CAD support and Control Algorithm Development for Building Micro-Grids

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by

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1 Introduction

Building infrastructures consume about 40% of the energy produced in developed countries [1]. Given this huge energy requirement, microgrids for networks of buildings have evolved as a reliable, cost effective, low carbon footprint power distribution alternative. A building microgrid controls locally available renewable energy resources and power generation units in coordination with power from the main grid, and satisfies the energy requirement of multiple community buildings in a cost-efficient, reliable and environmentally-aware manner.

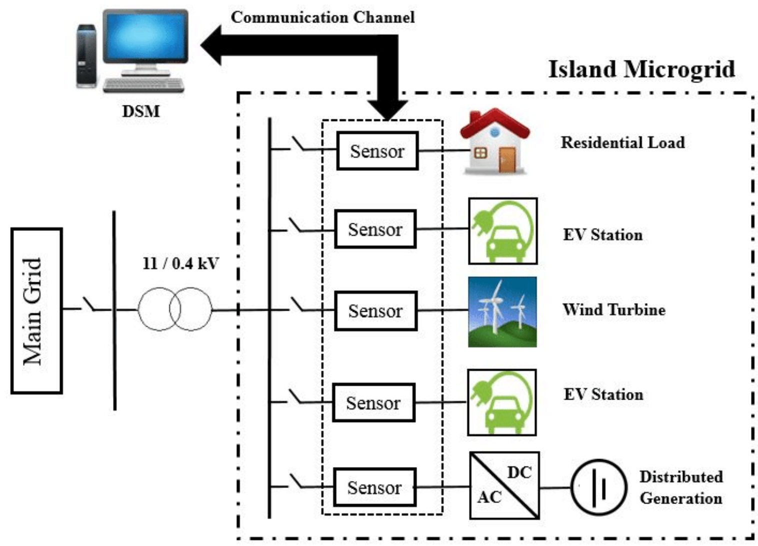

Figure 1: Microgrid Energy Systems[40].

For the increasing demand for more reliable ways to provide electricity and to incorporate renewable energy sources such as solar and wind, there has been extensive study on the microgrid i.e. distrubted generation system. The popularity of distributed generation systems is growing faster from last few years because of their higher operating efficiency and low carbon emission levels. According to U.S. Department of Energy Microgrid Exchange Group, the Microgrid system can be defined as *a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity concerning the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode*. Microgrids have large power capacity and more control flexibility which accomplishes the reliability of the system as well as the requirement of power quality. The microgrid concept lowers the cost and improves the reliability of small scale distributed generators.

1.1 Background Study and Summary of Contributions

1.1.1 Microgrid Structure

Microgrids offer various advantages to end-consumers, utilities and society, such as: improved energy efficiency, minimized overall energy consumption, reduced greenhouse gases and pollutant emissions, improved service quality and reliability.Microgrids can be of different types such as Campus Environment/Institutional microgrids, Community microgrids, Grid Connected microgrid, Isolated microgrid etc. In our works, we focus on community microgrids ie. microgrids with residential building loads. The main components of community microgrids are:

- distributed generation units i.e. renewable generation sources, ex. wind turbines, solar etc.
- cogeneration systems, ex. diesel generators, microturbine etc
- energy storage devices i.e. battery
- point of common coupling (the point where a microgrid is connected to a utility grid) and
- building loads.

1.1.2 Microgrid Control Mechanism

A centralized secondary control architecture consists of a central controller provided with the relevant information of every DER unit and load within the microgrid, and the network itself (e.g., cost functions, technical characteristics/limitations, network parameters and modes of operation), as well as the information from forecasting systems (e.g., local load, wind speed, solar irradiance) in order to determine an appropriate UC and dispatch of the resources according to the selected objectives. The central controller can make decisions using either online calculations of the optimal (or near optimal) operation, or pre-built and continuously-updated databases with information of suitable operating conditions, from offline calculations or other heuristic approaches. The general structure of a centralized secondary control for microgrids is shown in figure:2.

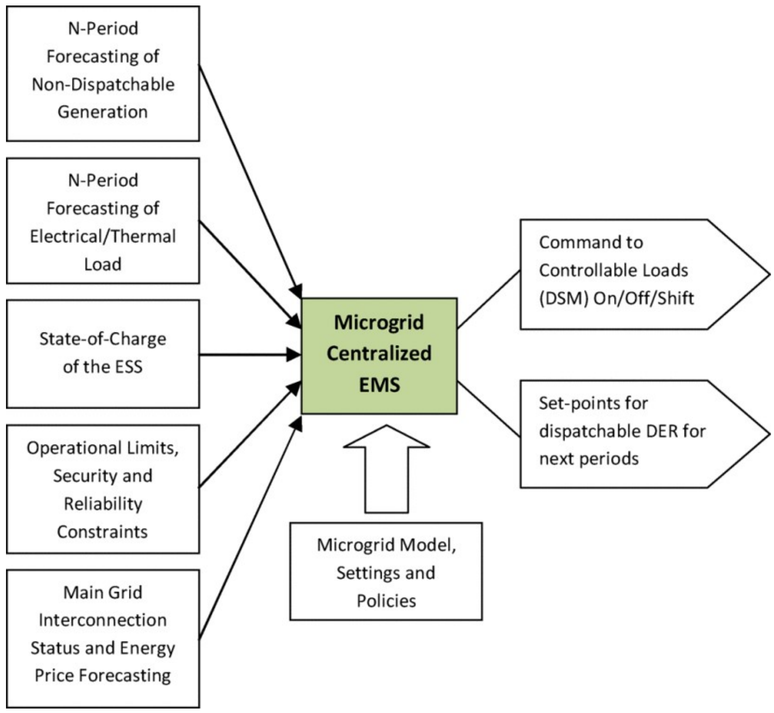

Figure 2: Microgrid control[43]

In small microgrids with a low number of generation scenarios, the offline calculation of the optimal operation for all the possible scenarios may be the best alternative in terms of cost and system's performance. All possible operation states are analysed offline and the optimal dispatch of the system for each scenario is calculated and stored in a look-up table to be accessed in real-time operation. Although this approach produces an instantaneous response of the system when the conditions change, the number of possible scenarios can become an issue if distribution system faults are considered, or if thermal loads are to be optimized jointly with the electrical loads. Furthermore, the presence of ESS in the microgrid introduces time dependence in the calculation of the optimal dispatch; therefore, the optimal dispatch is not solely determined by a particular demand scenario.

Microgrid optimal energy management problem falls into the category of mixed integer nonlinear programming. Thus, objective function may include cost functions of second or higher order polynomial equations with some start-up/shut-down decisions. Also, some complex constraints are involved to model the operational limitations of some generation/storage devices or to represent controllable loads and commitment decisions. Furthermore, considering network constraints (load flow) adds another degree of complexity to the microgrid optimal energy management problem. The minimization of total operating cost in stand-alone operation, and maximization of microgrid's revenue in grid-connected mode are two typically pursued objectives in secondary control. However, some approaches have also incorporated the reduction of Greenhouse gas (GHG) emissions as an additional objective for the microgrid operation.

1.1.3 Building HVAC Structure and Control

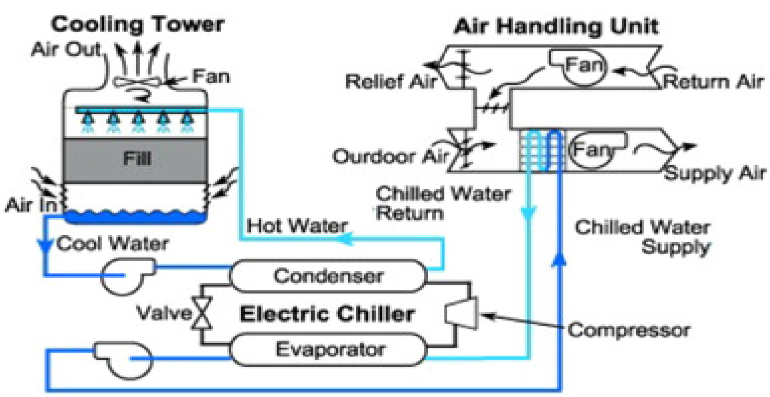

Figure 3: HVAC control[42].

