Optimal Placement of Internet of Things Infrastructure in a Smart Building

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Abstract Recently, there is a growing trend to improve the quality of life, while reducing energy consumption and emissions of CO_2. Here, the use of sensors, controllers, and indoor positioning brings us closer to achieving this goal. The aim of this note is outline an attempt at use of modern infrastructure for optimization of energy management in a building. An architecture of a solution that uses data from sensors to control the state of the object is presented. Performed experiments focus on optimal placement of networking infrastructure inside the building.

Keywords Smart building · IoT · Optimal infrastructure placement

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1 Introduction

Internet of things (IoT) is one of the fastest growing “branches” of ICT. While the concept originated in 1999 [2], recently its share of the market grew almost 10 times [35]. Currently, IoT deployments consist of over 25 billion of connected devices. It is also predicted that, by 2025, this number will surpass 75 billion [19].

IoT-based solutions are to improve quality of life, work efficiency and have positive environmental impact; for example, in building management [29]. Here, note that almost 90% of people spend most of their life inside of buildings [32]. Hence, the reduction of energy consumption by buildings (and thus of CO_2 emission) can make a difference. While the global demand for electricity is rapidly growing, buildings consume its significant share [10]. Moreover, in many countries (including Poland [16]), electricity is still obtained from non-renewable sources, with large, adverse, and environmental impact. Hence, the need for IoT solutions to manage electricity consumption, without decreasing the user comfort. Two of the most energy-consuming systems in a building are HVAC[1] and lighting. Automation of operation of these systems, using data from sensors, external systems, historical data, and appropriate controllers, should improve energy efficiency.

The aim of this note is to outline our initial explorations into intelligent building management system (IBMS) that aggregates, and processes, data from sources, such as: sensors, external services, user location and schedules, and other data influencing energy consumption. However, due to space limitation, we focus on simplifying installation of the infrastructure, by automatically creating a map of internal locations, and using it to plan deployment of components.

1.1 Internet of Things in Smart Buildings

The history of IBMSs dates back to the 1970s. The first prototypes were very simple with limited functionality. However, the development of devices and technology, resulted in a rapid progress [36]. The IoT-related theory and practice greatly influenced the IBMSs, delivering the “tools” needed for further development. Nowadays, an IBMS can collect data from sensors, such as: temperature, air humidity, motion, and light intensity [25]. Moreover, the use of *beacons*[2] accurately determines user location [11]. Furthermore, access to weather forecast may allow “preparation for incoming changes,” impacting future energy consumption [27].

There exist multiple *commercial* solutions optimizing energy consumption in smart buildings. However, little is known how they work. For obvious reasons, their specifications are a closely guarded intellectual property, and the available materials provide only a “residual commercial/marketing information.” Popular, robust commercial IBMS are delivered by: (i) Schneider: EcoStruxure™ Building and Elec-

[1] HVAC—heating, ventilation, air conditioning.

[2] Beacon—device that sends localization-oriented radio signals; accuracy $\sim$1.5 m.

tric StruxureWare™ [33], (ii) Siemens: Synco™ [34], and (iii) Honeywell [18] or Cylon [8].

In academic work, currently, the most frequent architecture of IBMS is *fog-based* [4, 6], consisting of three layers: (1) cloud, (2) fog devices, and (3) edge devices. Such architecture can be extended by adding elements like, for instance, data analytics modules, used to improve quality of building management [15].

Note that poorly maintained, degraded, or inadequately controlled IBMS can increase energy consumption from ∼15 to ∼30% (see, [20]). Hence, automating error/anomaly detection and system diagnostics are very important. Here, IBMS anomaly detection can be facilitated by an external diagnostics system (see, [23]). However, it can also be obtained by internal analysis of data within the ecosystem [22]. Appropriate data analytics can "catch" communication problems, as well as problems related to individual components [21].

