

Energy Management Systems with Intelligent Anomaly Detection and Prediction

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Abstract—In this paper, we present our Energy Management Systems (EMS) with intelligent anomaly detection techniques that achieve real-time detection of outlier(s), prediction of future fault(s), and extraction and amendment of historical data anomalies. The EMS has adopted advanced outlier detection theories and frameworks to optimize the use of key energy devices such as distributed energy storages with performance tracking and diagnosis mechanisms. Those advanced detection mechanisms have been integrated with our distributed EMS that communicates with one another to handle the current and potential outlier(s), which realizes the resilient operation of energy systems to avoid sudden interruption of operation. As one of the applications of the anomaly detection to energy management with distributed battery optimization, the framework has also been verified in the use case of demand charge (DC) cost reduction where the results based on modified load data by our proposed mechanism demonstrate the precise calculation of battery dis/charging profile, which reduces the cost incurred from the use of electricity in peak-time DC periods.

Index Terms—Energy Management System, Resilient Operation, Anomaly Detection, Outlier Prediction, Fault Recovery, Distributed Energy Storage, Demand Charge Management

I. INTRODUCTION

Energy management systems (EMS) are being developed to optimize grid operations as well as the use of energy systems including batteries, loads, photovoltaics (PVs), diesel engines, grid controller. In particular, distributed generation (DG) and energy storages are being deployed Behind-The-Meter (BTM) in the buildings of commercial and industrial (C&I) customers to satisfy their energy and cost-reduction needs [1], [2]. One of the important BTM applications, for instance, is on optimizing batteries' dis/charging profile to minimize the cost that customers incur from the peak prices such as Demand Charge (DC) rates [3].

Generally, operations and optimizations by EMS would be susceptible to the following data anomalies:

- Real-time measurement data with sudden or possible outlier(s) collected through monitoring process of energy devices. Obviously, real-time data tell us about current condition of the systems and furthermore their underlying relationships.
- Predicted energy data containing error(s) and/or indicating future system failure(s). Assessment in predicted data is necessary before utilizing the data in optimizations. Also, if the predicted data indicates future potential failure(s), we need to handle them well before that happens.

- Historical data stored in EMS containing anomalies in their profiles used in operation and optimization. Historical data are the source of forecasting behaviors, effective energy management, and optimizations. Utilization of data containing anomalies leads to ineffective results or future system faults.

In this context, one of critical problems that our EMS needs to address is that an operator should constantly be aware of unexpected events or accidents relevant to energy systems and grid condition when there exist abnormal behaviors in those systems. Therefore, detecting anomaly in the past data, current real-time data, and future predicted data to recover from the outlier based on the detection results are of significant importance in the operation of the energy systems as well as minimizing the risk of potential business loss.

Human knowledge and experience by professionals often become an important asset when improving the anomaly detection. The algorithms explained in this paper describes how the feedback from an expert such as an operator received after visualizing the detection results is utilized in refining the filtering process of outliers for the future anomaly detection process.

The paper is organized as follows: In Section II, we discuss related work. Section III introduces an autonomous resilient distributed architecture of our cloud-based EMS. Section IV provides our anomaly detection mechanisms for real-time, future, and historical data management with human feedback analysis. In Section V, the applications that have adopted the anomaly detection techniques are presented with demonstration and its results. Finally, we conclude with the summary of work and future directions in Section VI.

II. RELATED WORK

Anomaly and fault detection is an intensively studied area with advance in artificial intelligence and machine learning research. NEC Labs also have conducted a variety of research projects in the domain of fault and anomaly detection as in the product called SIAT (System Invariant Analysis Technology) for modeling time-series monitoring data from a variety of system types such as distributed systems [4], [5]. Those schemes have an advanced approach based on Autoregressive with Exogenous Input (ARX) with invariant relationships among systems to extract the underlying logical or physical connections among them, which has been applied to our EMS in anomaly detection.