For residential microgrids, the most significant controllable load is typically building temperature control systems, commonly known as the heating, ventilation, and air conditioning (HVAC) systems. The performance of HVAC control systems for large buildings strongly depend on the outside environment, building architecture and (thermal) zone usage pattern of the building. Modeling of HVAC system is essential for appropriate analysis and improvement of its control system. However, HVAC systems possess a complex structure comprising heat and mass transfer equipment such as the chiller, boiler, heating/cooling coils, thermal storage systems, air-handling equipment, air distribution system and liquid distribution systems. Figure:3 shows the schematic of a conventional chilled-water ventilation and air-conditioning system for commercial buildings comprising three main components: air handling unit, chiller and cooling tower. The system also consists of several sensors and controllers for regulating the controllable variables such as zone temperature, supply air temperature, supply air fan speed, duct static pressure, and chilled water temperature at their set-points. Because of having numerous mechanical, hydraulic and electrical components, the overall dynamics of HVAC plants are highly nonlinear. The interaction between the temperature and humidity control loops is relatively complex, and substantial constraints are imposed by the non-ideal behavior of actuators such as dampers and valves. Therefore, the modeling process of the HVAC system leads to dynamic, nonlinear, and very high-order models because of the physical properties such as high-thermal-inertia, real lag time, uncertain disturbance factors, etc. of the system.

Despite the similarity of HVAC control to other types of process control, certain features such as nonlinear dynamics, time-varying system dynamics and set-points, time-varying disturbances, poor data, complex interaction between the temperature and humidity control loops and at times conflicting control loops and lack of supervisory control (in many buildings) has made HVAC system control distinctive and challenging. Therefore, while developing a model for HVAC system or its components, attention should be given in determining the model order and parameter identification so that the ultimate control algorithm holds the ability to deal with disturbances, constraints, and uncertainties, to handle time-varying system dynamics and slow-moving processes with time delays and to cope with a broad range of operating conditions. According to ASRAE standard, comfort factor should have a range that indoor temperature lies between 19 and $24°C$.

Based on these overall goals, our contributions in the current work as well as the ongoing work are as follows:

- In the Problem-1:
  In order to address the building thermal model and HVAC operational uncertainties in the context of MPC-based microgrid economic dispatch, we model the unknown dynamics of HVAC system of the building loads using learning based technique. This model is gradually learned for generating power demand estimates for building HVAC operation. In this way we reduce the total electrical cost of the building loads by controlling the economic dispatch of microgrids.
- In the Problem-2:
  If we consider the problem of optimizing building HVAC control, we come across two parameters related to comfort and as well as the energy consumption of the building. As we cannot obtain optimal condition for both parameters at the same time, we need to trade off between these two parameters depending on the weather condition and dynamic pricing scheme of utility grid. Again in microgrid control for supplying power to building load is also an optimization problem. Hence it makes sense to co-optimize the microgrid and building HVAC model together depending on the available energy in microgrid. In this way , we can control both the microgrid and HVAC parameters to minimize the total energy consumption and maximize the comfort of the building.
  As it is a large scale optimization problem, we are using AI based technique, in this case Deep Reinforcement learning(DRL) for this problem.
- In the Problem-3:
  We provide a tool for microgrid design from high level design specification with automatic initial design generation and scheduling optimizations for various type of building loads.We also create an interface for the integration of the microgrid (generated from the tool) with a controller and different types of building model from Energyplus.

2 Contribution of Current Work (Problem-1)

In this work, we consider an MPC-based economic dispatch scheme with DERs and building loads being connected to a microgrid. In that way we do not consider the constraints from the underlying distribution framework in our formulation, as we assume they can be addressed in existing works. Rather we focus on the specific context of economic dispatch for a network of building thermal loads.

We consider a microgrid connected to a building network for which we have an approximate thermal model available. Our scheme is depicted in Fig. 4 given below.

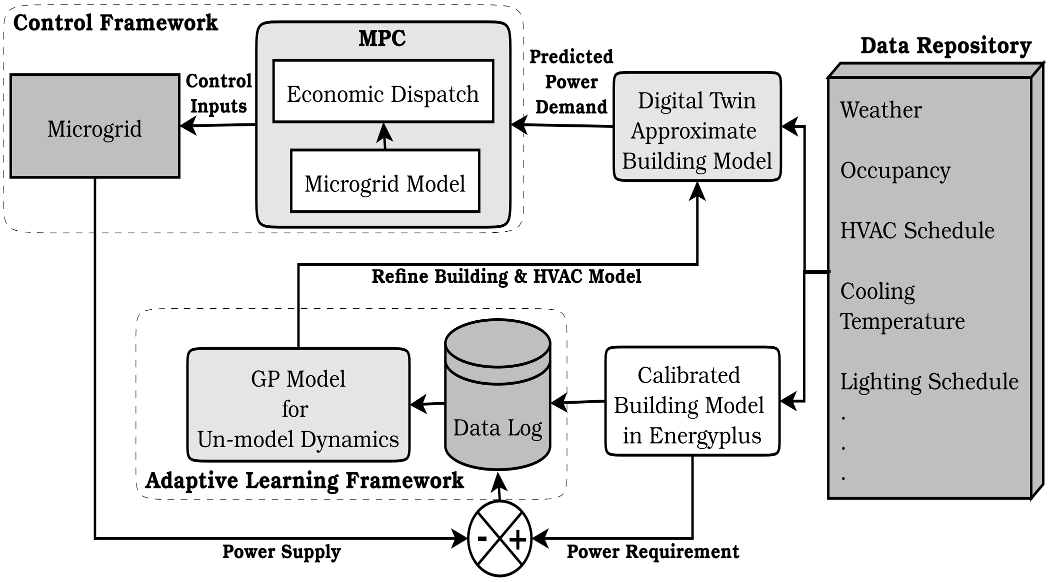

Figure 4: Data-driven microgrid control.

Unlike prior work, we do not assume a GP for the entire building model. Large buildings have complex nonlinear thermal dynamics which make system identification using data-driven learning based techniques a time consuming affair [4]. This is further complicated in case of a collection of buildings, which is more often the load for a community microgrid. Moreover, building thermal models are quite sensitive to year around weather patterns, which means sufficient training data for the model can only be generated by observing HVAC operations in a year around manner for each building. On the other hand, it is much easier to create approximate building thermal models using standard methods involving building topology, measurement data, and material datasheets [10]. In this work, we consider such thermal models as initial building models and the uncertainty emanating from errors in estimation of building and HVAC parameters as initially unknown additive dynamics, which are gradually learned while under operation. Given such a building model available as a digital twin, we generate power demand estimates for building HVAC operation and use them to control the microgrid economic dispatch for the building network.

To the best of our knowledge, this is the first work that accounts for building thermal model and HVAC operational uncertainties in the context of MPC-based microgrid economic dispatch. The overall working of our data-driven grid operation is given below.

