A DECENTRALIZED AND SERVICE-BASED APPROACH TO PROACTIVELY CORRELATING STREAM DATA

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Abstract
Stream data from devices and sensors are considered a typical kind of big data. Though being promising, they are useful only when we can reasonably correlate and effectively use them. Herein, services come back to the spotlight. The position paper reports some of our efforts in promoting service-based integration and correlation of such stream data in a real setting – monitoring and optimized coordination of individual devices in a power plant.

Keywords: IoT Service, Proactive Data Service, Service Hyperlink, Sensor Data, Correlating Stream Data

1. INTRODUCTION SENSORS AND IOT IN INDUSTRY: A TYPICAL SCENARIO

IoT (Internet of Things) allows industry devices to be sensed and controlled remotely, resulting in better efficiency, accuracy and economic benefit. With the new wave of the forth industry revolution, the IoT-based integration of physical systems and computer systems is gaining momentum (https://en.wikipedia.org/wiki/Industry_4.0. Industry 4.0 Wikipedia.). The massive real-time IoT data may drive computing processes and services, and can derive a new horizon of industry automation with decentralized sensing, reasoning and response. We will examine a partial but typical scenario of such change with the example of anomaly detection in a power plant.

In a power plant, there are hundreds of machines running continuously and thousands of sensors deployed to monitor machine status at real-time. The status attributes correlate with each other in multiple ways, and indicate equipment status and anomalies. Fig.1 illustrates some deployed sensors and their possible correlations in a real power plant. In this paper, we advocate a decentralized and service-based approach to dynamically correlating the sensor data and generating higher-level events for systems and people. This poses many research challenges, some of which are discussed in the paper include service modeling of big stream data as well as data-driven and programmable correlation through service hyperlinks.

Let us take the primary air fan (PAF) unit as an example. As left side of Fig.2 shows, a PAF is equipped with 44 sensors, which continuously generate stream data, such as temperature and vibration of fan bearing. The right side of

Figure 1. Snapshot of Partial Time-varying Correlations among Sensors in a Power Plant.

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Fig. 2 shows a partial process to detect anomalies in a PAF. The motivation is an observed event, which is the quick decrease of air pressure of a PAF. An air pressure decrease may cause fan stall, fan surge, or temporarily nothing. We cannot assure which result will be led at the beginning. It needs to make synthesized analysis with the other correlated sensor data and observe the data changes at runtime. For example, with the air pressure decreasing by 4kPa, the correlated sensor degree of valve control decreases by 10%. This may lead to the conclusion that the air pressure decrease is normal. But if the bearing vibration increases by over 0.045mm/s as well as the motor electricity decreases by over 5A next, there is a high possibility of the fan stall anomaly. Similarly, a fan surge can be confirmed if an air pressure decrease happens and the motor electricity decreases by over 20A. It is thus meaningful to correlate air pressure decrease and fan stall, and we need to check the bearing vibration and the motor electricity at runtime.

Note that we cannot just simply define a rule like ⇓

| air pressure decreases by 4kPa ∧ degree of valve control decreases by 10% \lra the air pressure decrease is normal \rarr to make the conclusion. The real case is much more complicated. Firstly, we cannot clearly give the boundary value for each rule. It is because the status of equipment and its environment keeps changing. Secondly, the runtime correlations among sensors vary along time. This leads to the multiple underlying correlations among sensors. Each one may lead to a kind of anomaly. Such path can only be clarified step by step at runtime following the process of situation changes and users’ decisions. As a result, the above rules may not be enumerated and pre-defined at the beginning, and they should be formed at runtime and gradually consummated. Hence, we wish such fast-changing data could be automatically grouped together to generate higher-level events with service mechanisms. In fact, the dynamic correlations among status attributes are significantly prevalent. More efficient and effective anomaly detection can be achieved by dynamically correlating the sensor data.

2. Positioning of Services in the Context of Industry IoT

Business applications usually follow the request-and-response pattern. However, an IoT application can be more ad hoc and reactive. Industrial sensors generate successive on-site big stream data. It turns impractical for human beings to grasp the whole status with the traditional way of top-down programming and request-response thinking. Sporadic events are generated from the dynamic correlations of decentralized sensors along with the environment changes. For a user, it is hard to clarify the complex relationships or predict sporadic events.

