

Energy data services with connected street lighting

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Abstract—Street lighting is a major component of electrical energy consumption in outdoor municipal infrastructures. Developments in light emitting diode (LED) and information and communication technology (ICT) are enabling deep energy savings in street lighting. We consider energy data enabled lifecycle services in the scenario of an upgrade from traditional street lighting to a connected street LED lighting system. Specifically, we present a data application programming interface (API) and methods for lifecycle energy data services covering three key aspects (i) installed power data management, (ii) upgrade savings estimation, and (iii) excess energy accounting. We use energy data from a connected group management lighting system to evaluate the proposed methods.

Index Terms—Connected street lighting, energy data services, analytics.

I. INTRODUCTION

Street lighting plays an important role in defining the visual aesthetics of the nighttime landscape, while adding to the sense of safety and security in a municipality. Street lighting based on traditional technologies like sodium-vapor lamps and metal halide lamps has been commonplace. The energy consumption of such street lighting systems is a major component of electricity consumption in outdoor infrastructures, with estimates up to 65% depending on the size of a municipality [1]. There is a gradual transition to more energy-efficient light emitting diode (LED) luminaires in outdoor lighting [2]. Furthermore, it is becoming possible to integrate ICT in lighting systems at lower costs and complexity. These developments are heralding a new generation of connected street LED lighting systems.

In this paper, we consider the scenario of a lighting upgrade from traditional street lighting to connected street LED lighting. A key energy service in such a scenario is to validate energy savings from the LED lighting upgrade. A simple approach to realize this service is based on manual audits of installed luminaires and heuristic assumptions on system operations [3]. However manual collection of lighting asset information in the case of large outdoor installations is cumbersome and error-prone, thus limiting the reliability of such a simple approach. Furthermore, this approach provides only a static value of expect energy saving and cannot take into account factors that may affect savings over a period of time.

With the advent of energy metering technologies [4], there is an increasing trend for lighting services to be more data driven. New business models like energy performance contracting and lifecycle services for lighting are emerging, driving the need

for energy baseline measurements and actual metering-based evidence to assess system performance.

A. Background literature

Past works have considered the incorporation of sensors and networking in street lighting systems, and control methods in such smart, networked street lighting systems. Smart street lighting management solutions using sensors and control strategies have been presented in [5], [6], [7]. A lighting control method that adaptively adjusts streetlight brightness based on current traffic conditions was considered in [8]. Energy savings achieved with a dynamic street lighting control and management in practical settings were presented in [9]. An overview of different IoT-enabled communication protocols for smart lighting systems were presented in [10]. Networked street lighting system architectures were presented in [11] and results showing realized from smart lighting controls on an implementation testbed were presented. A cost-benefit analysis achieving from dimming controls in networked street lighting was presented in [12]. A comparative analysis of theoretical energy use based on lighting design using accurate installation and road layout data and actual use was done in [13]. A car-mounted camera system for collecting and analyzing street lighting asset information was proposed in [14].

These previous works have laid out the building blocks - sensing, controls and connectivity of a connected street lighting system. The incorporation of sensing and connectivity opens up the possibility to offer value added data services with connected street lighting. In this paper, we specifically consider services enabled with lighting energy data.

B. Contributions and organization of work

In this paper, we consider a connected street LED lighting system with energy metering. A group light management system is presented as an illustrative architecture of such a connected system in Section II. We present a commissioning and data model in Section III that describes how energy data is provisioned via an API from the connected street lighting system. A first step in offering energy services is to monitor the installed lighting system power. Specifically, we consider the problem of estimating the installed LED lighting power with energy measurement data, and detect changes therein. Subsequently the realized savings from LED lighting controls with respect to conventional lighting are estimated. A final aspect in lifecycle services is to determine any excess energy consumption due to possible non-lighting loads being


```

"tag": "Area",
"children": [
  {
    "nodeID": "1427698",
    "nodeName": "Street 1",
    "parentID": "4076548",
    "tag": "Street",
    "children": [
      {
        "nodeID": "5076573",
        "nodeName": "Controller 1",
        "parentID": "17698",
        "tag": "Controller",
        "GeoLocation": {
          "latitudeInDecimal": "51.4110",
          "longitudeInDecimal": "5.4594"
        }
      }
    ]
  }
]
}

```

The context data model enables aggregation and other analytics of generated energy data around a desired hierarchical level specified in the parent-child relationship. The energy data reported from a controller/energy meter in JSON format is depicted below. For simplicity, only two hourly samples of accumulated energy consumption in kWh from Controller 1 with nodeID 5076573 are shown as illustration.

```

{
  "nodeID": "5076573",
  "energy": [
    {
      "time": "2018-01-10T21:00:04.000Z",
      "reading": "38476.32"
    },
    {
      "time": "2018-01-10T22:00:04.000Z",
      "reading": "38485.17"
    }
  ]
}

```

IV. ENERGY DATA SERVICES

Each energy meter in the system records the energy consumption of the associated street of luminaires every hour, and these values are stored at a backend. A manual audit with information on the installed LED lighting power and the installed power of traditional lighting prior to upgrade is available at the customer site level, and may also be available at some of the lower levels of hierarchy (e.g., zones, areas and streets).