- We consider a set of n buildings $B_1, \cdots, B_n$, with approximate thermal models for each building along with the integrated HVAC systems. Additionally, each building has an associated GP model. We consider the actual buildings to be represented by calibrated Energyplus [14] models.
- We consider the grid control operation to be performed in steps of some time interval h (15 minutes in our experiments). At some real time instant kh, let us assume that the control parameters up to time $(k+1)h$ are already computed. We simulate the approximate building system model for the interval $[kh, (k+H)h]$ for a given horizon H to generate the set of H power consumption estimates $P(k, H)$ (at time points $(k+1)h, \cdots, (k+H)h$). These estimates are augmented with the error estimates as provided by a separate GP model. Let the set of augmented estimates be $P'(k, H)$.
- For a given $P'(k, H)$, our MPC formulation for the grid computes grid control actions for the interval $[(k+1)h, (k+2)h]$.
- The Energyplus model is next simulated for the interval $[(k+1)h, (k+2)h]$ to generate the actual power consumption in the same interval. The estimated and actual power consumption as well as zone-wise temperature data for the interval are logged, and at well-defined time intervals the GP model is updated for further refinement.

Using the above methodology, it is expected that over time, the error between the estimated and observed power demands will decrease, so that the control performance of the microgrid gets increasingly better. The online nature of the learning ensures seasonal variations will be incrementally learned by the model whenever the observed error would be high. This ensures quick deployment of microgrids for building network loads without placing a huge requirement on initial data availability.

3 Literature Survey

In the literature, there has been a significant number of works on efficient control methods for microgrids, e.g. [6, 8, 7].The problem of economic dispatch is either modeled as an open loop for computing a day-ahead schedule; or solved as an hourly rolling optimization problem with the Model Predictive Control (MPC) strategy, considering real-time uncertainties in factors such as weather patterns and distributed energy resources (DER) status. The MPC-based strategies require accurate prediction on power consumption of key building loads like HVACs, which depend on the accuracy of building thermal models. Developing accurate thermal models from scratch is a time consuming and costly process [3]. An alternative is to use pure machine learning based algorithms that directly learn control strategies from sensor data. However, such methods typically require a large initial training dataset, which are often difficult to obtain.

In particular, the power demand for building thermal loads is difficult to predict. This is largely because, building temperature across different thermal zones can be effected by a large number of parameters ranging from building structure, material used, human occupancy, and other internal heat generation sources like lights and appliances. Moreover, we need to account for the effect of ambient temperature, relative humidity, and solar radiation. Such imprecise nature of building thermal models has been reported in the context of building HVAC control in the literature [5, 2, 3].Furthermore, building thermal models based on Gaussian Processes (GP) have been created for demand response (DR) applications as reported in [2, 3]. In these works, building models act as digital twins which are used to decide building HVAC control and related load curtailment based on smart grid demand response events.

4 Approximate Building Power Demand Models

4.1 HVAC system model

As HVAC systems typically account for the highest percentage of overall power demand in the building, we assume in this work that other electrical loads are constant. The overall power demand is estimated as the summation of the HVAC power demand and the constant term representing other electrical loads such as lighting. The major part of the power demand for HVAC is from its Variable Speed Driven (VSD) supply fan and chiller. Thus, we model the power demand of HVAC system as the summation of power required by the fan and the chiller. We estimate the power demand of the fan at instance t using the quadratic fan power model drawn from [16], given by $P_f(t) = k_f(\dot{m})^2$, where k_f is a parameter that captures both the fan efficiency and the duct pressure losses while $\dot{m}$ is the supply air mass flow rate of the fan. The chiller power demand at time t, drawn from [16], is estimated by $P_c(t) = \frac{c_p}{\eta}\dot{m}(T_s - T_c)$, where η is a coefficient of performance for chiller, c_p is the specific heat capacity of air, and T_s and T_c are the temperature of air in and out of the chiller respectively. Therefore, the overall power demand of the HVAC system, $P_H(t)$, is estimated as:

$$P_H(t) = P_f(t) + P_c(t) = k_f(\dot{m})^2 + \frac{c_p}{\eta}\dot{m}(T_s - T_c) \tag{1}$$

The power demand of HVAC system, as shown in Equation (1), depends on the mass flow rate, $\dot{m}$, of cold/hot air supplied by the HVAC into the multi-zone building. The optimal air mass flow rate $\dot{m}$ is determined by the controller of HVAC system considering the thermal dynamics of the building. The temperature T_j of a zone z_j is governed by the following equation:

$$\frac{d}{dt}(T_j) = \frac{1}{C_j}[\dot{m}_j c_p(T_c - T_j) + Q_j + q_{int\_j}] \tag{2}$$

where C_j is the thermal capacitance of the zone, $\dot{m}_j$ is the mass flow rate of cold air supplied to the zone, while c_p and T_c are the specific heat capacity and the temperature of cold air respectively. The quantity q_{int_j} is the forecasted internal thermal load of the zone from lighting, appliance, occupants, etc. The quantities $\dot{m}_j$ and T_c

are the control inputs to thermal zones. Q_j represents the total heat gain through its surrounding partition walls. The heat gain through a partition wall w into zone z_j is given by:

$$Q_w = \frac{T_w - T_j}{(R_i + \frac{R_w}{2})_w} \tag{3}$$

where T_w is the temperature at the centre point of wall w at half length of wall thickness, $R_i = \frac{1}{h_i A}$ and $R_w = \frac{L}{kA}$ are the thermal resistance for convection and conduction respectively. The quantities A and L represent area and thickness of the wall w, while k is the thermal conductivity of wall material and h_i is the convective heat transfer coefficient inside the zone. The temperature dynamics of wall w attached to zone z_j is given by the following equation:

$$\frac{d}{dt}(T_w) = \frac{1}{CW_w}[\frac{T_{oa} - T_w}{(R_o + \frac{R_w}{2})_w} + \frac{T_j - T_w}{(R_i + \frac{R_w}{2})_w} + \gamma A q_{rad}] \tag{4}$$

The symbol CW_w is the thermal capacitance of wall w. The air temperature on the other side of wall w, opposite to the zone z_j, is given by T_{oa}. $R_o = \frac{1}{h_o A}$ is the thermal resistance for convection of the air with convective heat transfer coefficient h_o. The term γ is the absorptivity coefficient of the wall, and q_{rad} is the total radiation heat that hits the wall such that γq_{rad} accounts for the portion of the radiation heat absorbed by the wall per unit area.

4.2 Thermal Dynamics of the Building Model

The individual zone/wall thermal dynamics (Equations (2) – (4)) are stitched together using resistance-capacitance (RC) network modeling technique following [10] to create the overall thermal dynamics of the building. On the resulting nonlinear model, we apply *Jacobian Linearization* with respect to set-point temperature of zones and create state-space model of the form:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Ed(k) \\ y(k+1) &= Cx(k+1) \end{aligned} \tag{5}$$

where $x(k)$ is the building state vector, $y(k)$ is the output vector, $u(k)$ is the input vector, and $d(k)$ is the disturbance vector. A, B, C, E represent state, input, output and disturbance matrix respectively. For our purpose, d comprises external weather related parameters like wind speed, direction, solar radiation.

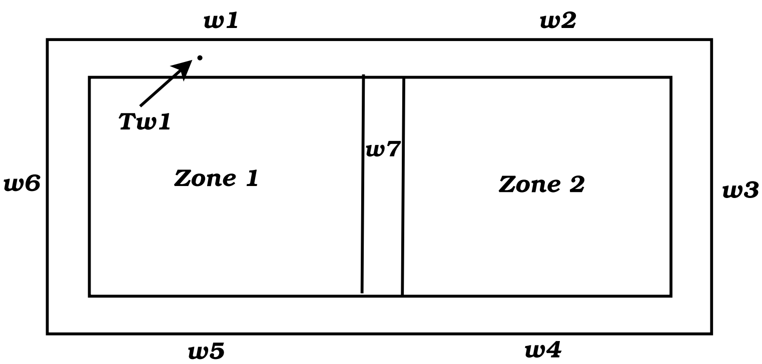

Figure 5: Example building containing two thermal zones.

