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A MULTI-PURPOSE IOT FRAMEWORK FOR SMART BUILT ENVIRONMENTS

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ABSTRACT

We describe a framework for storing and analyzing IoT data in smart buildings. The reference implementation of the framework uses MQTT communication protocol and OSIsoft PI system. What makes this approach different is its capability to leverage a context aware environment. Two case studies were used to test the performance of the proposed framework. The result from the case studies shows that the reference implementation is capable of supporting a real-time data analysis.

1 INTRODUCTION

A smart built environment (SBE) can be viewed as a collection of connected, interactive smart objects imbued with sensing and actuating capabilities. IoT infrastructure, supporting interactions of smart objects, can change the way how SBEs behave and how the inhabitants interact with them. Communication between IoT devices takes place on a local network that connect the IoT edge infrastructure. Different sensors in SBEs can use very different data formats. It is important to provide capabilities to convert different formats into a single reference format that is capable of representing raw data characteristic and provides easy access to the users. We present a multi-purpose framework for storing and analyzing data from IoT devices in SBEs (Gračanin et al. 2018). The communication infrastructure uses MQTT protocol due to its lightweight implementation based on the publish/subscribe paradigm.

2 APPROACH

We use OSIsoft PI system (http://www.osisoft.com) to store, integrate and analyze heterogeneous data sources in real-time. The OSIsoft Message Format (OMF) used by a PI system is an abstract message format that can transfer any payload into PI system. It can be used on any operating system using any language without using the OSIsoft PI system SDK. Consequently, the process of retrieving and processing the data for machine learning analytics is fast. Based on the number of messages received by the MQTT subscriber, the buffer size for transferring OMF messages can be defined on-the-fly or pre-determined based on a linear regression model. The OMF translator uses MQTT topics to create hierarchal structure for the elements and MQTT payload to build PI Tags for PI System. Figure 1 shows the proposed framework and the reference implementation. IoT devices connect to a local machine that converts the received information

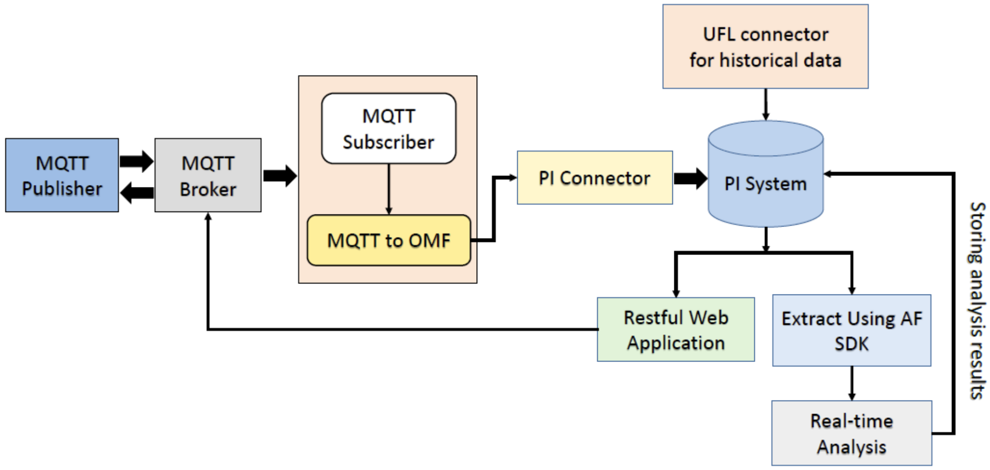

Figure 1: The proposed framework and the reference implementation.

into a payload. The local machine uses MQTT protocol to publish to the broker. The naming of a topic follows a hierarchical structure that allows the PI System to determine the IoT device publishing that topic.

The first case study measured the latency between sending MQTT messages and receiving the corresponding data points in the PI system. After a subscriber receives topic and payload information (JSON format), the OMF translator collects the messages from a buffer and uses the topic name to store/retrieve the payload information in the PI system. We conducted stress testing by simulating MQTT publishers and varying numbers of MQTT publishers (1–10), topics (1–10) and the sampling rate (1–100 samples/second). Increasing the number of payloads received by the subscriber resulted in increased variance of time needed to clear the buffer. The results are also affected by the quality of the network. It is possible to locate for which buffer sizes network latency increased and caused some outlier points. The resulting regression model is used for optimization. The second case study uses the ACS-F2 data set (Ridi et al. 2014) that includes two one-hour recordings of consumption signatures for 255 home appliances divided into 15 categories. The stored data was used as a training set for k-nearest neighbors (KNN) classification (Python Scikit library) to detect the appliance category. The result from the confusion matrix shows that as little as seven minutes of appliance consumption data is sufficient to determine the appliance category. The total time needed to analyzes seven minutes of data is less than ten seconds enabling sampling every ten seconds. This provides for a fixed periodic real-time analysis that matches the sample rate of the data set. The current implementation shows that it is possible to implement a system that can learn from users behaviors in SBEs. We used a simple KNN approach to detect and categorize users electric appliance usage. What distinguishes OSIsoft from other similar data management systems, is its capability of dealing with large-scale time-based data sources. This makes the process of analyzing data faster and easier, in turn making it possible to receive real-time feedbacks. The next step is to test the developed machine learning analysis in real-time, real-world SBE situations and to compare our approach to other similar frameworks.

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