A service flow over the connected lighting system lifecycle is depicted in Fig. 3. The three aspects of these energy services are now described in detail and supported by energy data from a group light management system.

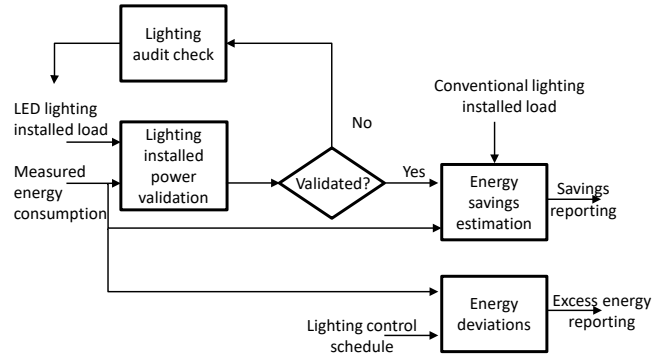


Fig. 3. Lighting energy services flow over system lifecycle.

A. Lighting installed power data management

The first aspect of the service is to validate that the measured lighting energy consumption is in accordance with the installed lighting power. Consider a series of hourly energy data samples $x_1, \dots, x_N, \dots, x_{(Q-1)N+1}, \dots, x_{QN}$. Divide these samples over Q frames, each of length N . Compute the α -trimmed means [16] over each frame i ,

$$\mu_q = \frac{1}{L} \sum_{l=1}^L x_{[l],q} \quad (1)$$

where $x_{[l],q}$ are samples arranged in increasing order within frame q and $L = N - 2\alpha$. The quantity μ_q in (1) provides an estimate of the mean energy consumption that is robust to a few outlier values given that the smallest and largest α values are discarded in the calculation. Next a CUSUM (cumulative sum) change detector [17] is applied to the sequence μ_1, \dots, μ_Q to detect a change in mean value. An alarm is generated by the detector once the cumulative sum computed using μ_1, \dots, μ_Q exceeds an adaptive threshold. An alarm leads to an additional audit check to ascertain changes that may have occurred in the system, e.g. addition of luminaires.

We apply the proposed method to energy data in an area over 53 days. The data was divided into daily frames, each with 24 hourly energy samples. In this area, luminaires were added over a few streets after a few weeks, thus resulting in gradually increased installed lighting power. We see from Fig. 4 that with the proposed method, an alarm is generated after a few days of the change in installed power and the start and end of the change are also identified.

B. Energy savings estimation

Upon validation of the audit data, the second aspect of the energy service is to estimate the energy savings from LED lighting control. The estimation is based on actual consumption in comparison to anticipated consumption using traditional luminaires, and based on actual burning hours. The savings may be monitored by computing energy consumption over a suitable period, e.g. weekly or monthly.

Let the period of interest for savings comparison contain M burning hours. Consider a specific area consisting of multiple

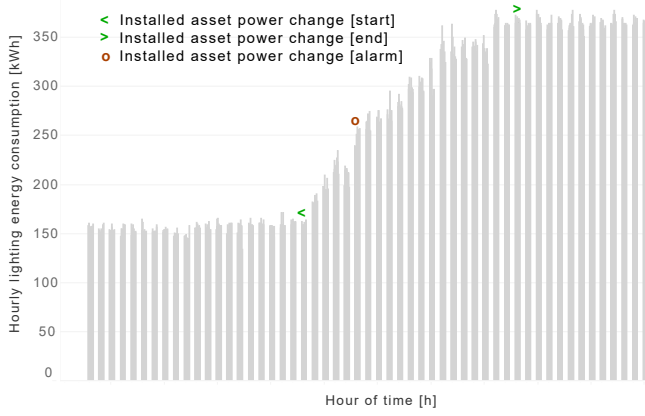


Fig. 4. Lighting installed power change detection.

streets of luminaires, with the streets indexed $k = 1, \dots, K$. Denote y_m^k to be the aggregated energy consumption in hour m in this time period over street k . Let P_C^k be the installed conventional lighting power over the street indexed k before upgrade. Then the lighting energy savings η (in percentage) achieved for the area under consideration are given by

$$\eta = 100 \times \frac{\sum_{k=1}^K \sum_{m=1}^M (P_C^k - y_m^k)}{\sum_{k=1}^K \sum_{m=1}^M P_C^k}. \quad (2)$$

The numerator in (2) represents the energy savings achieved due to the LED upgrade as well as dimming controls over the period of operation.

In Fig. 5, the realized lighting energy savings per week in an area consisting of 50 streets of luminaires is shown. The average savings with the group management LED street lighting system are about 58.3% over this area.