Example 4.1 *Let us consider a building with two thermal zones depicted in Fig.* **??**. *Zone 1 is surrounded by wall w_1, w_5, w_6 and w_7, whereas Zone 2 is surrounded by wall w_2, w_3, w_4 and w_7. Let us assume that the temperatures of wall w_1, w_2.., w_7 (at middle points) are T_{w1}, ..., T_{w7} respectively, and heat transmission takes place only through walls. The temperatures of Zone 1, Zone 2 and outside environment are denoted as T_1, T_2 and T_a respectively. Therefore, we get the temperature dynamics of two zones using Equations* (2) *and* (3)*, and the temperature dynamics of seven walls using Equation* (4)*. Overall, we can represent the building state vector $x(t) = [T_{w1}, T_{w2}, T_{w3}, T_{w4}, T_{w5}, T_{w6}, T_{w7}, T_1, T_2]^T$ and input vector $u(t)$ as $u(t) = [\dot{m}_1, \dot{m}_2]^T$. In general, $A \in \mathbb{R}^{9X9}$ contains building parameters like wall thickness and conductance,* *convection coefficients of internal air, etc. The input matrix $B \in \mathbb{R}^{9X2}$ includes building parameters and HVAC set-point temperatures for each thermal zone. The disturbance matrix $E \in \mathbb{R}^{9X4}$ contains building parameters pertaining to outside wall, window, etc.*

In this work, we consider building HVACs operated using Linear Quadratic regulator (LQR) based controllers, which determine the optimal control inputs (hot/cold air mass flow rate) to the zones of the building. The control inputs are used to predict the power demand of HVAC using Equation (1) for future time intervals. Our framework also works for other controller settings.

5 Learning Unmodeled Power Demand

In order to increase the accuracy of power demand prediction, we iteratively learn the un-modeled dynamics of the building thermal model and related HVAC power demand model. For this purpose, we propose a Gaussian Process Regression based learning approach.

5.1 Gaussian Process Regression

A Gaussian Process (GP) can be defined as a collection of random variables such that any finite collection of such variables exhibits a joint (multivariate) Gaussian distribution. In Gaussian Process Regression, the noisy output q w.r.t. an input r is represented using a function $f : \mathbb{R}^n \to \mathbb{R}$ as $q = f(r) + \epsilon$, where $\epsilon \sim \mathbb{N}(0, \sigma_n^2)$. The GP corresponding to q is fully specified by the mean $\mu(r;\theta)$ and covariance $s(r, r')$ of the process as follows [9]:

$$\begin{aligned} \mu(r;\theta) &= \mathbb{E}[f(r)] \\ s(r, r';\theta) &= \mathbb{E}[(f(r) - \mu(r,\theta))(f(r') - \mu(r',\theta))] + \sigma_n^2 \delta(r, r') \end{aligned} \tag{6}$$

Here $\delta(r, r')$ is the Kronecker delta function and θ is the hyperparameter. In short, $q \sim \mathcal{GP}(\mu, s; \theta)$ with the overall covariance matrix S having elements $S_{ij} = s(r_i, r_j)$. Given a training dataset $\mathbb{D} = (R, Q)$, where $R = [r_1, r_2, ...r_N]^T$ is the input vector and $Q = [q_1, q_2...., q_N]$ is the corresponding output vector, the covariance matrix can be written as $S_{ij} = S(r_i, r_j)$. Given (R, S), we can estimate θ by maximizing the likelihood $arg\, max_\theta\, Pr(Q|R, \theta)$. Now for a new input r_*, the distribution of the output q_* will be $q_* \sim \mathcal{N}(\overline{q}_*, \sigma_*^2)$ [3], where

$$\begin{aligned} \overline{q}_* &= \mu(r_*) + S_* S^{-1}(Q - \mu(r)) \\ \sigma_*^2 &= S_{**} - S_* S^{-1} S_*^T \end{aligned} \tag{7}$$

Here $S_* = [s(r_*, r_1), ...s(r_*, r_N)]$ and $S_{**} = s(r_*, r_*)$.

5.2 Augmenting the GP model

We augment the building thermal model with additive dynamical terms describing the error in initial system parameter values [13] as follows:

$$\begin{aligned} x(k+1) = {} & Ax(k) + Bu(k) + Ed(k) \\ & + g(x(k), u(k), d(k)) + w(k) \end{aligned} \tag{8}$$

where the term g represents the unknown dynamics to be learned and $w(k) \sim \mathcal{N}(0, \Sigma)$ is i.i.d. process noise with variance Σ. For estimating the error in the approximate thermal model, we consider a GP based approach to infer g as follows. Given a set of possible (state, input, disturbance) triples as input data set $[(x(k), u(k), d(k)), \cdots, (x(k+N), u(k+N), d(k+N))]$, we observe the difference between the observed outputs and the predicted outputs following the original thermal model without the additive unknown dynamical terms. This may be characterized as the output observations for the input data set given as follows:

$$\begin{aligned} e_x(k+j) &= g(x(k+j), u(k+j), d(k+j)) + w(k+j) \\ &= x(k+j+1) - (Ax(k+j) + Bu(k+j)) \end{aligned} \tag{9}$$

With $i(k) = [x^T(k), u^T(k), d^T(k)]^T$, we have a training data set $\mathbb{D}_k = [[i(k), \cdot\cdot, i(k{+}N)]^T, [e_x(k), \cdot\cdot, e_x(k{+}j)]^T]$. This is used to train a GP model for e_x with our choice of covariance function s being a squared exponential function [9]. Similar to the GP defined for difference in building state computed and measured (sensed zone temperatures), we additionally define a GP over the differences in power consumption as predicted by the thermal model and as observed in terms of actual building demand. The predicted power consumption $P_H(k)$ in period $[k, k+1]$ is given by Equation (1) for $t = kh$ (h being the sampling period) and we consider the observed difference as $e_p(k)$. Given a data set $\mathcal{P} = [[P_H(k), \cdots, P_H(k+N)]^T, [e_p(k), \cdots, e_p(k+N)]^T]^T$ generated from the system model and Energyplus measurements, we can similarly learn a GP for e_p, which can be used to augment the power consumption prediction model. For a given power consumption P_H as given by the approximate thermal model in Equation (1) in some sampling period, using the GP for e_p, we can obtain an estimate $e_{p*} \sim \mathcal{N}(\bar{e}_{p*}, \sigma^2_{e_{p*}})$ of the error in P_H. Thus, the overall power demand with GP adjustment would be

$$P'_H = P_H + e_{p*} \sim \mathcal{N}(\bar{e}_{p*}, \sigma^2_{e_{p*}}) \tag{10}$$

Note that our formulation of GP on building state also contributes to the overall error correction in power consumption estimation, since better zone temperature estimation leads to more accurate computation of the zone level mass flow rates $\dot{m}$ by the HVAC control law model. This helps in better performance of the power prediction model leading to more accurate computation of P_H w.r.t. actual consumption.

6 Microgrid Economic Dispatch

We consider a microgrid architecture comprising diesel generators (DGs) as nonrenewable energy source, PV systems as renewable sources and battery bank as the storage system.

