On Using Complex Event Processing for Dynamic Demand Response Optimization in Microgrid

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Abstract—Demand-side load reduction is a key benefit of Smart Grids. However, existing demand response optimization (DR) programs fail to effectively leverage the near-realtime information available from smart meters and Building Area Networks to respond dynamically to changing energy use profiles. We investigate the use of semantic Complex Event Processing (CEP) patterns to model and detect dynamic situations in a campus microgrid to facilitate adaptive DR. Our focus is on demand-side management rather than supply-side constraints. Continuous data from information sources like smart meters and building sensors are abstracted as event streams. Event patterns for situations that assist with DR are detected from them. Specifically, we offer a taxonomy of event patterns that can guide operators to define situations of interest and we illustrate its efficacy for DR by applying these patterns on realtime events in the USC Campus microgrid using our CEP framework.

Index Terms—Demand Response, Smart Grid, Complex Event Processing

I. INTRODUCTION

Smart Grids provide realtime monitoring capability of interconnected power grid elements, two-way communications between end-use devices, customers and utilities, and the opportunity to integrate and use information from diverse sources such as weather forecasts and event schedules. This information infrastructure enables the design of advanced information technology systems to improve the power grid efficiency and meet the rapidly increasing electricity demand.

Demand response optimization (DR) is a cornerstone component of Smart Grids, and deals with managing demand-side load in response to supply conditions. Traditional DR approaches require advanced planning, hours or days ahead, and operate on a broadcast principle that reaches to all customers. As the energy usage patterns of customers change, a more effective strategy is to target the most relevant customers or loads based on the current or impending energy usage profiles to meet the required curtailment target. The notion of dynamic DR (D2R) uses near-realtime information to understand dynamic energy consumption situations, and responds with precise curtailment actions, with low latency and high relevance. In particular, we focus on curtailing demand-side consumption when the supply-side constraints are known, using the USC Campus as a microgrid testbed to evaluate our approaches.

Complex Event Processing (CEP) is an information processing framework to detect the occurrence of specified pattern of events by examining hundreds or thousands of event data streams with a low latency on the order of seconds. CEP can help correlate continuous streams of data from the smart grid, and perform online analysis to detect situations of interest modeled as event patterns. For e.g., a CEP pattern could detect an opportunity for temperature reset in a classroom if it is not occupied, the setpoint temperature for the room is less than 72°F and no classes are scheduled for the next hour. Such insight into ongoing situations enables timely and opportunistic DR curtailment responses. While the application of CEP to smart grids is innovative, existing literature just offers anecdotal applications of CEP to smart grids and are tightly scoped to narrow scenarios. In particular, there is a lack of a detailed exploration into the categories of CEP patterns that can benefit demand-side management in DR, an accessible means to define them at a higher level of abstraction, and a practical illustration of such patterns in action. Such an effort will both convince operators of the novel value of defining CEP patterns and also ease the process of defining the patterns using exemplar pattern templates.

In this paper, we make the following contributions,

1) We introduce the use of semantic CEP framework to model event patterns relevant to DR (§ II).
2) We discuss a taxonomy of event patterns to guide different aspects of DR, along with examples for demand management in the USC campus microgrid (§ III).
3) We evaluate the efficacy of event-based DR by presenting pattern detection statistics from USC campus microgrid experiments(§ IV).

II. APPROACH OVERVIEW

A. USC Campus Microgrid

The University of Southern California serves as a testbed to experiment and evaluate DR technologies as part of the Department of Energy-sponsored Los Angeles Smart Grid Demonstration Project [16]. In particular, the research focus is on demand-side load management, under the assumption that the supply-side characteristics are known. USC is the largest private customer of the Los Angeles Department of...
Water and Power (LADWP) with over 60,000 students, faculty and staff spread over 170 buildings containing classrooms, residence halls, offices, labs, hospitals and restaurants. USC is well instrumented, with a campus-wide Building Area Network (BAN) that can monitor buildings and equipment to measure power usage, operational status, space and setpoint temperatures, airflow, occupancy and so on at minute-intervals from the Campus Energy Control Center.