Service-oriented paradigm has been seen as a mainstream approach for building large-scale distributed software systems. To decouple data to be shared from their sources, the concept of data as service or data service is proposed, which can provide semantically richer view and advanced querying functionality. The abstraction of sensor data services also gives us good opportunities to examine the way to build an IoT application. IoT applications possess some new intrinsic features that are different from other software applications. To deal with situational and ad-hoc problems, an IoT application should capture dynamic correlations of multiple sensors to respond more intelligently to various outside stimuli, like environment changes, sporadic events and so on.

Recently, efforts have been made to deal with big data by encapsulating common functionalities for storage, query, management, and analysis as services. For example, SenseWeb (Grosky, 2007) and Global Sensor Network (Aberer, 2007) provided platforms to assist users to share, manage, and access sensor data on-demand ubiquitously. Xu et al (Xu, 2014) and Perera et al (Perera, 2015) provided IoT data resources as services to support accessing cross-platform data by URI through Web for IoT applications.
our previous work (Han, 2015), we proposed a stream data service model to access stream data continuously in real-time, and implemented a carpooling service based on the stream data services. In practice, IoT applications always operate in highly dynamic environments. Some works (Potocnik, 2014; Buciarone, 2015; Cheng, 2016) concentrate on new types of services or incremental service composition methods to create situation-aware IoT applications. Potocnik et al defined a new service type — a Complex Event Aware (CEA) service that automatically reacts to complex events specified in its interface (Potocnik, 2014). And Cheng et al proposed an event-driven service coordination behavior model based on an extended event-condition-action (ECA) mechanism (Cheng, 2016).

We believe an IoT application should be built with the "stimuli-and-response" pattern. As shown in Fig 3, a novel type of service abstraction, called as proactive data service, is proposed to serve as the fundamental unit to form an IoT application. Although lots of researches have focused on how to encapsulate sensor data into services, their traditional service model like REST service is still with the "request-and-response" model. With the proposed service model, we hope to find a more automatic and real-time way for handling sporadic events with the "stimuli-and-response" pattern while maintaining the common data service capabilities.

We blend an event model into our services. Each proactive data service can selectively respond to all events received from other services. There are multiple options to generate an event. For example, we can pre-setup a set of events, which could be caught or thrown by a data service. An event also can be generated by dynamically correlating various sensors. Especially when considering situation changes, correlations among different sensors can be regarded as important sources to generate underlying situational events.

Correlations among data services influence event routing. When an event routes from a source service to a target service, the target service will be stimulated to behave autonomous to respond to that event. Through this way, with an event spreading over, data services on its routing path are essentially composed.

3. CORRELATING STREAM DATA WITH PROACTIVE DATA SERVICES

3.1 Proactive Data Services
Before defining the Proactive Data Service model for stream data, we first state some related concepts. An event can be denoted by e. Every event is associated with a corresponding event source, attributes with corresponding values, and occurrence time. A particular event can be classified as a sensor event or a service event. The sensor event is generated directly by sensors and the service event is generated by services.

![Figure 3. Rationale of Our Approach.](image-url)
**Definition 1. (Sensor Event):** a sensor event can be represented as \( e_t = (sid, p, t) \), in which \( sid \) is the unique identifier of the sensor which generated \( e_t \), \( p = (a, v) \) is a key-value pair, in which \( a \) means attribute and \( v \) means value, and \( t \) means the timestamp when the event occurs.

A service event is generated by transformation of multiple sensor events or the other service events.

**Definition 2. (Service Event):** a service event can be represented as \( e_s = (sid, E, P, t) \), in which \( sid \) is the unique identifier of the service generate \( e_s \), \( E = \{e_1,e_2,\ldots,e_n\} \), \( n \geq 0 \), which is an event set that include several sensor events or service events which collectively constitute event \( e_s \), \( P = \{(a_1, v_1),(a_2, v_2),\ldots,(a_n, v_n)\} \) is the concrete content generate by \( E \) which is a set of key-value pairs, and \( t \) means the timestamp when the service event is generated.