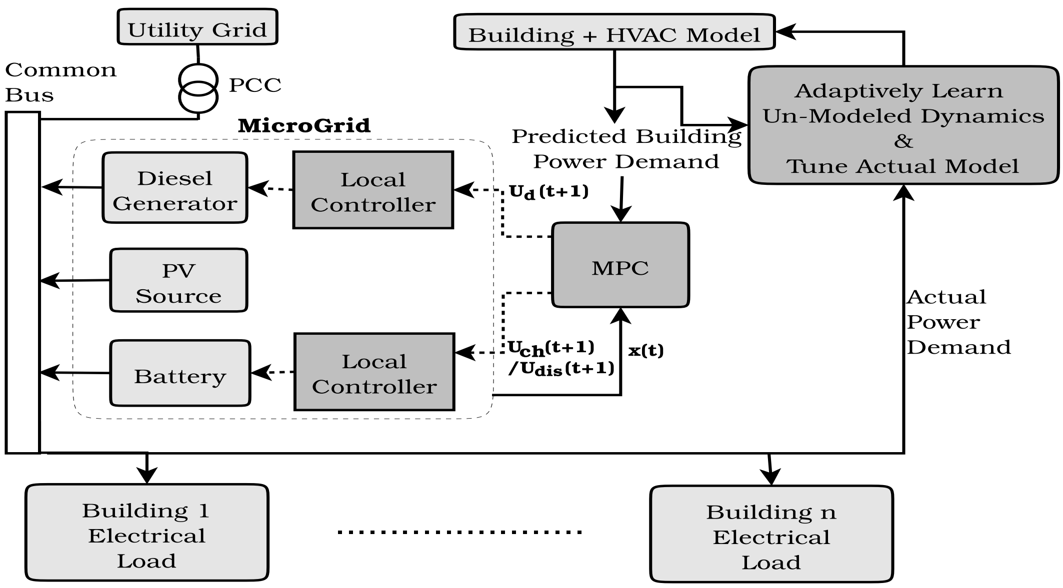

Figure 6: Microgrid control framework.

As shown in Fig. 6, the control scheme comprises an Model Predictive Control (MPC) based supervisory controller, which generates as control signals the setpoints for local controllers that regulate working of the DG, PV and battery subsystems. The MPC scheme cost-effectively decides the amount of power dispatched from the microgrid and drawn from the utility grid to meet the predicted power demand of buildings for a specified future time period. The MPC controller determines optimal control inputs for each DER to maintain the amount of power to be dispatched from microgrid with the objective of reducing overall electricity cost for the building network. In the microgrid model, the power generation of the PV source at some time k, can be modeled as the following [12]:

$$P_{solar}(k) = A * sr * h(k) * PR \tag{11}$$

where A is the total solar panel area, sr is the solar panel yield (%), $h(k)$ is the solar radiation, and PR is the performance ratio. For the storage system, i.e., the battery model, the charging/discharging dynamics of the battery is given as:

$$\dot{E}_{ss}(k) = -\delta_{ss}E_{ss}(k) - \frac{P_{ss}(k)}{\eta_{\sigma(k)}E_{ss}^{max}} \tag{12}$$

where $E_{ss}(k), P_{ss}(k)$ are the current state of charge (SOC) of the battery and the power supply from the battery respectively. δ_{ss} is the self-discharge rate of storage. $\eta_{\sigma(k)}$ represents discharging/charging efficiency based on the switching signal $\sigma(k) = 0/1$. E_{ss}^{max} is the maximum storage capacity of the battery. The storage system power dynamics is modeled using the first-order lag dynamic equation as the following [11]:

$$\dot{P}_{ss}(k) = -\frac{1}{\tau_{ss}}P_{ss}(k) + \frac{U_{ss}(k)}{\tau_{ss}} \tag{13}$$

where τ_{ss} is the average delay incurred between power command and delivery. $U_{ss}(k)$ is the power commanded to the battery by the supervisory controller. Power output dynamics of the diesel generator can be given the following [11]:

$$\dot{P}_{d}(k) = -\frac{1}{\tau_{d}}P_{d}(k) + \frac{U_{d}(k)}{\tau_{d}} \tag{14}$$

where τ_d is the average delay incurred between power command and delivery. $U_d(k)$ is the power commanded to the diesel generator by the supervisory controller. Using Equations (11) – (14), the discrete time power generation dynamics of the microgrid can be written as:

$$\begin{aligned} x_m(k+1)_m &= A_m x_m(k) + B_m u_m(k) + E_m d_m(k) \\ y_m(k+1) &= C_m x_m(k+1) \end{aligned} \tag{15}$$

where A_m, B_m, C_m and E_m are state, input, output and disturbance matrices respectively. The state $x_m(k)$, input $u_m(k)$, output $y_m(k)$ and disturbance $d_m(k)$ vectors thus become $x_m(k) \stackrel{def}{=} [E_{ss}(k)\, P_{ss}(k)\, P_d(k)\, P_{solar}(k)]^T$,
$u_m(k) \stackrel{def}{=} [U_{ch}(k)\, U_{dis}(k)\, U_d(k)]^T$,
$y_m(k) \stackrel{def}{=} [P_{ss}(k)\, P_d(k)\, P_{solar}(k)]^T$,
$d_m(k) \stackrel{def}{=} [D_{E_{ss}}(k)\, D_{P_{ss}}(k)\, D_{P_d}(k)\, h(k)]^T$, where $U_{ch}(k)$ and $U_{dis}(k)$ are the charging and discharging command at time k. We have $\sigma(k) = 0$ if $U_{dis}(k) = 1$ and $\sigma(k) = 1$ if $U_{ch}(k) = 1$. The terms $D_{E_{ss}}(k)$, $D_{P_{ss}}(k)$, $D_{P_d}(k)$ model disturbances in respective state variables and $h(k)$ is considered inside $d_m(k)$ since PV is an uncontrollable power source. The operational limits of DERs can be represented by bounds on state variables as:

$$\mathcal{X}^{min} \le x(k) \le \mathcal{X}^{max} \tag{16}$$

where vectors $\mathcal{X}^{min}$ and $\mathcal{X}^{max}$ contain the minimum and maximum allowed values of the microgrid state variables. The power command to the diesel generator $U_d(k)$ is bounded by the minimum and maximum power capacity of the diesel generator given as follows:

$$P_d^{min} \le U_d(k) \le P_d^{max} \tag{17}$$

In every k-th sampling interval, we are provided with the distribution $P'_H(k)$ for predicted building load using thermal model and GP approximation of unknown error dynamics. We have $P'_H(k) = P_H(k) + e_{p(k)_*} \sim \mathcal{N}(\overline{e}_{p(k)_*}, \sigma^2_{e_{p(k)_*}})$ following Equation (10). Since the power demand prediction exhibits uncertainty, we assume to be given some confidence value ϵ such that for k-th sampling period we need to maintain a guarantee that $P(P_{min}(k) \le P'_H(k) \le P_{max}(k)) \ge 1 - \epsilon$. Following the Lemma 16 from [15] (also used in [3]), we can conservatively approximate such confidence constraints as:

$$\begin{aligned} &\gamma \ge \sigma_{e_{p(k)_*}},\, P_{min}(k) - P_{max}(k) \le 2\Phi^{-1}(\epsilon^*/2)\gamma \\ &P_{min}(k) - \overline{e}_{p(k)_*} \le \Phi^{-1}(\epsilon)\gamma,\, \overline{e}_{p(l)_*} - P_{max}(k) \le \Phi^{-1}(\epsilon)\gamma \end{aligned} \tag{18}$$

where ϵ must lie inside the interval $(0, \frac{1}{2}]$. Φ^{-1} is the inverse cumulative distribution function of standard Gaussian distribution, γ is an auxiliary variable, and $\epsilon^* = \epsilon/1.25$. Thus, in any sampling interval, the inferred GP distribution parameters $\overline{e}_{p_*}, \sigma^2_{e_{p*}}$ can be used as constraints in Equation (18) along with ϵ for generating the interval $[P_{min}(k), P_{max}(k)]$, inside which the actual power demand shall be residing with minimum probability $1-\epsilon$. In order to satisfy the predicted power demand, we add the following constraint:

$$P_{max}(k) \leq P_{ss}(k) + P_d(k) + P_{solar}(k) + P_g(k) \tag{19}$$

The objective of the MPC-based control scheme for the dynamical system in Equation (15) is to satisfy the estimated power demand of the building network using the microgrid and the utility grid, while minimizing the overall electricity cost and microgrid operation and maintenance cost. The overall cost $J(k, k+H)$ for some interval $[k, k+H]$ can be written as:

$$J(k, k+H) = \sum_{n=k}^{k+H} [C_m^T(n) y_m(n) + C_g(n) P_g(n)]$$

where vector $C_m(k)$ represents the generation/operational cost (in power/unit) from battery, diesel generator and PV source. $C_g(k)$ is the grid power cost/unit. $P_g(k)$ is the power drawn from utility grid within interval $[k, k+1]$. The overall MPC formulation for the microgrid thus becomes:

$$min_{u_m(k),\cdots,u_m(k+H)} J(k, k+H)$$

subject to constraints (15) – (19). $U_{ch}(k) \in \{0,1\}$, $U_{dis}(k) \in \{0,1\}$, and $U_{ch}(k) = \neg U_{dis}(k)$ with all constraints holding at each instant $k, k+1, \cdots, k+H$, where H being the prediction horizon.