The demand curtailment strategies available within the campus microgrid include direct control strategies, like Global Temperature Reset (GTR) and Duty Cycling, and voluntary curtailment strategies through email notifications sent to building occupants. Currently, these strategies are scheduled at pre-determined time periods, day(s) ahead, based on historical power usage trends. However, these strategies need to be initiated based on near-realtime energy usage conditions and also supplemented with nimble strategies that leverage dynamic demand reduction opportunities on campus. Realtime buildings and equipment information from the campus BAN, campus schedule, facility details and weather forecasts can be analyzed to detect additional curtailment opportunities.

B. Semantic Complex Event Processing

CEP is an information processing framework to detect the occurrence of a pattern of events over event streams. Continuous, time-series data from sensors and other information sources in the microgrid can be abstracted as event streams. For example, an event stream may be comprised of timestamped KWh energy usage of an HVAC (heating, ventilation, and air conditioning) unit in a particular room reported every minute. Weather conditions for a particular zipcode provided every hour by the NOAA (National Oceanic and Atmospheric Administration) web service can also form an event stream. Dynamic DR situations of interest are modeled as combination of these event occurrences, i.e., as event patterns.

Patterns over semantic events are specified using a two-segment pipeline query model, i.e.,

Semantic Event Pattern ::= output definition stream declaration [semantic filtering subpattern] * | [syntactic CEP subpattern]

where the output definition projects event attributes to query results using keyword SELECT, stream declaration associates event variables with source streams using keyword FROM. Semantic filtering subpatterns are represented using SPARQL [1] queries and CEP subpatterns are represented using event processing language provided by the native CEP engine. For example, the following pattern specifies the temperature readings in an office room increased by 3°F within 5 minutes on the space temperature stream.

```
SELECT (?e1, ?e2) FROM (?e1, ?e2, stsstream)
WHERE {?e1 evt:hasSource ?src . ?e2 evt:hasSource ?src . ?src bd:hasLocation ?loc . ?loc rdf:type bd:Office} | SEQ(?e1, ?e2 (reading-?e1.reading>3) within 5min)
```

Here office is a conceptual term, available to the user, which transparently maps to rooms classified as such within the ontology. SEQ is an event processing operator to correlate sequential events. Other operators also include JOIN correlation as well as aggregation operators SUM, AVG.

More advanced semantic CEP patterns, discussed later, can be used to correlate events from multiple streams to detect meaningful DR situations for realtime decision support.

C. System Architecture

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Fig. 2. Microgrid Event-based D2R Architecture
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Figure 2 shows the proposed architecture of event-based
D2R in the campus microgrid. Our semantic CEP engine matches patterns by monitoring event streams from sensors in the microgrid. Another part of the architecture, i.e., the action rule engine, which map detected patterns to curtailment actions is currently under development. Pattern actions include direct control of equipment, such as GTR and duty cycling, in buildings determined by the pattern, sending notifications to DR participants, or activating additional patterns. In the following we focus on the core event processing engine and discuss event patterns that can be defined for dynamic DR optimization in microgrid.

III. DR Event Pattern Taxonomy

The potential space of event patterns is enormous. In the absence of investigation and classification, it becomes onerous for operators to go beyond facile patterns and exploit the innovation and expressivity of semantic CEP patterns for different aspects of dynamic DR. We offer a taxonomy of DR event patterns motivated from scenarios and semantic concepts observed in the USC microgrid, but generalizable to other environments. Figure 3 shows top-level orthogonal dimensions of this taxonomy that are key characteristics to consider when defining a DR pattern. Patterns are not exclusive to one dimension but have a specific feature from each dimension.