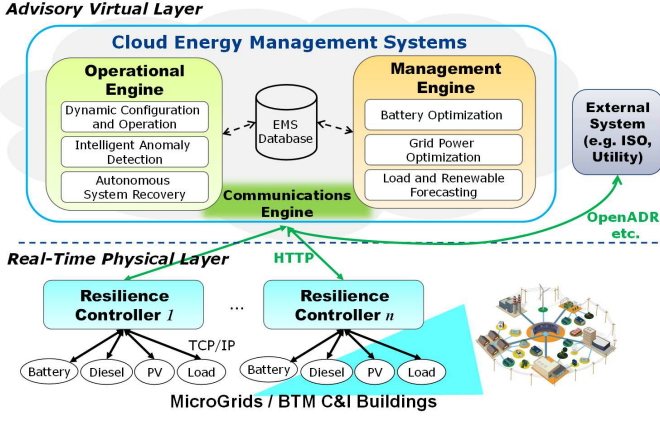


Fig. 1. Resilient distributed architecture of energy management systems.

The fault detection targeting energy cyber-physical systems has been researched based on the intelligent anomaly detection framework, although those approaches have centered on the theoretical models to improve anomaly detection given a stream of energy data sets [6], [7]. The latest detection scheme currently is a state estimation and anomaly detection algorithm that combines model-based approaches such as Recursive Bayesian Filtering and data-driven approaches as in Autoregression with Exogenous Inputs and Exploratory Factor Analysis. The integration of model-based and data-driven strategies leverages the selective superiorities of both into a comprehensive system.

Furthermore, some vendors have worked on the fault prediction with data analytics approach. For example, Avantis PRISM [8] is a solution that can provide early warning notification and diagnosis of equipment issues days, weeks, or months before failure. The approach is based on the prediction and thresholds to extract abnormal condition before operational alarms.

However, it has still been challenging to precisely detect outliers and none of outlier detection techniques is able to perfectly capture anomaly without obvious criteria to classify data into faults such as thresholds [9]. In most cases, the feedback from an expert such as a system operator can contribute to improving filtering anomaly. Our EMS has a sophisticated feedback analysis of human inputs, which distinguishes our technology from existing ones.

Our EMS has integrated advanced anomaly detection and prediction framework and enabled a noble consistent mechanism to capture real-time and future outliers as well as extract anomaly to correct historical data to be used in optimizations with renewables and batteries. The EMS also solves the problem by utilizing human feedback that improves the error filtering process.

III. RESILIENT EMS ARCHITECTURE

To realize resilient grid operation, in our previous work [10], we have introduced an autonomous distributed energy management platform that enables dynamic configuration and

operation, fault detection, and system recovery. Figure 1 describes the current EMS platform that NEC labs have developed utilizing Amazon Web Services (AWS). The EMS consists of Operational Platform, Management Engine, Resilience Controller(s), and EMS Database, all of which are connected through the Internet communications protocols, data connection protocols such as Java Persistence API (JPA), or local network protocols.

Operational Platform is introduced to make the EMS operations more resilient and dynamic where the autonomous mechanisms are enabled with system upgrade, maintenance, enhancement, and failure recovery. Management Engine aggregates Distributed Energy Resources (DERs) to conduct economic optimization and dispatches management commands to the energy resources [11], [12]. It basically receives the input of historical data on load and renewable profiles and conducts forecasting to generate optimum battery and grid-power profiles based on the electricity price, battery degradation, and demand charge rates. Resilience Controller, which is described with application of real-time anomaly detection in Section IV-A, aggregates the devices that require controls with seconds typically installed in the microgrid/BTM premises.

Intelligent anomaly detection functions have been implemented in Operational Platform and Resilience Controller and data analyzed or corrected is utilized by the Management Engine. Figure 2 describes the overall procedure on how the anomaly detection and prediction have been integrated to make the EMS operation more resilient, efficient, and robust. We have developed visualization engines on top of the EMS components that enable human interaction with experts of energy operations such as power system operators. Through the user interface, an operator is able to keep track of the systems' behavior and modify parameters used in the anomaly detection.

IV. ANOMALY DETECTION AND PREDICTION WITH EMS

As in the procedure in Figure 2, the EMS integrates the following functions and is designed to incorporate an operators knowledge to sophisticate anomaly filtering process. In the EMS, several advanced anomaly detection frameworks have been implemented to apply data-driven model to energy management systems. See our work [6], [7] for further clarification.

A. Real-Time Outlier Detection for Energy Devices under Operation

Detecting any possible outliers and faults in real time is one of the most primary and necessary functions in operation of microgrids and BTM applications. This module realizes the automation of the framework and optimization of anomaly filtering based on human interactions. The following is the procedure of real-time outlier detection with human inputs. All the notations and definitions can be found in TABLE I.