7 Results

For experiments, we used two benchmark buildings: an academic building and an office building from [17]. The buildings are designated as "medium sized". The building model benchmark provides the structural information of the buildings, which is used by us to create the MATLAB based approximate thermal model. These buildings are also available as calibrated models in EnergyPlus, and are simulated as real plants giving actual zone temperature and power consumption measurements. We also create a MATLAB based microgrid model with parameters as given in Table 1.

Parameter name	Value	Parameter name	Value
δ_{ss}	0.04%/hr	η	0.9
(τ_{ss},τ_d)	(0.1,0.3) sec	$[E_{ss}^{min}, E_{ss}^{max}]$	[400, 800] KWh
$[P_{ss}^{min}, P_{ss}^{max}]$	[-200, 200] KW	$[P_d^{min}, P_d^{max}]$	[0, 150] KW

Table 1: Microgrid Parameter Values

For comparison purposes, we employ both Neural Networks (NN) and Gaussian Process (GP) based learning techniques for learning the power prediction error in the building thermal model incrementally. We perform an initial model validation and feature selection phase using eight weeks of synthetic data generated from EnergyPlus. The weather data is taken from [18]. We used 80% of the data for the training and 20% of the data for validation of the models. In this phase we use Root Mean Square Error (RMSE) as the evaluation metric. We converge to a feature set comprising 18 features that have entries like air mass flow rates, zone temperature set points, solar radiation index, etc. Also, with GP, we consider the fitness of squared exponential as a covariance function [9]. For our set of features and covariance function, the RMSE performance score was 3.7769×10^3 Watts (W).

Simulation with online system deployment: We deploy our framework with the weather data scenario of Kolkata given in [18] for a specific year (1986, designated as **year1**) for 100 days starting from January 1, using GP and NN models separately. For the first week, we do not train the model, and the approximate thermal model is used to predict power requirement. The GP models are trained on January 8 using the generated dataset leading to reduction in prediction error as shown in Fig. 7. We consider $\epsilon = 0.05$, $H = 8$, and sampling window size of 15 minutes in the microgrid MPC for all experiments in this work. We calculate the Mean Absolute Percentage Error (MAPE) in prediction of power consumption estimate over a rolling window of 4 hours. In every sampling window, the MAPE value is checked; and whenever the value crosses a threshold, the GP models get updated. We set the threshold as 145 W in the current experiment. The model update points are marked using red star in Fig. 7. Note that significantly large error spikes are followed by model updates. Thus the experiment establishes the usability of the proposed scheme in spite of the unavailability of all the data at initial deployment.For the NN model, we employ an NN with four hidden layers. The choice of NN training algorithm is Bayesian Regularization (useful in small data scenario).

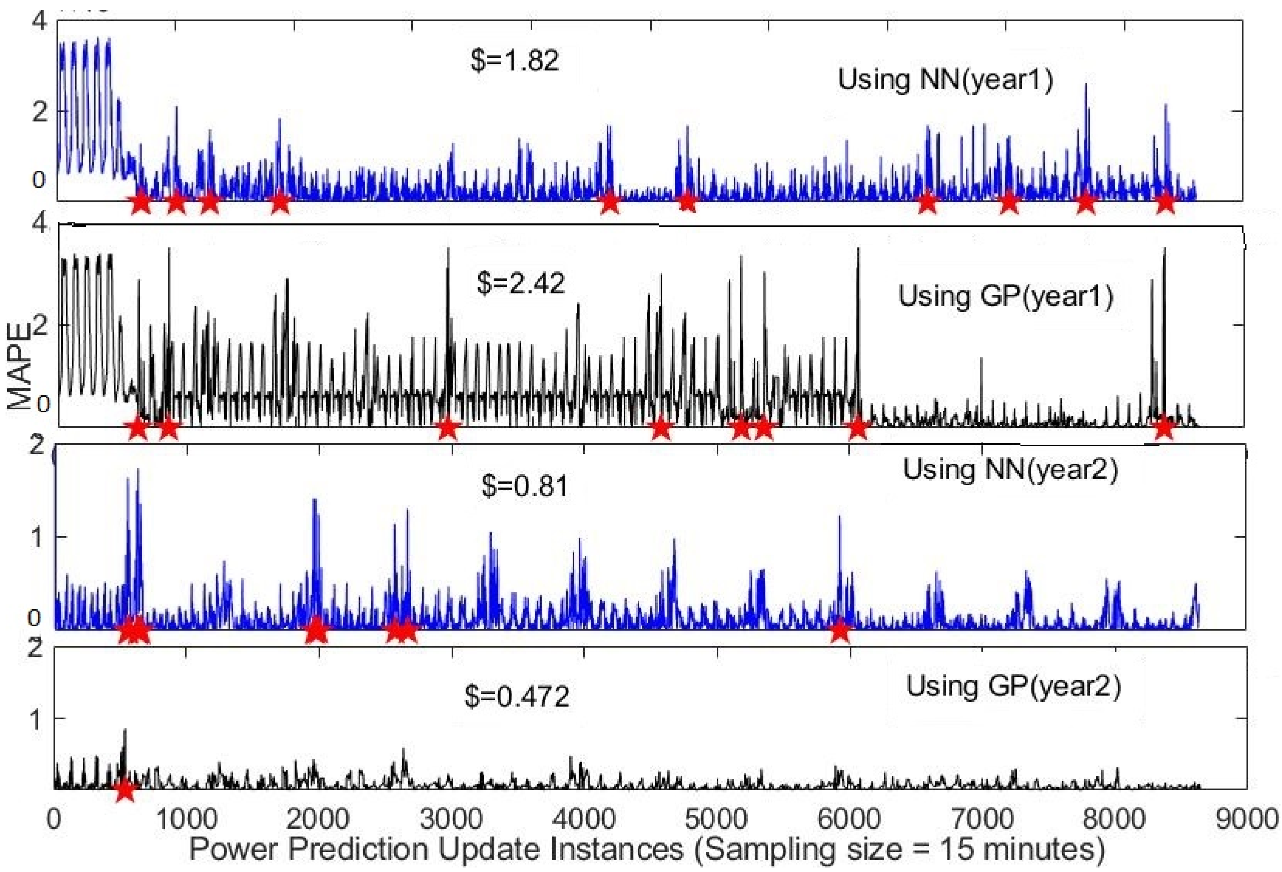

Figure 7: MAPE in building power predictions during 100 days. '$' : average % prediction error.