A. End-use Purpose Dimension

Patterns can be categorized based on the objective of their end-use, as shown in Figure 4. These categories are typically exclusive. The obvious example are curtailment patterns that can identify curtailment opportunities that can detect transient power wastage, or trigger direct and voluntary curtailment actions. However, patterns can also play a role in situation monitoring and early warning. Meter readings can be aggregated to monitor demand levels, and indirect influencers of power usage used to predict demand trends. These monitoring and prediction patterns can trigger control/notification actions or initiate detection of specific curtailment patterns. This can enable incremental and opportunistic DR curtailment.

1) Monitoring Pattern: Patterns in this category evaluate demand profiles of spaces and equipments at fine granularity by analyzing and aggregating meter and sensor data. A sample monitoring pattern is,

Example 1. The power used by building “MHP”, averaged over 5 minutes, exceeds a given pre-peak load of 27 KW.

Let ?m represents events from the meter’s KW reading stream meterstream, the pattern to detect the above situation is,

\[
\begin{align*}
\text{SELECT} \{ \text{avg} \} \text{ FROM} (?m, \text{meterstream}) \\
\text{WHERE} \{ ?m \text{ evt:hasSource ?src . ?src bd:hasLocation bd:MHP} \} \mid \text{ AVG(?m,sliding,5min) HAVING(avg>27) }
\end{align*}
\]

The above pattern detects the need for curtailment and help initiate low-latency curtailment strategies such as changing the setpoint of a variable frequency drive unit in the building where the pattern was seen to avoid peak demand.

We further classify monitoring patterns as demand monitoring and response monitoring patterns (Figure 4). Example 1 is a demand monitoring pattern. Response monitoring patterns evaluate the effectiveness of a curtailment operation, and can be used to determine if a more aggressive curtailment strategy is required. An example response monitoring situation is,

Example 2. 15 minutes after a global temperature reset (GTR) operation was performed in “MHP”, the building’s power consumption remains greater than 30 KW.

A sequence CEP pattern can be used to detect such an insufficient curtailment situation and trigger further actions such as HVAC unit duty cycling.

2) Prediction Pattern: Traditional demand prediction models are ill suited for energy forecast at fine temporal and spatial scales, particularly as consumption profiles change [6]. In a campus microgrid, dynamic events like scheduling or cancellation of classes, space occupancy changes and holidays can help predict power consumption trends [5]. Prediction patterns are categorized as direct and indirect predictions (Figure 4). Direct predictions forecast demand solely based on prior energy consumption using timeseries models or historical baselines. Alternatively, indirect predictions combine demand influencers to predict future changes in demand.

Example 3. Power usage in an empty computer lab is currently < 0.5KW, and a class is scheduled in 1 hour.

Semantic subpatterns can be defined over class schedule stream schstream and meter measurement stream to filter events based on the location type. Qualified events, denoted as ?m and ?c, can be piped to the following JOIN CEP subpattern,
segments. Virtual spaces may be physically contiguous, such as virtual spaces or objects such as organizations and customer in their physical event streams based on their location.

Curtailment patterns can be classified based on the action taken as shave, shift or shape (Figure 4). Shave patterns detect non-critical or wasteful power usage that can be eliminated.

**Example 4.** The temperature in a meeting room is lower than 73°F when it is unoccupied.

Shift patterns identify non-urgent power demand from certain equipments which can be rescheduled to off-peak periods. Such equipments may include washing machines and campus EVs. Lastly, shaping patterns flatten demand curves by dynamically selecting, for example, HVAC units to duty cycle:

**Example 5.** More than 6 fan coils are operating concurrently in “MHP” during peak hours.

**B. Spatial Scale**

Besides end-use purpose, DR patterns are usually associated with a spatial dimension. This dimension helps identify the target spatial entity, either physical or virtual, on which some end-use action is required (Figure 5).