2 Explored Approach

Based on analysis of commercial solutions and literature, we have decided to explore an extended version of a *Fog architecture*. Its main components have been outlined in Fig. 1.

Functions of depicted modules are as follows:

- *Cloud* is the "central element" of the system. It facilitates data processing/analysis and visualization [17]. It can be realized as a "local cloud" (within the IBMS), or using an actual (external) cloud infrastructure. For instance, the implemented simulator uses the *Azure IoT Hub* [3].
- *Server* module can be realized (a) within the *cloud*, or (b) as a physical server (as in Figure 1). Its combines data processed in the *cloud* with that from *external modules* to effectively manage HVAC and lighting *controllers*. The *server* communicates also with the *mobile application* to obtain location of users inside the building. Finally, the *server* collaborates with the *anomaly detection module*, which spots anomalies in the infrastructure.

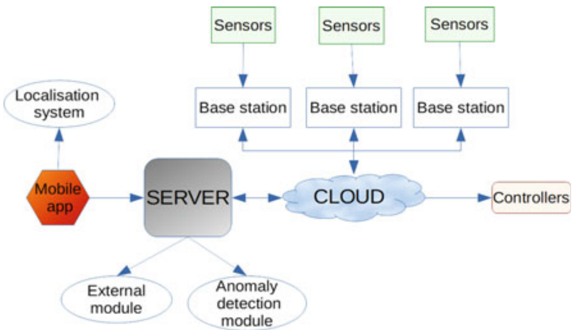

Fig. 1 Overall structure of the system

- *Base stations* pre-process data to increase the throughput of data streams (see, [7]) and support communication between *sensors*, with limited capabilities (e.g., low power Wi-Fi signal), and the *cloud*. The correct placement of the *base stations* in the building is crucial for the efficiency of the IBMS. *Base stations* should efficiently relay data streams from *sensors* to the *cloud*. Note that placing too many *base stations* is a waste of resources. Problem of optimal arrangement of *base stations* is NP-complete [5] and was solved using a genetic algorithm, described in Section 3. Note that the *base station* can be realized, for example, by a *Raspberry-Pi* SoC [30].
- *Sensors* are distributed throughout the building to collect all pertinent information needed to optimize energy consumption [25]. They communicate with *base stations* using open communication protocol(s) [28].
- *Controllers* deliver actions needed for actual management of key building elements such as: HVAC and lighting, in an attempt to reduce electricity consumption (and the total cost of building operation [37]).
- *Mobile application* monitors employee position in the building. It is assumed that it will be used by all (or, at least, a majority) of regular users. Such application can use an NFC reader[3] located at the entrance to the building to capture when the user enters and leaves it.
- *Localization system* determines the exact position of users in the building, by interacting with the *mobile application*. Such system may require installation of additional sensors, e.g., beacons [1, 11].
- *Anomaly detection module*—facilitates autonomous detection of infrastructure errors, e.g., using root cause analysis (RCA [31]).
- *External modules* deliver additional information used by the IBMS. They communicate with the *server*. Examples of possible *external modules* are:
  - *Employee information*, which facilitates schedules of all employees (including, for instance, holidays, business trips, or absence from work).
  - *Weather information* provides current/future weather information [27].
  - *Building information* may provide parameters necessary for proper functioning of the IBMS. It also may calculate selected information, related to building control, using data provided by the *server*.

3 Placing Networking Infrastructure Within the Building

The IBMS requires plan of the building, in which it is installed. Knowing how rooms are arranged, where *sensors* are placed, and where people are located, is used to optimize energy consumption. Building plans used by different IBMSs may be in different formats [1]. There exist wizards [24] that produce building plans, but they may not deliver the needed format. This problem can be solved with help of, for

[3]NFC—Near-field communication—a communication standard that allows for short-distance wireless data exchange.