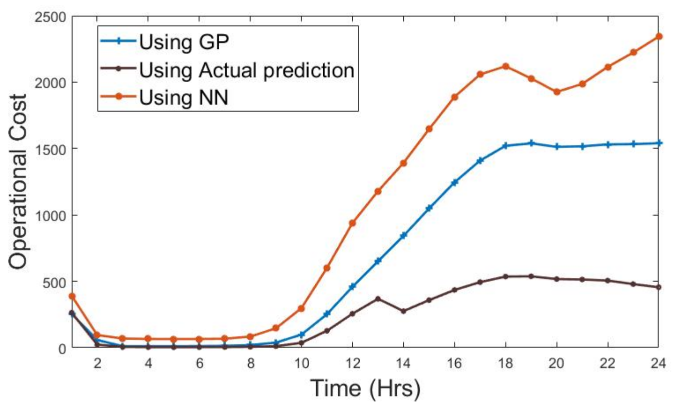

Figure 8: Comparison of operational cost for building load.

For the second experiment, we consider weather data for the same location for another year (1990, **year2**) given in [19]. We deploy the model iteratively trained in **year1** for use in **year2** during the same period of the year (100 days include 9600 samples, from January 1st). We observe that the errors for both models in the second year reduce significantly, along with the number of update points (demarcated by '$*$') required for training. For the last 40 days in **year1** and whole period of **year2**, GP reports much smaller MAPE than NN.

The focus of our framework is to reduce the overall operational cost while employing approximate load thermal models initially. We provide in Fig. 8, the operational cost for both approaches along with the case of perfect prediction. For every one-hour period, the operational cost during that period averaged for the last 30 days of the operational window is provided in this figure. We observe that the cost is significantly less for GP models than for NN models. We think this is due to two factors. First, with GP, the % error in power prediction is smaller during this period. Second, for NN, we consider a standard MPC without confidence constraints; while in our GP augmented MPC formulation, we have confidence constraints provided by the GP formulation, leading to better resource management.

8 Ongoing Works

8.1 HVAC-aware Deep Reinforcement Learning based Residential Microgrid control

We demonstrate the effectiveness of our additive GP models in the context of MPC-based microgrid control of building networks. Our framework learns the errors of approximate building thermal models in an online manner and adjusts power dispatch accordingly and try to get an accurate building thermal model.

Now we know, most of the electricity consumption of building is due to the HVAC system. The aim of Building Energy Management System (BEMS) is to reduce the total electricity bill for normal operation of a building. For reducing electricity bill, we need to reduce the energy consumption of the building which again affects the comfort factor of the building. According to ASRAE standard [31], comfort factor should have a range that indoor temperature lies between 19 and 24 °C.

8.1.1 Introduction

The BEMS must maintain a balance between two contradictory factors, one is related to the electrical consumption and the other is comfort of a building in order to reduce the total electricity cost of the building. In general, distributed energy resources such as microgrids are used for affordable, reliable and environment-friendly energy supply. As renewable power generation is highly dependent on the weather condition, it is also required to connect the utility grid for reliable power supply to the building loads. Due to the dependency on weather in microgrid and dynamic pricing scheme in utility grid, we require a trade-off between the comfort need and electricity consumption of the building. For example, if minimizing electricity bill is of high priority during peak hours, we have to relax the comfort need of the building.

8.1.2 Motivation

In case of BEMS, it is often intractable to get accurate dynamics of the temperature inside the building which is affected by many factors. In order to adress these issues and as compared to model-based BEMS as explained in [24] , we use Q-learning based DRL method which does not require any prior knowledge regarding transition probabilities in the system. It makes this process suitable for handling such systems which deals with real-time data without any prediction process. Most of the research focus on the calculating energy schedules in BEMS using predicted day-ahead data rather than real-time experience and information. In recent work , HVAC control using DRL method has been done [5]. In that case, the dimension of the action space increases exponentially with no of zones and air flow rate levels. This increases the training time and reduces the efficiency of the control action. But in this work, instead of controlling the whole HVAC system, we tune two control parameters(w_E and w_C in [24]) of HVAC for maintaining a good balance between the electricity bill and the comfort level of the building. The predicted electric demand which trades off the cost and comfort, is used to decide *charging/discharging* of battery in microgrid along with forecasted utility price and uncertainty in power generation of PV. This work is the first(to the best of our knowledge) to apply DRL technique for microgrid control along with tuning of the HVAC system parameters for desirable comfort level and energy efficient residential microgrid system.

8.1.3 Goal of the Work

The main contributions of this work are summarized below:

1. We present a Deep Reinforcement Learning based model which optimizes the microgrid control and operation ie. the energy storage system charging and discharging along with the parameters of MPC-based HVAC controller design of the building. We design this problem as a Markov Decision Process(MDP) with suitable environment states,actions and reward function.

2. We design an optimal strategy for joint control of the energy management system and the HVAC controller parameters of the residential microgrid based on Deterministic Policy Gradient(DPG).

3. We compare the performance of the proposed RL-based algorithm with the pure model-based control of residential microgrid and also with an RL-based integrated Microgrid-building HVAC control.

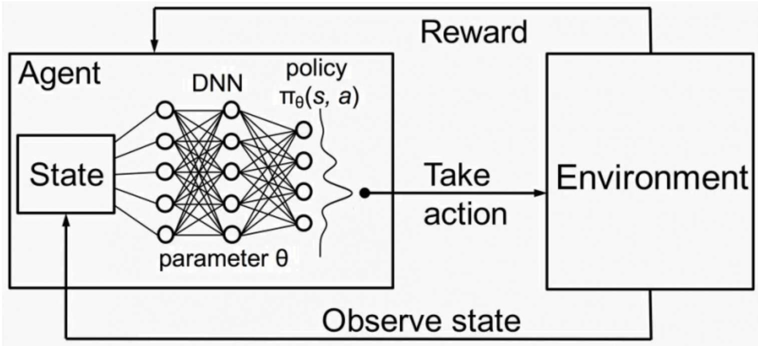

Figure 9: Deep Reinforcement Learning Flow.

In residential microgrids, the energy level of the storage system at next time slot depends on the current energy level and current discharging/charging power, not on the previous states and actions. In building loads, the comfort factor at next time slot is dependent on the indoor temperature, HVAC power input, and environment disturbances (e.g., outdoor temperature and solar irradiance intensity) in the present time slot.In this study, Q-learning method is applied to Microgrid for calculating the optimal cost effective operation schedule of the generating units ie PV unit,energy storage device and utility grid. Additionally we try to optimize the weight parameters of MPC-based HVAC controller in order to reduce the electrical demand further resulting in reduction in electricity bill by keeping the comfort factor within desirable range. In a conventional RL based HVAC controller, it controls the air mass flow rate to regulate the temperature . But instead of that we predict the values of the MPC parameters(w_E and w_c) within the range for minimizing the electrical consumption of the building load further and also maximizing the comfort factor. We will formulate the sequential decision making problem in the residential microgrid as a MDP(Markov Decision process). A MDP is formally defined as a five-tuple $M = (S, A, P, R, Y)$, where S is the set of environment states and A is the set of actions.In this work, the agent denotes the learner and decision maker (i.e.,microgrid with HVAC controller), while the environment comprising many objects outside the agent (e.g., renewable generators, battery ,HVAC system, utility grid, indoor/outdoor temperature). The agent observes environment state s_t and takes action a_t. Then, environment state becomes s_{t+1} and the reward R_{t+1} is returned. In the following parts, we will design key components of the MDP, including environment state, action and reward function as shown in Figure 9.