Step1: At time t , collect current measurement data from energy nodes such as load, PV, and battery.

Step2: For each energy node i , check current measurement data $x_i(t)$ to see if the data is within the normal range, which

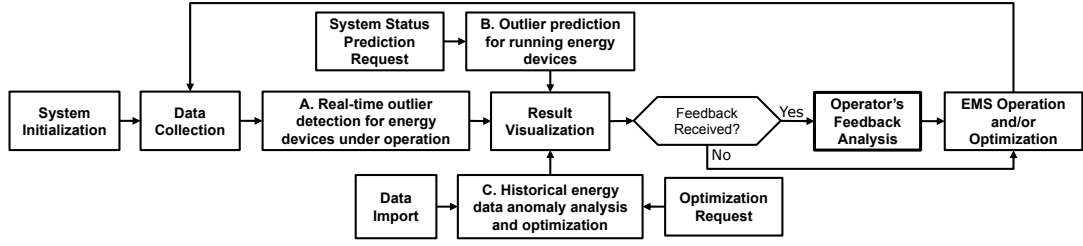


Fig. 2. Overall procedure of achieving real-time anomaly, future fault prediction, and past data analysis for energy management and optimization.

TABLE I
NOTATIONS AND DEFINITIONS

$x_i(t)$	Measurement data of an energy device/node i at time t .
$\bar{x}_i(t)$	Predicted data of an energy device/node i at time t .
$e_i(t)$	Residual defined as $e_i(t) = x_i(t) - \bar{x}_i(t) $.
$\varepsilon_i(t)$	Residual threshold to filter residuals defined as $\varepsilon_i(t) = \alpha \times \arg_r\{Prob(e_i(t_k) < r) \simeq \beta\}$. This means deciding r so that $(\beta \times 100)\%$ of the set of residual time series $E_i = \{e_i(t_k)\}$ are classified less than r relaxed by α .

is determined based on the nature of energy device. If $x_i(t)$ is over normal range, visualize it to the operator.

Step3: Predict value $\bar{x}_i(t)$ at t using past data of energy device i to calculate the residual $e_i(t) = |x_i(t) - \bar{x}_i(t)|$.

Step4: Calculate residual thresholds $\varepsilon_i^1(t)$ and $\varepsilon_i^2(t)$ based on $\{\varepsilon_i^1(t), \varepsilon_i^2(t)\} = \{\alpha_1, \alpha_2\} \times \arg_r\{Prob(e_i(t_k) < r) \simeq \beta\}$ over past residuals $E_i' = \{e_i(t_k)\}$ where $T' = \{t_k\}$ is a past time frame before current time t . The filtering parameters α_1 , α_2 , and β are initialized as 1.1, 1.5, and 0.995, respectively.

Step5: Classify the residual $e_i(t)$ into either one of the following three cases:

- Green Case: $e_i(t) \leq \varepsilon_i^1(t)$
- Yellow Case: $\varepsilon_i^1(t) < e_i(t) < \varepsilon_i^2(t)$.
- Red Case: $e_i(t) \geq \varepsilon_i^2(t)$

Step6: Visualize possible outliers with measurement data $x_i(t)$ at time t . In Green Case, the data $x_i(t)$ is labeled as normal (green) data. In Yellow Case, $x_i(t)$ is categorized as a warning (yellow) data. In Red Case or $x_i(t)$ is over normal range, $x_i(t)$ is categorized as an outlier (red) data so that EMS autonomously starts using a back-up energy device of the failed device i .

Step7: Check if there is any input from an operator about the data $x_i(t)$ being normal, warning, or outlier. Modify the filtering parameters α_1 , α_2 , and/or β based on the input from an operator, see Algorithm 1.

Step8: Proceed to EMS operation and optimization.

Now, the measurement data $x_i(t)$ at time t is categorized into three cases. For the operator side, s/he has an option to adjust the level of anomaly possibility of $x_i(t)$ to make the outlier filtering better in the next-step operation. EMS and the operator may make the same decision over the possibility of the current measurement data being an outlier or not, or EMS and the operator may differ in deciding on anomaly possibility.

