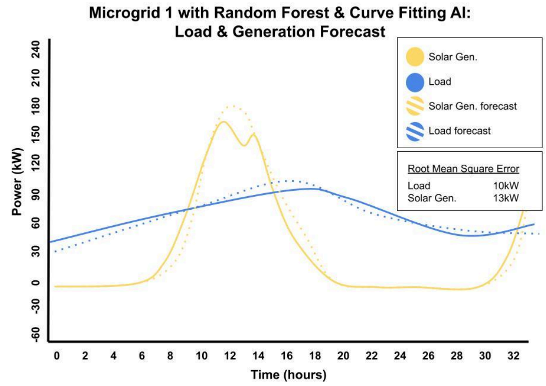
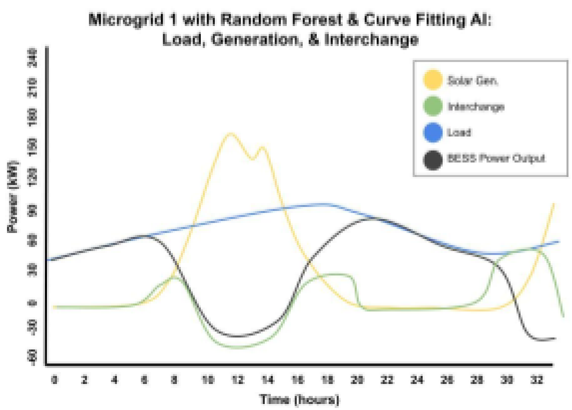


Figure 6.4

Figure 7



For answering the research question, plots of energy loss, generation & load curtailment, and forecasts will be the most useful for characterizing the effectiveness of power allocation and forecasting by the AI.

This study has limitations which were deemed appropriate for the scope of research. The model of the grid is abstracted by the following assumptions: no connection to a host grid (thus all power must be generated by the MMG), only solar PV is considered for generation, and all load devices are assumed to be lumped together as a single AC load. The power flow and efficiency of grid connections between the PV, battery storage, and loads is limited to converter efficiency only. Finally, the data collected by the embedded systems is only from a single location at the site of each simulated microgrid. For the controller and HILS it is assumed that primary and secondary control can be abstracted for each microgrid into a single algorithm; financial costs are not considered in this study; only one week of the MMG network operation is simulated; and the tertiary controller does not operate in real time (rather, one hour intervals). To reduce these assumptions, future studies could use more embedded devices to more accurately model a microgrid, simulate a MMG network with varying AC and DC loads, consider a grid-connected microgrid, and model power flow between generation and loads.

Conclusion

Based on these results from the HILS used in this study, a comparison will be made between the size of a MMG network and the types of AI used to manage the network. Thus, the optimal form of regression and classifier could be concluded. The study may also quantify the degree to which tertiary power management can reduce power curtailment and energy loss. If none of the AIs show a considerable impact in improving power management, it could indicate the need for alternatives to AI or the need for the algorithm to operate more in real time.

One of this study's goals is to improve forecast accuracy of load and generation (root mean square error), which is an important and improvable set of variables as forecasting is intrinsic to optimizing tertiary power control. Reliability of power in a MMG network is also improved by forecast accuracy, because accurate prediction of load and generation enables adapting infrastructure to minimize power loss and appropriately curtail load or schedule energy storage. Furthermore, this study demonstrates the integrability of distributed energy resources with current infrastructure, which provides a springboard for carbon mitigation plans (such as that of UMass) to lower carbon emissions. This study provides a way of modeling tertiary power control using AI analysis, which can be generalized for other smart grids, a larger MMG network, or a longer prediction time scale than a week as predicted in this study. It further demonstrates the feasibility of integration of DERs with current energy infrastructure and showcases the value of AI-based energy management.

Broader Impact

At present, renewables are inefficient at matching load with generation; current power grids based on renewables either produce more energy than needed and curtail generation or use fossil fuels when load surpases generation. According to Barath Raghavan, an assistant professor in computer science at USC's Viterbi School of Engineering, "The way things are going, in five years, the amount of renewable power wasted in California each year will be equivalent to the amount of power L.A. uses each year" [13].

This study will potentially fill gaps in the use of HILS and MMG networks in demonstration of AI-based control's efficacy. Two Raspberry Pi 4s will simulate a multiple microgrid network that would occur in a real-world setting. They will use data from the SMART* dataset, collected weather data, and estimated solar generation for microgrids. In theory, this will provide a framework for further studies focusing on MMG network simulation.

This study could provide novel scientific value. Application of HILS to a MMG network with AI and embedded systems is a new approach which could provide a framework for future studies focusing on this type of simulation. With the results of this study, future research could be conducted for a grid connected microgrid, longer duration simulation, different forms of energy storage, simulation of the primary and secondary controller, and considerations for financial cost.

Using the hardware-in-the-loop simulation technique analogous to that of Jeon et al.'s study [7] enables testing of new infrastructural techniques for MMG networks prior to mass implementation, which helps compare efficacy of similar systems of microgrid architecture, forecasting and allocation algorithms without a resource-intensive full-scale implementation. Better integration of sensing and computing layers for MMGs will lead to lower operating costs of an MMG network during a grid failure [6]. Additionally, this implementation will lower energy cost for the public as better forecasting will lead to a more stable energy supply and demand ratio. With improved understanding of MMG tertiary control, the grid will be better equipped to support needed integration of renewable energy and will be a large step toward achieving net zero carbon emission.

The increase in modularity of energy infrastructure and use of renewables would benefit those who do not have access to electricity currently as it would facilitate expansion of infrastructure in a sustainable way that is less reliant on fossil fuels. It would aid communities that would benefit most from aforementioned services who are also at the frontline of climate change activism and reside near sites of fossil fuel power plants (i.e., poor, working class and BIPOC communities). Global planning of energy expansion in accordance with this and similar studies would also create jobs in creation, simulation and study of microgrids, and be in accordance with the Green New Deal's mission to "achieve net zero greenhouse gas emissions, create millions of good, high-wage jobs, invest in energy infrastructure, secure basic needs for Americans for generations to come, and promote justice and equity" [14].

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