Correspondingly, a sensor can generate an event stream \( \mathcal{E} \):

\[
\mathcal{E} = [e_1, e_2, \ldots, e_n]
\]

In which, each sensor event has the same \( sid \) and the same attribute, and each sensor event disappears when new event appears by default. And service events with the same \( sid \), same event set \( E \), and same attribute sets can also form an event stream \( \mathcal{E} \):

\[
\mathcal{E} = [e_1, e_2, \ldots, e_n]
\]

In particular, we note an event \( e \) in event stream \( \mathcal{E} \) as \( e \) \( [t] \), in which \( t \) is the timestamp when \( e \) occurs, and \( e \) \( [t] \) \( a \) refers to \( e \)’s value of attribute \( a \).

Traditional data service is software components that provide rich metadata and APIs for service consumers to send data requirements and receive data from service providers. Data service is a specialization of Web service which can be deployed on top of data stores, other services, or applications (Carey, 2012). However, because of the request-response model for traditional data service, it suffers certain limitations in an IoT environment, such as to collect, process, deliver and correlate continuous sensor data. To address these limitations, we define our proactive data service model based on the above definition of event and operation.

**Definition 3. (Proactive Data Service):** We define a proactive data service as a 6-tuple as following (shown in Figure 4):

\[
S = (uri, in\_events, out\_events, operations, filter, hyperLinks)
\]

In which, \( uri \) is the unique identifier, \( in\_events \) represents the input event channel receiving all event streams which arrive at the service, \( filter \) is responsible for deciding how to operate the received event streams and \( operations \) contains the corresponding operations, \( out\_events \) represent the output event streams generated by \( operations \), and \( hyperLinks \) refer to a routing table which is composed with multiple routing paths, and directs output events to the target services.

**Figure 4. The Structure of Our Proactive Data Service.**

Specifically, each operation in \( operations \) can be represented as \( op_{out} \), \( \{\text{filter}, \text{operations}, \text{hyperLinks}\} \), in which, \( \text{filter} \) is a set of input event stream, \( \text{operations} \) is the transformation function, and \( \text{output}_\text{events} \) is an output event stream, in which each event is a service event.

We present some transformation operations refer to (Wang, 2016). Table 1 shows part of frequently used operations. Sensor and service events are both denoted by \( e \).

Table 1. Event Processing Operations.