There are in total 7 cases to describe the gap in decisions made by an operator and EMS as follows:

- Case1: EMS detected $x_i(t)$ as a normal (green) data \mathcal{X} but an operator set $x_i(t)$ as a warning (yellow) data \mathcal{Y} .
- Case2: EMS detected $x_i(t)$ as a normal (green) data \mathcal{X} but an operator set $x_i(t)$ as an outlier (red) data \mathcal{Z} .
- Case3: EMS detected $x_i(t)$ as a warning (yellow) data \mathcal{Y} but an operator set $x_i(t)$ as a normal (green) data \mathcal{X} .
- Case4: EMS detected $x_i(t)$ as a warning (yellow) data \mathcal{Y} but an operator set $x_i(t)$ as an outlier (red) data \mathcal{Z} .
- Case5: EMS detected $x_i(t)$ as an outlier (red) data \mathcal{Z} but an operator set $x_i(t)$ as a warning (yellow) data \mathcal{Y} .
- Case6: EMS detected $x_i(t)$ as an outlier (red) data \mathcal{Z} but an operator set $x_i(t)$ as a normal (green) data \mathcal{X} .
- Case7: Both EMS and an operator made the same decision or $x_i(t)$ is out of the normal range.

All the filtering process of residuals $E_i' = \{e_i(t_k)\}$ is based on thresholds $\varepsilon_i^1(t)$ and $\varepsilon_i^2(t)$ that depend on the filtering percentage of whole data β and relaxing factors α_1 and α_2 . Depending on which case the gap of the decisions is categorized into, the parameters of α_1 , α_2 and β are accordingly calculated with the rule shown in Algorithm 1 that covers the cases from 1 to 7. If the decisions on the measurement value $x_i(t)$ of both an operator and EMS are the same or the value goes beyond a normal range, the parameters of α_1 , α_2 , and β remain the same. Otherwise, an operator re-labels the state of data so that α_1 , α_2 and β are updated based on the current residual $e_i(t)$. For instance, if the gap is categorized as Case3, α_1 is updated to $\alpha_1 \leftarrow e_i(t) / \arg_r\{Prob(e_i(t_k) < r) \simeq \beta\}$, while α_2 and β remain the same. While other techniques try to refine the theoretical modeling and performance, incorporating human knowledge, expertise, and even intuition into the outlier filtering process improves the detection of outliers.

B. Outlier Prediction Engine for Running Energy Devices

In our EMS, there are mainly two ways to realize outlier prediction.

1) Future energy profile analysis: First, we analyze the predicted energy profile from current point to the future (e.g. day ahead, week ahead, month ahead) to see if it goes beyond the normal range decided based on the power system's property. Forecasting the profiles is based on our advanced scheme as seen in [13]. If the point(s) beyond the defined threshold(s) exist, this procedure extracts its date(s) and time(s) to let an operator know about when the failure(s) will happen.

Algorithm 1 Optimizing filtering parameters based on human inputs in real-time anomaly detection.