8.1.4 Problem Formulation (Problem-2)

The optimal solution of the given problem can be solved by observing the current system states. If e_t^b denotes the State of charge (SOC) of the energy storage device (ESS) and E^B is the maximum capacity of ESS. For preventing overcharging and underdischarging of ESS, we introduce a factor γ as a safety factor. Then we can write

$$\gamma.E^B \leq e_t^b \leq (1-\gamma).E^B \tag{20}$$

We define the net power demand e_t^{net} of the building load(assuming HVAC load(e_t^{HVAC}) as load(e_t^{const}) and other loads as constant) at a time step t as

$$e_t^{net} = e_t^{HVAC} + e_t^{const} - e_t^{PV} \tag{21}$$

assuming there is no loss in ESS while charging,discharging or staying idle. e_t^{PV} is the predicted PV power for time step t. The time is repeated with a period of 24 hours, the state of the time stamp($\widehat{t}$) is considered to be repeated over a period of 24 hours.We denote the dynamic electricity price of the utility grid as v_t and the parameters related to two contradictory factors(energy consumption and comfort) of the BEMS as w_e and w_c. The state of the Microgrid with the building load can be written as $s_t = [e_t^b \quad e_t^{net} \quad v_t \qquad w_e \quad w_c \quad \widehat{t}] \in S$ where S is the state space of the energy management system of the building.

Let us denote the power exchange between the microgrid and utility grid as P_{ut} and ESS charging/discharging power as B_t. The range of B_t is $[-d_{max}, c_{max}]$ where d_{max} is the maximum discharging power and c_{max} is the maximum charging power. For maintaining the power balance, the power supply should be equal to the power demand. Then we can have

$$P_{ut} + e_t^{PV} - B_t = e_t^{const} + e_t^{HVAC} + B_t \tag{22}$$

Again we know e_t^{HVAC} is a function of w_e and w_c. For reducing the overall electrical consumption, we have to tune these two parameters. Let the action related to the tuning parameters be T_p

In this case the action space A is: $A = \{B_t \quad T_p\}$.

Let $r(s_t, a_t)$ be the reward function that gives the cost of the energy that the microgrid sell to the utility company. In other words, for minimizing overall The reward function can be defined as :

$$r(s_t, a_t) = r^b + r^{net} \tag{23}$$

where,

$r^b = -[e_t^b.u_t + \epsilon.(E^B)] \cdots e_t^b \leq \gamma.E^B$,
-[$e_t^b.u_t + (1-\epsilon).E^B] \cdots e_t^b \geq (1-\gamma).E^B$

and

$r^{net} = -[e_t^{net}.u_t + \kappa^{up}(w_c - w_c^{max})], w_c > w_c^{max}$,
-[$e_t^{net}.u_t + \kappa^{low}(w_c^{min} - w_c)], w_c < w_c^{min}$,
-[$e_t^{net}.u_t$],otherwise.

Here ϵ is the penalty factor for overcharging or discharging the ESS and κ^{up},κ^{low} are penalty factor for the MPC based HVAC parameter values that are out of range . The values of the parameters are in the range is [0,1].Selling electricity price u_t can be defined as $u_t = \sigma v_t$ where σ is a constant.

In the proposed Deep neural network model , the Agent learns how the changes in MPC-based HVAC controller parameters affect the total power consumption of the building.

The estimation of the function f illustrates the relationship between the parameters and the total energy consumption E_{total} and comfort factor shown as:

$$\widehat{f}(w_c, w_e, E_{t-1}^{total}) = E_t^{total} \tag{24}$$

where $\widehat{f}$ represents the approximated function that explains the relationship between the input data.

8.2 Design Automation Support for Residential Micro-Grid Model generation and co-simulation

As residential Micro-Grids provide a viable alternative to the ever-increasing power requirements and increased use of non-renewables for clean and reliable power supply.

8.2.1 Introduction

The existing modeling and simulation tools for micro-grids require domain expertise related to power flow analysis, state estimation and control,knowledge of CAD tools. Using power systems simulators for Micro Grid Design requires designing with vendor specific libraries,designing from low level library elements. Moreover there is a lack of high level automation, lack of scheduling optimizations specific to MicroGrids. So we build component libraries for Microgrids in an Opensource tool and provide high level design specification, automatic initial design generation and scheduling optimizations. Along with this we will validate the model using a test-bed.

8.2.2 Goal of the Work (Problem-3)

The main contributions of this work will be :

- We propose a first of its kind toolset for Microgrid design, supported by open source modelica component models benchmarked w.r.t. an actual testbed.
- Component models can be parameterized for capturing a wide class and range of real life components.
- Our high level specification will enable automated generation of simulatable initial designs reducing the design effort for micro-grids.
- We propose implementing power and reliability optimizations for intelligent micro-grid control as automated compiler optimizations which shall be push-button features of our toolset.
- We will then interface an MPC controller with the designed microgrid. We will have a library of energyplus building as the load of the microgrid. We will create an interface for the integration of the microgrid (generated from the tool),controller(matlab/openmodelica),building model(Energyplus). The flow is explained in the following figure 10.

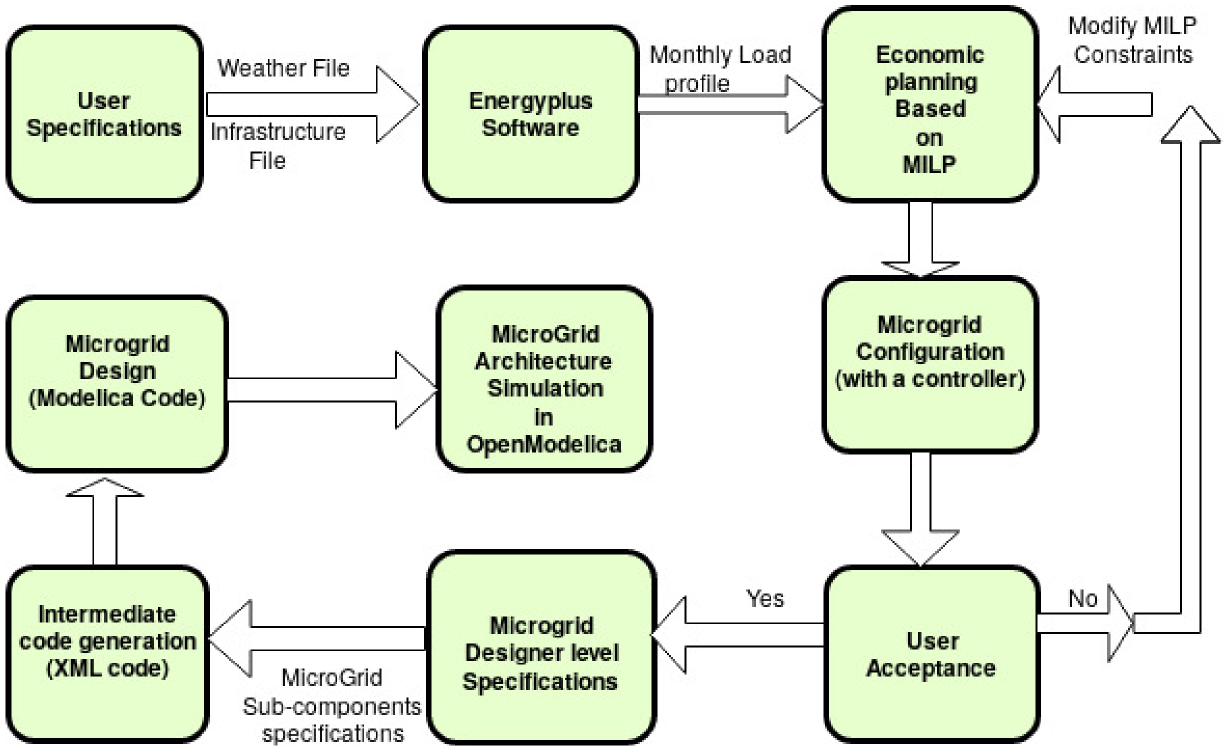

Figure 10: Workflow of the Tool[41]

9 Dessemination

Rumia Masburah*, Rajib Jana, Ainuddin Khan, Soumyajit Dey, Qi Zhu,"*Microgrid Economic Dispatch for Building Networks using Gaussian Process based Learning*",American Control Conference,2020**[communicated]**

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