<table>
<thead>
<tr>
<th>Function</th>
<th>Expression</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CON((\land))</td>
<td>( e_1 \land e_2 )</td>
<td>Conjunction of ( e_1 ) and ( e_2 ) without occurrence order</td>
</tr>
<tr>
<td>DIS((\lor))</td>
<td>( e_1 \lor e_2 )</td>
<td>Disjunction of ( e_1 ) and ( e_2 ) without occurrence order</td>
</tr>
<tr>
<td>NEG(-)</td>
<td>( \neg e_1 )</td>
<td>Negation of ( e_1 )</td>
</tr>
<tr>
<td>SEL</td>
<td>( \text{SEL}(e_1) )</td>
<td>Select an event from input events</td>
</tr>
<tr>
<td>ANY((\exists))</td>
<td>( \exists(e_1) )</td>
<td>Any event that occurs of ( e_1 ) and ( e_2 )</td>
</tr>
<tr>
<td>SEQ</td>
<td>( \text{SEQ}(e_1) )</td>
<td>Select a given sequence of events from input events</td>
</tr>
<tr>
<td>EVERY(</td>
<td>(\forall))</td>
<td>( \forall(e_1) )</td>
</tr>
<tr>
<td>AVE</td>
<td>( \text{AVE}(a_1, e_1, e_2) )</td>
<td>Average value of ( a_1 ) in ( e_1 ) and ( e_2 )</td>
</tr>
<tr>
<td>SUM</td>
<td>( \text{SUM}(a_1, e_1, e_2) )</td>
<td>Summation value of ( a_1 ) in ( e_1 ) and ( e_2 )</td>
</tr>
<tr>
<td>DIF</td>
<td>( \text{DIF}(a_1, e_1, e_2) )</td>
<td>Difference value of ( a_1 ) in ( e_1 ) and ( e_2 )</td>
</tr>
<tr>
<td>EQ</td>
<td>( \text{EQ}(a_1, e_1, e_2) )</td>
<td>Judge the equality of ( a_1 ) in ( e_1 ) and ( e_2 )</td>
</tr>
<tr>
<td>COUNT</td>
<td>( \text{COUNT}(e_1) )</td>
<td>Occurrence number of ( e_1 )</td>
</tr>
<tr>
<td>MAX</td>
<td>( \text{MAX}(a_1, e_1, e_2) )</td>
<td>Maximal value of ( a_1 ) in ( e_1 ) and ( e_2 )</td>
</tr>
<tr>
<td>MIN</td>
<td>( \text{MIN}(a_1, e_1, e_2) )</td>
<td>Minimum value of ( a_1 ) in ( e_1 ) and ( e_2 )</td>
</tr>
<tr>
<td>FIRST</td>
<td>( \text{FIRST}(e_1, e_2) )</td>
<td>First event of ( e_1 ) and ( e_2 )</td>
</tr>
<tr>
<td>LAST</td>
<td>( \text{LAST}(e_1, e_2) )</td>
<td>Last event of ( e_1 ) and ( e_2 )</td>
</tr>
<tr>
<td>WITHIN</td>
<td>( \text{WITHIN}(t, t_i, t_f) )</td>
<td>( e_1 ) occurs within time intervals ( t_i ) and ( t_f )</td>
</tr>
<tr>
<td>DURING</td>
<td>( \text{DURING}(e_1, t) )</td>
<td>( e_1 ) occurs during ( t )</td>
</tr>
<tr>
<td>WINDOW</td>
<td>( \text{WINDOW}(e_1, t) )</td>
<td>( e_1 ) occurs for time period ( t )</td>
</tr>
<tr>
<td>AT</td>
<td>( \text{AT}(t, e) )</td>
<td>( e_1 ) occurs at time ( t )</td>
</tr>
</tbody>
</table>

The \( filter \) and \( hyperLinks \) in our proactive service are the key distinctions compared to the traditional data service model. In particular, \( filter \) stores a set of rules, noted as conditions, to process the received events. Each type of
input event $E_i$ has a corresponding condition to determine which operations event $e$ (i.e. $E_i[e]$) in $E_i$ will be sent to. A condition can be formalized as:

- **on** event streams $E_i$
  - **if** constraint$_i$ is satisfied
  - **then** invoke operation 1
  - **if** constraint$_i$ is satisfied
  - **then** invoke operation 2

... ... A condition includes $n$ constraints (constraint$_1$, constraint$_2$, ..., constraint$_n$), in which constraint$_i$ indicates the constraints (Li, 2009) on the content and timestamp of the context received events of the service. If constraint$_i$ is satisfied, the filter will invoke the corresponding operation $f$ with the received events timestamp and content.

After processing with the operation, we encapsulate the output event with the result of the operation, current time, and predefined event attribute. Then send the generated output event to the hyperLinks. hyperLinks refers to a routing table which is composed with multiple routing paths, and directs output events to the target services. Each routing path $\{E, S\}$ indicates the target service when send the event stream $E_i$. We will define hyperLinks after we define correlation.

### 3.2 Service-based Data Correlation and Hyperlinks

In the field of statistics, data correlation means the relationship between multi stochastic variables. Statists try to analyze and understand the data correlations. Herein, each series of sensor or service events can be regarded as samples of a variable. Thus, to understand the correlation among them, we can learn from statistical correlation.

Furthermore, according to the definition proposed previously, each service may have multi event streams. To measure correlation between services, we define the correlation among event streams.