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1: Let  $\mathcal{X}$ ,  $\mathcal{Y}$ , and  $\mathcal{Z}$  be normal, warning, and outlier data, respectively.
2: Let  $label_s(x_i(t))$  be the label on data  $x_i(t)$  assigned by EMS.
3: Let  $label_o(x_i(t))$  be the label on data  $x_i(t)$  assigned by an operator.
4: Let  $\epsilon$  and  $\theta$  be certain small values.
5: if  $label_s(x_i(t)) = \mathcal{X} \cap label_o(x_i(t)) = \mathcal{Y}$  then
6:    $\alpha_1 \leftarrow \frac{e_i(t) - \epsilon}{argr\{Prob(e_i(t_k) < r) \simeq \beta\}}$  given  $E'_i = \{e_i(t_k)\}$ .
7:   if  $\alpha_1 < 1.0$  then
8:      $\alpha_1 \leftarrow 1.0, r \leftarrow e_i(t), \beta \leftarrow Prob(e_i(t_k) < r)$ .
9:   end if
10: else if  $label_s(x_i(t)) = \mathcal{X} \cap label_o(x_i(t)) = \mathcal{Z}$  then
11:    $\alpha_1 \leftarrow \frac{e_i(t) \times 0.8}{argr\{Prob(e_i(t_k) < r) \simeq \beta\}}$  given  $E'_i = \{e_i(t_k)\}$ .
12:    $\alpha_2 \leftarrow \frac{e_i(t)}{argr\{Prob(e_i(t_k) < r) \simeq \beta\}}$  given  $E'_i = \{e_i(t_k)\}$ .
13:   if  $\alpha_2 \leq 1.0$  then
14:      $\alpha_1 \leftarrow 1.0, r \leftarrow e_i(t) - \theta, \beta \leftarrow Prob(e_i(t_k) < r)$ .
15:      $\alpha_2 \leftarrow \frac{e_i(t)}{argr\{Prob(e_i(t_k) < r) \simeq \beta\}}$  given  $E'_i = \{e_i(t_k)\}$ .
16:   end if
17:   if  $\alpha_1 < 1.0$  then
18:      $\alpha_1 \leftarrow 1.0, r \leftarrow e_i(t), \beta \leftarrow Prob(e_i(t_k) < r)$ .
19:   end if
20: else if  $label_s(x_i(t)) = \mathcal{Y} \cap label_o(x_i(t)) = \mathcal{X}$  then
21:    $\alpha_1 \leftarrow \frac{e_i(t)}{argr\{Prob(e_i(t_k) < r) \simeq \beta\}}$  given  $E'_i = \{e_i(t_k)\}$ .
22: else if  $label_s(x_i(t)) = \mathcal{Y} \cap label_o(x_i(t)) = \mathcal{Z}$  then
23:    $\alpha_2 \leftarrow \frac{e_i(t)}{argr\{Prob(e_i(t_k) < r) \simeq \beta\}}$  given  $E'_i = \{e_i(t_k)\}$ .
24: else if  $label_s(x_i(t)) = \mathcal{Z} \cap label_o(x_i(t)) = \mathcal{Y}$  then
25:    $\alpha_2 \leftarrow \frac{e_i(t) + \epsilon}{argr\{Prob(e_i(t_k) < r) \simeq \beta\}}$  given  $E'_i = \{e_i(t_k)\}$ .
26: else if  $label_s(x_i(t)) = \mathcal{Z} \cap label_o(x_i(t)) = \mathcal{X}$  then
27:    $\alpha_1 \leftarrow \frac{e_i(t)}{argr\{Prob(e_i(t_k) < r) \simeq \beta\}}$  given  $E'_i = \{e_i(t_k)\}$ .
28:    $\alpha_2 \leftarrow \frac{e_i(t) \times 1.2}{argr\{Prob(e_i(t_k) < r) \simeq \beta\}}$  given  $E'_i = \{e_i(t_k)\}$ .
29: else
30:    $\alpha_1, \alpha_2$ , and  $\beta$  stay the same.
31: end if

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2) Future residuals analysis: Another analysis is the combination of residual prediction and its filtering technique. The future residuals can be predicted based on the historical residuals and related data such as temperature data recorded in EMS. This procedure forecasts the error trend by analyzing if the residual is within the range of its threshold trained beforehand. If it is out of the range, EMS extracts its time stamp(s) to notify when the outliers will happen.

Following are the steps to conduct the future outlier analysis.

Step1: Request system status prediction and estimation for a future time frame $\bar{T} = \{t_1, t_2, \dots, t_f\}$.

Step2: For each energy node i , based on its historical data, predict future data $\bar{X}_i = \{\bar{x}_i(t_k)\}$ where $t_k \in \bar{T}$.

Step3: For each predicted data $\bar{x}_i(t_k) \in \bar{X}_i$, check if $\bar{x}_i(t_k)$ is within the normal range.

Step4: For predicted data points over the normal range, mark the date and time t_k and its predicted value $\bar{x}_i(t_k)$.

Step5: For each node i , based on past residuals as training data, predict future residuals $\bar{E}_i = \{\bar{e}_i(t_k)\}$ where $t_k \in \bar{T}$.

Step6: For each predicted residual $\bar{e}_i(t_k)$, compare $\bar{e}_i(t_k)$ with the threshold $\bar{\epsilon}_i^2(t)$, which is calculated based on $\epsilon_i^2(t) = \alpha_2 \times argr\{Prob(e_i(t_j) < r) \simeq \beta\}$ given past residuals $E'_i = \{e_i(t_j)\}$. α_2 and β are the trained parameters in real-time anomaly detection phase explained in Section IV-A. If $\bar{e}_i(t_k) > \bar{\epsilon}_i^2(t)$, mark the date and time t_k and its predicted

energy data $\bar{x}_i(t_k)$.