![Spatial and Temporal dimensions](image)

Fig. 5. Spatial and Temporal dimensions

**1) Physical Space and Equipment:** Physical grid entities include campus, buildings, rooms as well as individual equipment. The spatial granularity may vary by DR participants or end use. For example, campus managers can specify campus-level monitoring patterns to trigger global curtailment operations, while building managers define room or equipment demand prediction and curtailment patterns. Physical objects can be further classified as stationary and mobile. The latter include EVs and portable appliances and benefit from the transparency offered by semantic patterns in masking variation in their physical event streams based on their location.

**2) Virtual Space:** DR Patterns can also be defined for virtual spaces or objects such as organizations and customer segments. Virtual spaces may be physically contiguous, such as a department located in neighboring buildings, or scattered, such as a customer segment that is environmentally conscious.

**Example 6.** The total power demands from EE department exceed 600 KW.

```sql
SELECT(sum) FROM(?m, meterstream)
WHERE {?m evt:hasSource ?src . ?src bd:hasLocation ?loc . ?loc bd:belongsTo org:EEDepartment} | SUM(?m) AS sum
HAVING(sum>600)
```

Upon detecting the above pattern over the (virtual) department space, the department’s coordinator can be notified to initiate local curtailment strategies within the department.

**C. Temporal Scale**

The interval nature of events means that DR pattern include temporal properties such as the frequency of evaluating patterns and the latency time for response after detection (Figure 5).

**1) Frequency:** The frequency of a DR pattern is determined by its time window constraints. There are two types of time windows: sliding and batch. Window width can either be specified using the number of events or a length of time period. For a sliding window, events are processed by gradually moving the window in single event increments. Example 1 used a sliding window. For a batch window, events are processed by moving the window in discrete, non-overlapping time/event blocks. A batch window is useful, for example, when we want to monitor a building’s aggregated consumption every hour.

**2) Latency:** The latency of a pattern is the difference between the time of its detection and the time of its consequence. Most patterns, including the monitoring and curtailment patterns, have immediate impact, i.e., zero latency. A prediction pattern however has a positive latency as it is anticipatory and detects a future situation. A curtailment pattern may also have a positive latency when it is used to schedule a future curtailment operation rather than trigger one immediately.

**D. Representation**

As shown in Figure 6, DR patterns are specified at different abstraction levels, primarily determined by the underlying event models. If only using traditional CEP systems, syntactic patterns have to be defined over raw data streams. This has been explored in other literature [2], [7]. The event attributes can be either crisp values or fuzzy concepts, depending on the uncertainty in matching. Our semantic CEP framework allows users to intuitively define patterns over one or more domain ontologies. Examples 1–6 illustrate such patterns.

**E. Life Cycle**

The life cycle of an event pattern is the time period during which it is active. As shown in Figure 6, some DR patterns may run persistently, some only be active for scheduled periods, and others activated on-demand (say by other patterns that are detected). Most monitoring and prediction patterns
Events from the same type of sources are pushed to a single logical stream. The campus microgrid domain ontologies are described in [17]. These capture properties of and relationships between physical space, electric equipments, and organizations on campus.

B. DR Patterns and Empirical Evaluations

The four DR patterns introduced in Section III are evaluated over the above event streams. Specifically, we analyze the detection of pattern 1 (average power consumption exceeds a peak load), 4 (space temperature of unoccupied room less than 73°F), 5 (more than six fan coils are concurrently active) and 6 (load on EE department exceeds 600KW).

The experiments were conducted from Friday May 4th to Tuesday May 7th, 2012. Figure 7 shows the detection of these four patterns over the six event streams during that time period. The detection frequency of some patterns were limited since this time period coincided with the final exam week when classes and DR curtailment were not actively scheduled.

In Figure 7, pattern 1’s detection indicates that the power consumption of the MHP building exceeded its pre-peak threshold from around 8:20AM to 4:00PM on Friday and from around 8:40AM to 5:00PM on Monday. The power load of MHP during weekends is below the pre-peak threshold because it is primarily used for teaching. However, we observe from Pattern 6 that the power consumption of the EE department exceeds its pre-peak threshold even on the weekend. Detection of these patterns helped the facility managers decide when and where tocurtail energy use on campus – these patterns do not activate actual curtailments yet, but offer an insight into the potential.