**Definition 4. (Event Correlation):** Given two sensor or service event streams $E_i, E_j$, we define the correlation between event stream $E_i$ and $E_j$ in time range $T$ as the following matrix:

$$\text{Cor} \left[ E_i, E_j, T \right] = \begin{bmatrix}
\text{Cor} \left[ E_i[a_{i1}, E_j[a_{j1}], T \right] & \cdots & \text{Cor} \left[ E_i[a_{im}], E_j[a_{jm}], T \right] \\
\vdots & \ddots & \vdots \\
\text{Cor} \left[ E_i[a_{in}], E_j[a_{jn}], T \right] & \cdots & \text{Cor} \left[ E_i[a_{jm}], E_j[a_{im}], T \right]
\end{bmatrix}$$

where $E_i[a_{pi}] (p = 1, 2, ..., \text{m})$ is an attribute in event stream $E_i$ and $E_j[a_{qj}] (q = 1, 2, ..., \text{n})$ is an attribute in event stream $E_j$, and $\text{Cor} \left[ E_i[a_{pi}], E_j[a_{qj}], T \right]$ is the correlation degree between the attribute $E_i[a_{pi}]$ and $E_j[a_{qj}]$ in time range $T$.

There are many classical measures of correlation degree among variables such as covariance matrix, Pearson correlation coefficient, longest common subsequence (LCSS), and probability.

As mentioned above, service hyperlinks are a collection of routing tables of a service. We collect them by the event correlations. We present the formal definition of service hyperlink on top of the previous concepts.

**Definition 5. (Service Hyperlink)** Given a service $S_r$, we define the hyperlinks of service $S_r$ as the set of event correlations with source service $S_r$. Formally,

$$\text{hyperLinks} \left[ E_r, S_r, T \right] \text{Cor} \left[ E_r, E_j, T \right]$$

where $E_r[\text{u}]$ is an event stream in $S_r$, $E_j[\text{v}]$ is an event stream in a target service $S_j$. $\text{Cor} \left[ E_r[\text{u}], E_j[\text{v}], T \right]$ refers to the event correlation between $E_r[\text{u}]$ and $E_j[\text{v}]$ in a time range $T$, and $\delta_{\text{min}}$ refers to the minimum value of the correlation value.

As following is an example of hyperlinks, service $S_1$ has two output event streams $E_i$ and $E_j$; service $S_2$ has one output event stream $E_k$; and service $S_3$ has one output event stream $E_l$. Service $S_1$ continuously studies the correlation between $E_i$, $E_j$, and $E_k$, and find that $E_i$ correlates with $E_j$, $E_j$ correlates with $E_k$. Thus the hyperlinks of service $S_1$ is $\left\{ \left[ E_i | S_1 \right], \left[ E_j | S_1 \right], \left[ E_k | S_1 \right] \right\}$.

### 3.3 Quick and Dynamic Response with Proactive Data Services

Our service model aims at responding to the incoming events with runtime consideration. Receiving an event with certain content, our service model may take totally different reactions and operations in case of various environment, which correlates the other events already arrived at the service or on the way, so that each service can make its own decision in a bottom-up way, but not with a global intelligence.

When building a service, we first design the operations, input events, and output events of the service based on its aimed functionality. Then we design the filter logic by filling it up with conditions. The conditions dynamically react to each arrived event according to the events’ content, filtering undesired events, and handle the desired events to corresponding operations. Next, we train each service’s hyperlinks by computing the correlations between their output event streams and other service’s output event
streams within a sliding window. If the output event stream correlates to another service’s output event stream, we save a routing path in the hyperLinks to direct that output event stream. As the event stream flushing in the sliding window, we need to recalculate and update the correlation between services.

Our claim of our service model’s dynamic event correlation is twofold. First, we calculate the hyperLinks at runtime, which route the output events to the target service, thus the routing of the events among services is dynamic. Second, our service model’s filter is composed with multiple conditions, whose reaction dynamically considers the other arrived events. As a result, receiving an input event, our service model may generate various reactions at runtime.

4. DISCUSSION WITH THE RUNNING SCENARIO

We now discuss the use of our service model in the scenario we introduced in section 1. Our data set includes the data collected from the 44 sensors deployed on the PAF, during the period from 2014-07-01 to 2016-01-31. Generally, we collect 278400 data records and observe 28 PAF anomalies including 15 fan stalls.