Step7: Visualize all the future possible outliers that are marked by the previous steps. Replace or restore the system(s) before the predicted failure time if necessary.

Step8: Proceed to EMS operation and optimization.

EMS utilizes the historical residuals of the measurement energy data to predict future residuals $\{\bar{e}_i(t_k)\}$ where $\bar{T} = \{t_k\}$ is a future time range. All the predicted residuals are compared with the threshold $\bar{\epsilon}_i^2(t)$ where t is the current time. If the residual(s) go beyond the threshold, the possible future failures are visualized to an operator.

C. Historical Energy Data Anomaly Analysis and Optimization

Use of the damaged profiles to optimize the grid or energy systems will cause miscalculation of control points such as dis/charging profiles of batteries. For instance, EMS would not be able to capture the load peak and lose chance to curtail the peak load by battery because of miscalculation of battery profiles, which eventually increases the cost of demand charge for BTM customers. The module for handling historical energy data realizes its anomaly detection and data patch that improve the performance of the EMS operation and optimization.

Step1: Import an energy data profile of device i to EMS or download energy data from EMS per optimization request.

Step2: For each $t_k \in T'$ of historical time frame $T' = \{t_1, t_2, \dots, t_h\}$, calculate past predicted data $X'_i = \{\bar{x}_i(t_k)\}$ and past residuals $E'_i = \{e_i(t_k)\}$.

Step3: Filter the past residuals to list up the possible data anomalies. For each past predicted data $e_i(t_k) \in E'_i$, check if $e_i(t_k) > \epsilon_i(t)$. If $e_i(t_k) > \epsilon_i(t)$, put $x_i(t_k)$, $\bar{x}_i(t_k)$, and $e_i(t_k)$ in data anomalies set F_i^s , its predicted values \bar{F}_i^s , and its residuals set E_i^s , respectively.

Step4: Visualize the filtered anomaly data points for an operator to choose which data are outliers.

Step5: If necessary, utilize the predicted data $\bar{x}_i(t_j^s) \in \bar{F}_i^s$ instead of $x_i(t_j^s) \in F_i^s$ to patch the outlier and store the modified profile data in EMS.

Step6: Modify the filtering parameters α and β based on the feedback from an operator, see Algorithm 2.

Step7: Proceed to EMS operation and optimization.

Algorithm 2 describes feedback analysis of human inputs in past anomaly detection. F_i^s and F_i^o are the list of possible historical failures selected by EMS and an operator, respectively. The important check point is that the possible outliers can be precisely captured by the system or not, which can be filtered by $F_i^o \subseteq F_i^s$. If all of them are captured by the system, the EMS checks whether the number of the detected possible outliers is too large or not by looking at the capturing rate $P = |F_i^o|/|F_i^s|$. If not, EMS modifies α and β to capture wider range of residuals.

V. DEMONSTRATION AND RESULTS

A. Resilience Controller Dashboard

Resilience Controller (RC), as introduced in Section III, mainly realizes the real-time control to adjust the balancing

Algorithm 2 Optimizing filtering parameters based on human inputs in historical anomaly detection.

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1: Let  $T' = \{t_1, \dots, t_h\}$  be historical data time frame.
2: Let  $F_i^s = \{x_i(t_k^s)\}$  be anomaly data points detected by EMS.
3: Let  $F_i^o = \{x_i(t_k^o)\}$  be anomaly data points selected by an operator.
4: Let  $E_i^s$ ,  $E_i^o$ , and  $E_i^r$  be residuals over  $T'$ , residuals detected by EMS, and residuals selected by an operator, respectively.
5: if  $F_i^o \subseteq F_i^s$  then
6:    $P = |F_i^o|/|F_i^s|$ .
7:   if  $P < 0.8$  then
8:      $r' = \arg_r \{Prob(e_i(t_k^s) < r) \simeq 0.8\}$  where  $e_i(t_k^s) \in E_i^s$ .
9:      $\alpha \leftarrow \frac{r'}{\arg_r \{Prob(e_i(t_k) < r) \simeq \beta\}}$  where  $e_i(t_k) \in E_i^r$ .
10:  end if
11: else
12:  Select minimum value  $e_i(t_{min})$  from  $E_i^o$ .
13:   $\alpha \leftarrow \frac{e_i(t_{min})}{\arg_r \{Prob(e_i(t_k) < r) \simeq \beta\}}$  where  $e_i(t_k) \in E_i^r$ .
14:  if  $\alpha < 1.0$  then
15:     $\alpha \leftarrow 1.0$ ,  $r \leftarrow e_i(t_{min})$ , and  $\beta \leftarrow Prob(e_i(t_k) < r)$ .
16:  end if
17: end if

