Microgrid Operational Planning using Deviation Clustering within a DDDAS Framework

Joshua Darville[1] and Nurcin Celik [2]

[1] University of Miami, Coral Gables FL 33124, USA
jmd437@miami.edu
[2] University of Miami, Coral Gables FL 33124, USA
celik@miami.edu

Abstract. As climate change progresses and the global population continues to increase, meeting the energy demand is an issue that has been brought to the forefront of the conversation. Microgrids (MGs) are groundbreaking tools that have risen in popularity to combat this crisis by capitalizing on renewable, distributed energy resources to efficiently satisfy the energy demand from environmental sensors via telemetry. In this work, we present a deviation clustering (DC) algorithm within a dynamic data-driven application systems (DDDAS) framework to reduce the length of the MG dispatch model's planning horizon while retaining the temporal characteristics of the initial load profile. The DDDAS framework allows for the adjustment of the current dispatch decisions in near real-time. We develop two modules embedded within this framework; the first is a proposed rule-based policy (RBP) that modifies the sensing strategy and the second is the DC algorithm which reduces the execution time of the MG simulation. Numerical analysis was conducted on the IEEE-18 bus test network to assess the performance of the proposed framework and determine an appropriate threshold for clustering. The limitations of the presented framework were also determined by comparing the tradeoff between its the speed of the solver's solution time and the accuracy of the resulting solution. The results indicate a decrease in solution time within the desired accuracy limits when using the proposed approach as opposed to traditional load dispatch.

Keywords: Microgrids, Clustering algorithms, Data analytics, Climate change, Distributed feedback devices

1 Introduction

Energy surety remains the primary concern for many countries. In the wake of existing factors such as the rising global population [1], high frequency of natural disasters [2], and accelerating climate change due to carbon emissions (CO_2) [3], the utilization of distributed energy resources (DERs) into existing main grid technology is essential to effectively sustain the global population. Moreover, unexpected factors such as the COVID-19 virus [4] have re-emphasized the need for a quicker response to real-time situations as many people continually remain in quarantine consuming power (hence increasing residential demand). This dilemma presents both a challenge to reliable energy systems in times of crisis and an opportunity to utilize a load profile generated by the quarantined clusters for operational planning. Thus, understanding the parallel characteristics across various applications, is crucial for innovation [5]. Microgrids are sub-networks that utilize DERs in parallel with the main grid to efficiently dispatch power, ensuring reliable distribution with quicker response time than their traditional, manual counterparts. Therefore, the challenge to obtain real-time situational awareness requires the regulation of large heterogeneous data for anomaly detection within the microgrid (MG) system. Consequently, the MG simulation will need to steer the instrumentation to acquire the most relevant sensory data at the appropriate fidelity for near real-time decision making.

The powerful paradigm, Dynamic Data-Driven Application Systems (DDDAS), first introduced by [6] resolves this challenge in a holistic manner [7]. DDDAS equips the proposed framework with the ability to ascertain how the system and environmental data should be harvested as the MG simulation receives near real-time data from the MG system. Furthermore, DDDAS has had tremendous success across a vast and diverse spectrum of fields [4]. Examples of these fields include materials modeling [8], aerospace engineering [9], cybersecurity [10], smart cities [11], [12], cloud-data access [13], [14] and energy-aware optimization [1], [3], [15]. Similarly, derivatives of DDDAS such as [16], [17] are utilized within the context of bulk-power systems by dynamically receiving data into an executing MG simulation and utilizing an online learning algorithm to feed the database for faster future computations.

However, rapid future computations incur an engineering tradeoff between computational resources and the desired accuracy within an appropriate time as the MG dispatch model scales. For large scale bulk-power systems, this approach becomes less applicable as the error rises for a highly clustered load profile or becomes too computationally expensive to solve the initial load profile. Hence, it is imperative to efficiently cluster the initial load profile and consequently, the number of timesteps (blocks) throughout the planning horizon within an acceptable margin of error. Among the variety of clustering techniques, the most common is k-means use by [18] on spatial data to aggregate similar load profiles, and achieve accurate long-term load forecasts based on land use or location. However, [19] clusters based on the user's load characteristics to reduce the complexity of communication between the grid and the users. Previous studies throughout the literature further note the relationship between the scale of the MG dispatch model and the number of blocks that define the planning horizon [20].