To detect anomalies of PAF based on our model at runtime, the first step is to extract data correlations among sensor data and the PAF anomalies. In fact, we cannot generate an overall idea of all correlations of the PAF problems. But connecting pieces of extracted correlations can also lead us to a non-trivial part of anomalies. This is the basic idea which our service model comes from. With the growing amount of sensors deployed, and the growing knowledge on the PAF problem by digging on the runtime and historical data, we can extract more correlations and detect more anomalies with confidence at runtime.

Now let’s come back to our scenario, we first build up all necessary services to run the scenario. Table II shows the basic information of the proactive data services used in our scenario, including the name of the service, the operations, and the type of the output events. The Anomaly Alert service \( S_5 \) is responsible for generating the logic of anomaly detection, and sends alert to corresponding maintenance staff when an anomaly happens. The Air Pressure Sensor service \( S_1 \), the Vibration Sensor service \( S_2 \), and the Electricity Sensor service \( S_3 \) collect sensor data, conducting no operation, and transform the collected data into sensor events. The Air Pressure Decrease Anomaly service \( S_4 \), the Vibration Increase Anomaly service \( S_5 \), and the Electricity Decrease Anomaly service \( S_6 \) catch the sensor events, filtering no events, and conduct corresponding operations to generate service events to feed our anomaly detection service. All events in our service model has one single attribute as described in Table II, e.g. \( E^1 \)'s event attribute is decrease of air pressure.

\( S_7 \) conducts two operations: 1) when it receives an event of air pressure decreases by over 4 kPa, and receives both vibration increases by over 0.045 mm/s and electricity decreases by over 5 A within a time window, \( S_7 \) generate a fan stall alert; 2) when it receives an event of air pressure decreases by over 4 kPa, and receives both event of electricity decreases by over 20 A within a time window, \( S_7 \) generate a fan surge alert. \( S_2, S_3, \) and \( S_7 \)'s operation calculate the value decrease/increase of the input events individually.

Next, we fill the service filters with conditions. Services \( S_1, S_6, \) and \( S_7 \) need no conditions in their filters. For services \( S_2, S_3, \) and \( S_6 \), they all have one single operation, and all input events are necessary for value change monitoring, thus their conditions send all input events directly to their corresponding operation. For service \( S_5 \), as mentioned above, three type of input events are considered to be processed: \( E^1 \), \( E^2 \), and \( E^3 \). As shown in equation (1), (2), and (3), we used 3 conditions for \( S_5 \) to process the input events. Since an air pressure decreases by over 4 kPa may cause fan stall or fan surge, we invoke both operations of \( S_7 \) as shown in equation (1) with all such air pressure decrease events. Since an increase of vibration by over 0.045 mm/s in case of the air pressure decrease over 4 kPa may increase our

<table>
<thead>
<tr>
<th>ID</th>
<th>Name</th>
<th>Operations</th>
<th>Output Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Anomaly Alert service</td>
<td>( E^1 )</td>
<td>fan stall ( E^1 );</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( E^2 )</td>
<td>fan surge ( E^1 );</td>
</tr>
<tr>
<td>S2</td>
<td>Air Pressure Decrease</td>
<td>( E^1 )</td>
<td>decrease of air pressure</td>
</tr>
<tr>
<td></td>
<td>Anomaly service</td>
<td>( E^2 )</td>
<td>( E^1 )</td>
</tr>
<tr>
<td>S3</td>
<td>Vibration Increase</td>
<td>( E^1 )</td>
<td>increase of vibration</td>
</tr>
<tr>
<td></td>
<td>Anomaly service</td>
<td>( E^2 )</td>
<td>( E^1 )</td>
</tr>
<tr>
<td>S4</td>
<td>Electricity Decrease</td>
<td>( E^1 )</td>
<td>decrease of electricity</td>
</tr>
<tr>
<td></td>
<td>Anomaly service</td>
<td>( E^2 )</td>
<td>( E^1 )</td>
</tr>
<tr>
<td>S5</td>
<td>Air Pressure Sensor</td>
<td>( E^1 )</td>
<td>air pressure ( E^1 )</td>
</tr>
<tr>
<td></td>
<td>service</td>
<td>( E^2 )</td>
<td>vibration ( E^1 )</td>
</tr>
<tr>
<td>S6</td>
<td>Vibration Sensor service</td>
<td>( E^1 )</td>
<td>electricity ( E^1 )</td>
</tr>
</tbody>
</table>
invoke operation (1) of $S_i$ (shown in Table II) with such vibration increase events. We conduct similar condition design for the decrease of electricity to form condition 3.