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example, Estimote Beacons, which automatically generate plan of a building [13]. Note that many beacons can capture: motion, temperature, light intensity, or air pressure, which can be used in the IBMS [14]. They also can facilitate person localization. Building layout can also be automatically generated using: (i) a dedicated application or (ii) the UWB[4] (see, [12]).

3.1 Determining the Position of the Base Stations

Let us assume that the map of a building is available. Now, we need to address the question how to optimally place the *base stations*s. Here, the IBMS should use as few of them as possible (considering cost and radio pollution). On the other hand, minimization of their number should not affect system operation. Note that the *base station*s can communicate with *sensor*s using different protocols. Each of them has a predetermined maximum range, which may be further limited by used construction materials, building structure, and the elements therein (see, [9]). The problem of optimal placement of multiple *base station*s in a building is NP-complete [5]. Hence, there is no polynomial-time algorithm. Therefore, we have decided to apply a genetic algorithm, which is one of well-known approaches to solving similar problems (see, [26]).

The system stores the plan of the building as a set of points, with coordinates expressed in centimeters. The algorithm represents the building (floor) as a rectangular grid with accuracy of 1m $\times$ 1m. This mesh is transformed into a matrix of size $N \times M$, where N is the total length, and M is the total width. The matrix holds: 0 for "empty field," 1 for field with the *base station*. While, in initial experiments, we have used rectangular floor plans, proposed approach can be adjusted to deal with more complex geometry. The algorithm parameters are: P_1—coverage error—representing cells not covered by any *base station*, P_2—*base station* overlapping, representing cells where the coverage from multiple stations overlaps, and P_3—the total cost (of installed stations). The fitness function is a simple weighted sum:

$$f = \sum_{i=1}^{3} \alpha_i \cdot P_i,$$

where α_i is the weight of the ith parameter.

The key optimization parameter is the coverage error (P_1), since the sensors may need to be located "anywhere." Hence, the corresponding weight is the largest. We have assumed that the least important parameter is the total cost of the *base station*s. After running a number of experiments, we report results for: $\alpha_1 = 30$, $\alpha_2 = 1$, and $\alpha_3 = 0.3$, which gave us reasonable price/coverage ratio. However, obviously, differ-

[4] UWB—a radio communication technique based on the fast sending of short-term pulses.

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ent choice of weights is possible. The optimization parameters have been calculated as follows:

$$P_1 = \frac{n_{\text{or}}}{n_{\text{total}}}, \quad P_2 = \frac{\text{overlaps}}{n_{\text{bs}}}, \quad P_3 = n_{\text{bs}} * c,$$

where n_{or} is the number of cells out of range of *base station*s, n_{total} is the number of cells, $overlaps$ is the number of cells with coverage overlap, n_{bs} is the total number of *base station*s, and c is the cost of a single *base station*. Note that the strength of signal of a *base station* is represented in the two coverage-related parameters.

In our work, we have used standard genetic algorithm, with cross-over (probability 0.9) and mutation (probability 0.1) and elitist selection. Mutation turned no-station locations into ones with stations and vice-versa. The “building matrix” was turned into the “vector-gene.”

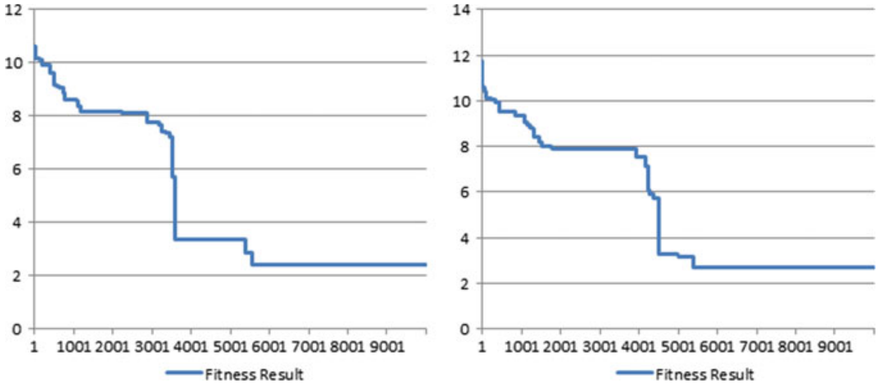
The proposed approach was tested for multiple, relatively simple, and floor plans. Here, we report results obtained for two of them (depicted in Fig. 2) with *base station*s with different ranges (final placement of *base station*s is also presented. We have tried two initial population of *base station*s: (a) random population (Set 1) and (b) no stations (Set 2). In the latter case, the initial populations was “all zero” and stations have been introduced via mutation. Presented results are averages of multiple runs. Note that similar results were obtained for all experiments (regardless of floor layout, *base station* strength, or initial population).