Main contributions of this work are twofold. First, a rule-based policy (RBP) is presented to integrate the transmission system operator (TSO) into the considered DDDAS framework. Despite DDDAS's autonomous operational design for efficacy, anomalous data derived from various sensors (in error or fault) could result in blackouts, load spikes and/or a series of events leading toward an unplanned islanding. Thus, a human-in-the-loop system could be necessary. This necessity is represented by the TSO and is embedded within the proposed DDDAS framework. Second is the deviation clustering (DC) algorithm which clusters the initial load profile based on the standard deviation (σ) of similar load levels, enhancing the MG simulation's execution time. An engineering tradeoff between the speed of the solver's solution time and the accuracy of the resulting solution was developed to evaluate this performance of the presented approach.

This study is organized as follows. In Section 2, the various modules embedded in the MG framework design are outlined including the rule-based policy and the deviation clustering algorithm. In Section 3, numerical analysis is used to examine the engineering tradeoff between the speed of the solver's solution time and the accuracy of the resulting solution along with the benefit of using the DC algorithm. Finally, Section 4 concludes the results of this study.

2 Microgrid Framework Design

The proposed framework can be described via three cycles (see Fig.1.). Cycle 1 is the main loop that integrates the MG Simulation with the DC algorithm and the RBP. Initially, near real-time data from the MG system is fed into the MG Simulation. The simulation produces the load profile according to the received data, which is then fed into the DC algorithm. After DC processes the initial load profile, the newly clustered profile is sent to the RBP as depicted in Fig.1.

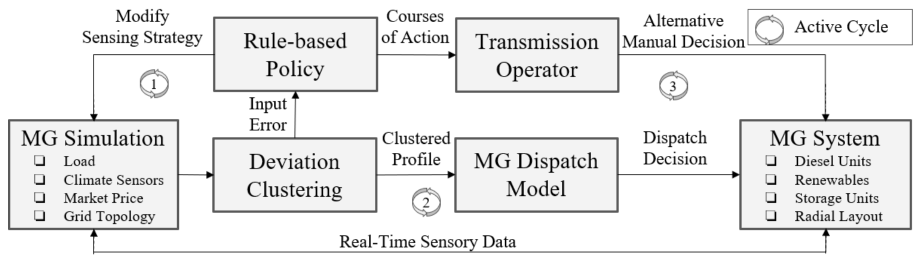

Fig. 1. Proposed MG operational planning within a DDDAS framework

The RBP then determines whether to continue the operation with cycle 2 or cycle 3, which reflects autonomous operation or some degree of TSO intervention, respectively. The MG dispatch model used in cycle 2 is based on [16] with an extension for energy storage capabilities. Both cycles 2 and 3 are mutually exclusive, and the unselected cycle will become inactive. As cycle 1 recursively scrutinizes the data according to the RBP, cycle 2 typically follows utilizing the MG dispatch model for decision-making unless the MG simulation receives anomalous data; In this case, cycle 3 would be chosen to involve some degree of TSO intervention.

The DDDAS paradigm supports this symbiotic, feedback loop requesting information unique to potential anomalies while receiving near real-time data. This two-way communication feature of DDDAS helps to better mimic the real-world MG system by capturing the current system's state and investigating extreme values to revise the current MG dispatch decisions. The RBP determines the operation plan, categorized by the risk associated with data, where the conditions are predicated on the tradeoff of using the DC algorithm.