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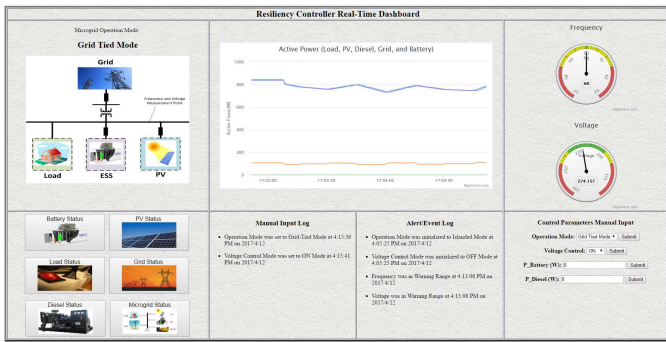


Fig. 3. Real-time Resilience Controller (RC) Dashboard.

of demand and supply. It receives the real-time measurement data to balance the power and restore the nominal frequency. RC dashboard has been developed to keep track of the constant change in power and grid dynamics represented in the Figure 3. This dashboard pops up any event in “Alert/Event Log” part of the screen based on the anomaly detection techniques and mechanisms described in section IV-A. An operator can check the dynamic status and alert logs so that s/he can change the parameters for or send commands to energy devices.

Here, we conducted experiments on how the trained filtering parameters of α_1 , α_2 , and β perform better than the initialized parameters. TABLE II shows the number of detections using a real load profile of a certain school in August 2012 where we have injected 10 random outliers in its profile. We first trained the parameters using previous months in 2012 from the annual load profile of the same place. “Captured” detections stand for

the correct detections of outliers by EMS whereas “Missed” detections are the points that EMS was unable to capture. “Red Case” means the anomaly points EMS labeled as outliers and “Yellow Case” is, in this case, the potential outliers or peak data indicated as warning data. “Total” detections are the summation of Red and Yellow Cases. We define the Capturing Rate (CR) as $CR = \frac{\text{Captured Detections}}{\text{Injected Outliers}} \times 100$. From TABLE II, CR with initialized parameters for the August load profile of the school is 50% where the CR with trained parameters is 80%, which shows the performance improvement with feedback analysis of human input on outlier detection.

B. Possible Outlier Prediction Result

Detection of any possible anomaly leads to resilient operation of the energy systems including batteries by preventing the energy management systems from missing sudden change in their behavior as well as from unexpected interruption caused by their failures including blackouts.

The Figure 4 demonstrates the possible anomalies in predicted future load in July based on the results of the detection mechanism described in Section IV-B. The historical load profile is provided by the same aforementioned school. Those anomalies are calculated based on forecasted energy data and residuals analysis applied to the profile, which indicate possible peaks that need special attention when optimizing energy systems especially in calculating dis/charge power of a battery. In the load profile with possible anomalies in July, the larger the size of those circles is, the higher the possibility of being anomaly becomes. In this case, expected load peaks have been captured by EMS that actually are utilized in the demand charge optimization in the following section.

C. Demand Charge Reduction

Non-residential utility customers incur two types of electricity charges on their bills: one for the energy volume used and another one for the maximum power used during a certain billing period. The second charge type is known as Demand Charge (DC), which has often been discussed as one of the important topics in resilient power as in some regions, it can account for well over half of a customers electricity bill.