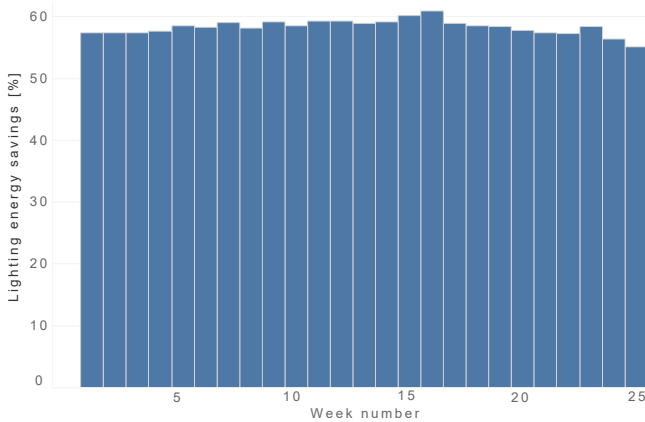


Fig. 5. Weekly lighting energy savings of an area of luminaires over 25 weeks under a group management control schedule.

C. Excess energy reporting

An aspect of energy consumption monitoring is to detect any excess energy use that is not due to lighting and account for such use. Specifically, this problem is one of detecting deviations and their size.

Consider energy metering data for a particular street. Corresponding to a given dimming control level (e.g., fully on), denote the hourly energy consumption values by z_1, z_2, \dots, z_S , where S is the number of samples within a time window over which we determine energy deviations. We adopt a heuristic algorithm based on the median absolute deviation (MAD) [16], [18] rule. The MAD, denoted by ρ , is given by

$$\rho = \text{median}_{i=1}^S \{|z_i - \text{median}_{s=1}^S \{z_s\}|\}. \quad (3)$$

The function $\text{median}\{\cdot\}$ in (3) computes the median of the sample values. An energy value z_s is declared to be a deviation if

$$z_s - \text{median}_{j=1}^S \{z_j\} > \delta \rho. \quad (4)$$

The parameter δ is chosen in a way that the MAD is unbiased for normal distributions [16], [18]. In our application, however, the energy consumption data may not follow a normal distribution. The threshold δ is chosen to ensure that deviations that are too small are not detected.

We consider deviations in hourly lighting energy data over a monitoring period of one week ($W = 84$), with $\delta = 10$. In this particular street, luminaires are turned on between 6 and 7 pm and turned off between 6 and 7 am following a twilight lighting control schedule. To detect deviations in the period when the lighting system is on, we consider energy consumption data in the period 7 pm to 6 am (since the energy consumption varies in the transitional hours 6-7 pm and 6-7 am depending on the twilight period across days). The detected deviations over a two week period from a particular street are shown in Fig. 6. Over the last three days in the second week, there are five deviations detected daily with an hourly consumption almost 3 kWh in excess of the expected hourly lighting energy consumption.

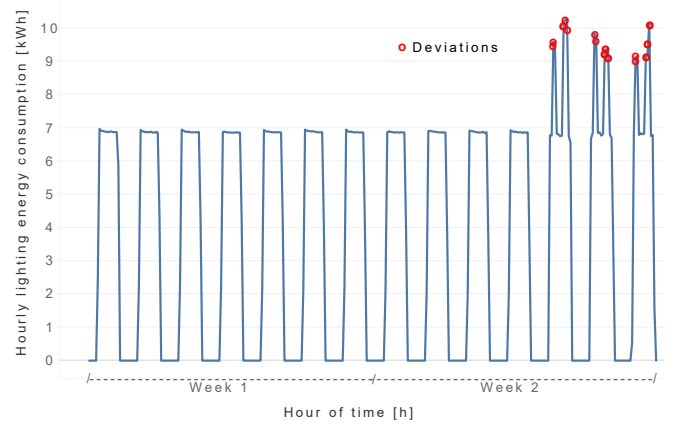


Fig. 6. Energy deviations detected over two weeks on a particular street.

Deviations may be reported on a daily basis for each street via an API, an example of which is illustrated in the deviation data model below. This enables a service provider to investigate the root cause of deviations on a timely reactive basis.

```

{
  "nodeID": "5076573",
  "data": [
    {
      "time": "2018-01-10T21:00:04.000Z",
      "deviation": "2.94",
      "type": "Excess energy usage",
      "value": "6.9"
    },
    {
      "time": "2018-01-10T22:00:04.000Z",
      "deviation": "2.85",
      "type": "Excess energy usage",
      "value": "6.88"
    }
  ]
}

```

V. CONCLUSIONS AND DISCUSSION

We presented energy data driven services over the lifecycle of a connected street lighting system. The first aspect was to validate and maintain data pertaining to the LED lighting installed power. The second aspect of the service was to estimate actual energy savings achieved with LED street lighting controls. The third aspect of the energy service was to provide a detailed account for excess energy usage that is beyond the estimated lighting load. The analytics underlying these services were presented using energy data from a connected group management street lighting system.

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