2.1 Rule-based Policy

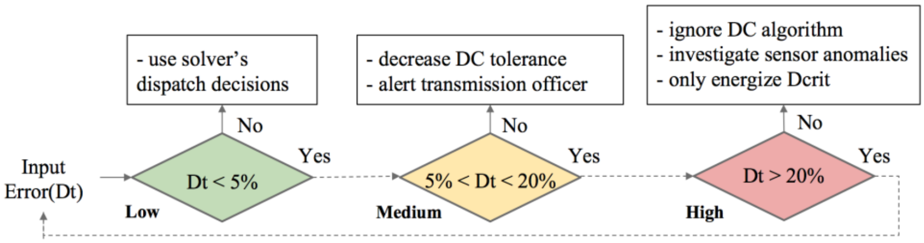

Fig. 2. Rule-based policy to determine MG operational plan

In Fig. 2, which is nested in Fig.1, the proposed RBP chooses which cycle should be used to determine the MG operational plan based on the load input error before and after clustering (Dt). The RBP is categorized into three major abnormality levels as low, medium, and high. Cycle 2 utilizes the MG dispatch model decisions when there is low risk for efficiency. However, cycle 3 integrates the TSO when there is a potentially higher risk. TSO may then follow the suggested courses of action from the RBP or make an informed decision having been provided with alternatives. The courses of action associated with each abnormality level are outlined in Fig. 2 and a subset of the initial load reflecting public safety facilities (Dcrit) is energized despite the risk.

2.2 Deviation Clustering Algorithm

Deviation Clustering (DC) is an algorithm used to cluster the initial load profile to reduce the length of the planning horizon while retaining the initial load's temporal characteristics as explained in Table 1.

Table 1. Algorithm for Deviation Clustering.

Input: x load profile, σ threshold
1. Initialize counter
2. Initialize an empty array (no load profile)
3. Add the first element of x to the empty array
4. Conduct a pairwise comparison between the elements of x
5. If the pair's standard deviation is < σ, cluster the load
6. Else add the current element from x to begin a new cluster
7. Conduct another pairwise comparison on x
8. If the elements in the pair are not equal, increase the counter
Output: the clustered load profile, the new planning horizon in blocks

In summary, DC clusters the load profile based on the standard deviation (σ) of sub-clusters throughout the planning horizon, where σ is the threshold value for all sub-clusters. As σ increases, so does the size of each sub-cluster resulting in fewer blocks to define the planning horizon. Moreover, the clustering occurs chronologically to preserve the temporal characteristics of the initial load profile.

3 Numerical Analysis

The IEEE-18 is selected as the testbed for this study where the data can be found at [22] for replicability purposes. After collecting the data, the proposed approach for MG operational planning was applied to examine the effects of implementing the DC algorithm within a DDDAS framework.

3.1 Deviation Clustering Tradeoff

When utilizing the DC algorithm, a varying degree of distortion in the initial load profile was observed by incrementing the sigma value as shown in Fig. 3. As previously mentioned, sigma value (σ) is a threshold for all sub-clusters.

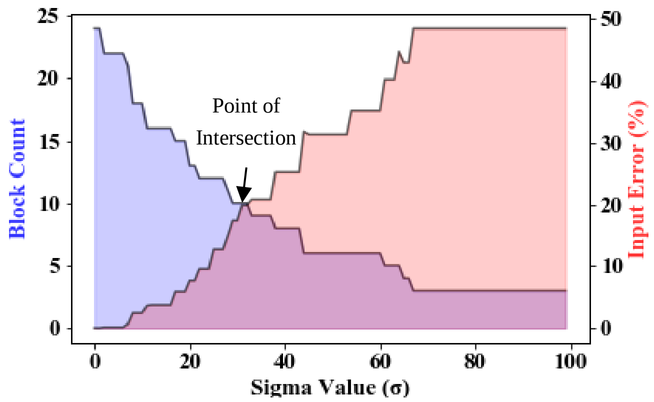

Fig. 3. Tradeoff analysis between reducing the planning horizon (block count) and retaining the initial information (input error) at various sigma values (σ)

In Fig. 3, the sigma value (σ) acts as a control parameter for the DC algorithm used to adjust the degree of clustering. The resultant level of distortion is captured by the input error and the resultant length of the planning horizon is captured by block count simultaneously. Input error captures change in the load profile between the MG simulation and the MG system as previously mentioned in Fig. 2. Block count is defined as $BC = 24\,blocks/t\ hours$ where its minimum is set as 24 blocks per day. Notably, this approach scales to consider smaller hourly time-steps. This allows for the realization of short-term MG operational planning. For example, a 1-min schedule would contain 1440 blocks, since $BC = 24\,blocks/1/60\ hours = 1440\ blocks$. Hence, it is imperative to find a suitable (σ) which effectively utilizes computational resources during nominal operation.