Figure 5 describes the difference in DC costs using original, patched, and outlier load profiles from the school and a certain grocery store in August 2012 when conducted battery optimization to minimize DC costs (see the whole framework explained in [11], [12]) as an application of the procedures explained in Section IV-C. An actual battery product size of capacity 85 kWh with max power 30 kW is used with the load of the school and the battery size of capacity 410 kWh with max power 100 kW is used with the load profile at the grocery store. “Original” case is the DC costs of using a load profile without outliers. “Patched” case is the DC costs of using a modified load profile based on the anomaly detection and prediction technique while “Outlier” result is from using the load profile injected with random 10 outliers. For each case, there are three DC costs that consist of anytime, partial-time, and peak-time periods with different DC rates,

TABLE II
DIFFERENCE BETWEEN INITIALIZED AND TRAINED PARAMETERS WITH A SCHOOL LOAD PROFILE IN AUGUST 2012

	Captured	Missed	Red Case	Yellow Case	Total
Initialized	5	5	5	4	9
Trained	8	2	9	6	15

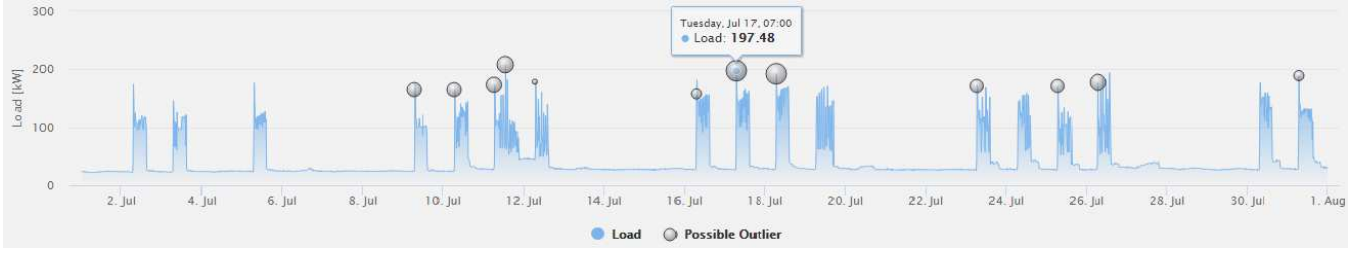


Fig. 4. Possible data anomalies or sudden peaks in the future load data of a school in July.

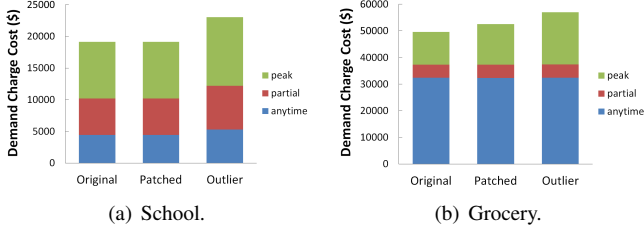


Fig. 5. Difference in Demand Charge Costs using original, patched, and outlier load profiles.

among which the peak-time period incurs the highest rate. The load peaks were originally missing from outlier data especially injected in the summer peak time of the school and grocery premises. However, the anomaly detection and amendment algorithms could patch the outliers so that properly calculated DC threshold captures load peaks to be shaved, which eventually reduces the DC costs as in Figure 5.

VI. CONCLUSIONS AND FUTURE WORK

Our EMS has integrated and automated three aforementioned important modules on anomaly detection and prediction to extract outliers from the historical, current, and future data profiles. Effectively integrating those core modules is inevitable in conducting resilient operation of EMS to quickly discover and restore system faults to prevent a business loss from unexpected operational interruptions of energy systems.

Among individual detection functions, an essential procedure is the efficient human-feedback analysis that improves the detection performance of actual outliers by showing potential anomalies to an operator to decide on the possibility of outliers. The theoretical frameworks proposed before did not consider an important factor of operators' inputs to optimize the parameters used in filtering outliers. Therefore, filtering outliers has always been a difficult challenge with high potential of wrong detection. On the basis of demonstration results, the feedback from an expert who possesses enough knowledge and experience such as a system operator can contribute to improving filtering anomalies in most cases.

Outlier prediction in our EMS is also not only applying thresholds to the predicted profiles of the data but also analyzing the meta data of residuals attached to the profile. The analysis of the residuals' tendency enables our EMS to capture the error trend where if the residual is being larger,

there would be anomalies such as sudden load or renewable peaks in future behavior of the device.

Direction of the future work is to testify the mechanisms with a further variety of energy devices in a scalable environment. Increase of the number of energy devices will make performance tracking by an operator difficult. Therefore, we need to propose a mechanism to cluster the energy devices based on the similarity of the filtering parameters and nature of power systems.

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