Pattern 4 and 5 show opportunities for curtailments. From pattern 5, we know that more than 6 fan coils in MHP operate concurrently from ~8:00AM to 5:00PM on weekdays. By duty cycling the operations of fan coils during this period, we can flatten the demand curve. In a separate experiment, we observed over 27%curtailment in peak demand by duty cycling fan coils in MHP. Pattern 4 monitors a meeting room in the EE department. Several group meetings were scheduled on Friday and Monday. It is observed that as people leave the
room without resetting the thermostat, it causes power wastage when the room is unoccupied — which is during most times, especially the weekend.

These patterns and situations are detected in realtime, which helps undertake fine grained, timely and intelligent DR strategies. We are currently developing the action rule engine that can initiate automated actions and help complete the event-based DR loop in Figure 2. A comprehensive suite of experiments across ~40 buildings on campus is planned for the next peak load season. This will offer an accurate estimate of the improvement in curtailment response using dynamic event-based DR approaches as compared to static schedules.

V. RELATED WORK

Existing DR strategies use incentive-based and time-based programs. Incentive-based programs such as dynamic pricing offer benefits to customers who perform voluntary curtailment. This requires manual intervention by customers and the outcome is less reliable. Open Automated Demand Response Communications Specifications (OpenADR) model [14], [9] is increasingly used to communicate pricing signals to customers in realtime. These signals are mapped to operation modes of building control systems through production rules. Our work supplements this approach by providing the capabilities to correlate heterogeneous microgrid events to initiate and target the curtailment strategies.

Time-based demand schedules are commonly used for DR in Smart Grids. These approaches model DR as a mathematical optimization problem, maximizing the user or the utility’s benefit. In [11], optimal schedules of generation units and demand-side reserves were discussed, where the objective function was formulated as a two-stage stochastic programming model. In [4], DR models were proposed for a single household which schedule appliance activities attempting to minimize user bills. In [3], [13], the authors discuss models for microgrid which compute the optimum energy plan, i.e., the amount of power to be purchased, sold, transferred, and stored for a time period to minimize the total operation cost. Nevertheless, these DR approaches are predicated on accurate mathematical modeling which require in-depth knowledge of the system and are not sustainable as the power grid evolves continuously, and unpredictable events that influence power consumptions occur dynamically. An opportunistic DR scheme driven by real-time monitoring data can hence supplement these existing approaches.

CEP itself has received much attention in a variety of domains [2], [7]. There is also increasing interest using CEP for Smart Grid applications recently. In [8], the authors proposed a CEP approach to detect building occupancy changes for energy saving. However their event patterns are specified at low level over raw events. In [15], the vision of using CEP over linked Smart Grid data was discussed in general, but these are anecdotal rather than comprehensive uses of CEP. In [10], a semantic CEP system for light management in smart offices was introduced while the domain ontologies only capture spatial semantics of lightning devices. A comprehensive analysis of event patterns to guide event-based Smart Grid application development is still missing. To our knowledge, our work is among the first efforts to analyze and implement semantic CEP for DR applications at a microgrid scale.

VI. CONCLUSION

We have discussed the use of semantic CEP for dynamic demand-side management in a campus microgrid. By abstracting realtime sensor information and domain knowledge as semantic events, our approach enables DR end-use needs, such as as monitoring, prediction and curtailment, to be intuitively modeled as high-level patterns without knowledge of raw events. Our taxonomy, informed and validated by DR techniques in the microgrid, offers a structure for operators to develop their own suite of DR patterns for their service area. We believe CEP offers a powerful analytical tool for achieving realtime DR, but this requires in-depth study of their real world use; our work is a step to translate this potential into reality. The ability to automatically mine for self-adaptive patterns can lead to a paradigm shift in informatics-driven demand management for a reliable and efficient Smart Grid.

REFERENCES