Similarly, the intersection between the block count and input error reflects the σ at which the tradeoff no longer exists because it shares an equivalent response relative to their scales. Since the σ is directly proportional to the input error but inversely proportional to the block count, the point of intersection (POI) will vary for each initial load profile. A single replication of the load profile was used in Fig. 3 and the best σ was determined to within [0, 30], which up to the POI; this interval reflects low to medium risk and gives preference toward accuracy instead of speed. Conversely, a high risk is associated with σ outside [0, 30] which reflect preference toward speed instead of accuracy. Designating the appropriate range based on the POI updates σ and consequently the proposed DC and RBP modules according to the most recent data. Additionally, this preferred region of operation can be adjusted before the POI by the TSO as a safety factor.

3.2 Utility of Deviation Clustering

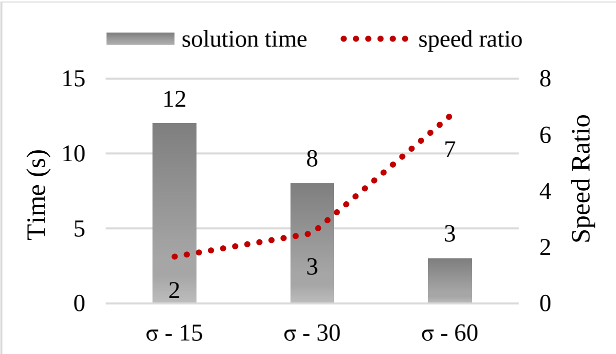

Fig. 4. DC's effect on solution time for the MG Dispatch model

In Fig. 4, we observe a decrease in solution time at higher σ values which consequently enhances the execution speed of the MG application reaffirming the previous observation in Fig 3. The speed ratio is defined as the solution time of traditional dispatch where σ = 0 divided by the new solution time post deviation clustering, to capture any improvement. For example, a speed ratio of 2 at σ = 15 indicates that clustering at σ = 15 results in obtaining a solution twice as fast compared to traditional dispatch σ = 0. Conversely, σ results are directly proportional to the speed ratios which validates their use as control parameters for clustering and consequently the scale of the MG dispatch model. It should be noted that this benefit of obtaining a faster solution is limited by level of risk incurred previously mentioned in Fig.3 and reflected in Table 2 with increasing output error, where output error is the error change in dispatch decision with the initial, unfiltered load profile. The MG simulation benefit of solution speed and limitation of distorted information using the DC module are summarized in Table 2, for the TSO to determine acceptable risk independent of the regions outlined by the proposed RBP module in Fig. 2.

Table 2. Summary of the DC effect on the MG application.

Load Profile	Block Count	Input Error	Speed Ratio	Output Error
Sigma = 0	24	-	-	-
Sigma = 15	16	3.7	2	2.8
Sigma = 30	10	17.4	3	7.23
Sigma = 60	6	35.2	7	9.6

4 Conclusion

This study presents a symbiotic benefit between a microgrid simulation and its execution in relation to data updated from a real system, within a dynamic data-driven application systems (DDDAS) framework. The DDDAS paradigm was applied to a microgrid (MG) simulation using two modules, a deviation clustering (DC) algorithm to reduce the dispatch model's scale, consequently enhancing the MG simulation's execution time, and a rule-based policy (RBP) to blend the transmission system operator (TSO) with smart grid operation design. Fig. 1 provides an overview of all the modules within the proposed DDDAS framework for MG operational planning. The proposed DC algorithm clusters the initial load profile using the standard deviation as a control parameter for each sub-cluster.

Numerical analysis was conducted on the IEEE-18 bus test network and standard deviation within [0, 30] was selected based on the engineering tradeoff between the speed of the solver's solution time and the accuracy of the resulting solution. Furthermore, it was observed that the temporal characteristics of the initial load profile were retained at $\sigma = 15$ but not $\sigma = 60$ since the input error increases from 3.7% to 35.2%. Moreover, the DC algorithm generates a solution 50% faster with a 3.7% risk at $\sigma = 15$ when compared to traditional forms of microgrid dispatch. Numeral analysis has shown that standard deviation was directly proportional to input error but inversely proportional to block count, which reflects distortion in the load profile and the length of the planning horizon, respectively. Hence, these intervals can be used to develop conditions for the proposed RBP and detect anomalies other than those resulting the DC algorithm including the ones resulting in load spikes, blackouts and/or unplanned islanding.

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