**on** decrease of air pressure ($E_2$)

  - if $E_2$ is pressure decrease $\leq 4$ kPa
  - then invoke operation (1) and operation (2)

**on** increase of vibration ($E_6$)

  - if $E_6$ is vibration increase $\geq 2$ 055 mm/s
  - then invoke operation (1)

**on** decrease of electricity ($E_8$)

  - if $E_8$ is electricity decrease $\leq 2$ A
  - then invoke operation (1)

  - if $E_8$ is pressure decrease $\leq 3$ kPa
  - then invoke operation (2)

Next, let us connect the built services together, and tell them when and where to send each event by filling their hyperLinks. Initially, with no events running in our scenario, we calculate the output event correlations based on the historical data, and generate routing paths in the hyperLinks according to the correlations. Since fan stall and fan surge correlates to $E_2$, $E_6$, $E_8$, we save a routing path (8, S1) in $S_2/S_3$’s hyperLinks. Since $E_1$ correlates to $E_6$, we save a routing path (8, S1) in $S_1$’s hyperLinks. Similar for hyperlinks of $S_8$ and $S_9$.

Formally, $S_i$’s hyperLinks could be represented as $\mathcal{H}_i \subseteq \mathcal{H}$, similar for the other services.

Now the PAF anomaly detection service scenario is done. Let us take a runtime example with which generates a fan stall alert in steps:

1. $S_1$ sends 3 events $e_1, e_2, e_3$ to $S_3$ with the content key-value pairs of <air pressure, 95.6kPa>, <air pressure, 92.5kPa>, <air pressure, 88.4kPa>,

2. $S_2$ calculates the air pressure decrease according to the received events from $S_1$ and sends them to $S_3$. In our scenario, $S_2$ sends 2 events $e_1, e_2$ with the key-value pairs of <air pressure decrease, 3.1kPa>, <air pressure decrease, 4.1kPa> to $S_3$.

3. $S_3$’s filter handles the received events with condition (1). The event $e_2$ indicates the air pressure decreases by more than 4 kPa, according to condition (1). $S_3$ invokes both operations of $S_3$.

4. Neither of $S_3$’s two operations can generate a quick response to $e_1$’s invoke, since both operations expect other input events. Thus $S_1$ holds $e_1$’s timestamp and wait for the other input events.

5. $S_3$ generates the events of <vibration, 0.125mm/s>, <vibration, 0.178mm/s> and sends them to $S_1$. $S_3$ generates the event of <electricity, 138A>, <electricity, 129A> and sends them to $S_1$.

6. $S_3$ generates the event of $e_3$ <vibration increase, 0.053mm/s>, and sends it to $S_1$, invoking operation (1). $S_4$ generates the event of $e_4$ <electricity decrease, 9A>, and sends it to $S_1$, invoking operation (1). As a result, operation (1) generates a positive result. Since $e_4$ does not pass condition (3)’s checking constrains, operation (2) generates a negative result.

7. $S_1$ encapsulates the positive result of operation (1), and forms a fan stall alert.
5. SUMMARY

Data-driven approaches supporting locality and stimuli-response thinking are gaining momentum. This position paper presents our efforts in exploiting such possibilities on the basis of data service mechanisms. A novel service model for transforming and correlating massive stream data is proposed. This service model shows potential in realizing various middle-way programmable nodes to form larger-granularity software-defined sensors in an IoT context.

6. REFERENCES


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