Results for Floor 1 are presented in Fig. 3. The best fitness function result has been reached after approximately 6000 epochs. Moreover, results for the optimization process starting from randomly placed *base station*s were slightly better. Interestingly,

(a) Floor 1: size $9m \times 11m$, *Base station* range $4m$

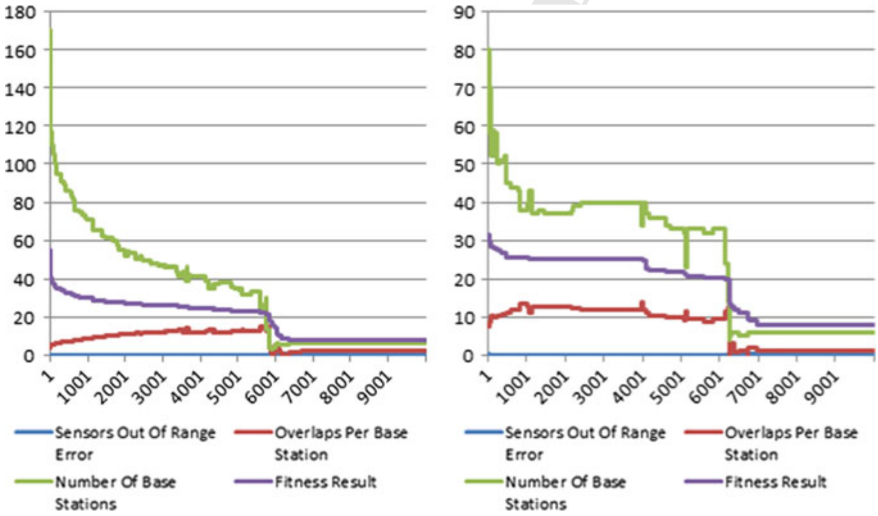
(b) Floor 2: size $30m \times 20m$, *Base station* range $6m$

Fig. 2 Localization of *Base stations*



(a) Fitness function for Set 1 (b) Fitness function for Set 2

Fig. 3 Comparison fitness functions for Floor 1



(a) Results for Set 1 (b) Results for Set 2

Fig. 4 Results for Floor 2

in majority of our experiments, no overlap between *base station* coverage has been reported.

In the case of Floor 2 (results depicted in Fig. 4), the population consisting of randomly distributed *base station*s achieved a better result for only one parameter, the *coverage error*:

$$\text{Fitness function} - 7.73 < 7.8$$
$$\text{Coverage error} - 0.12 < 0.16$$
$$\text{Device overlapping} - 2.33 > 1.0$$
$$\text{Number of base stations} - 6 = 6$$

The last step in infrastructure setup is to place the *sensor*s, as needed to track selected parameters and/or fit into the building. Proposed approach to the determination of the position of *base station*s allows to avoid places where the *sensor*s will not be able to communicate, due to lack of coverage. Upon slight modification it can also allow estimating/taking into account how many sensors can be associated with each individual *base station*.

4 Concluding Remarks

We have developed an IBMS simulator that allows control of: (i) user positioning system, (ii) employee schedule, (iii) users entering and leaving the building, (iv) system time, (v) outdoor temperature/weather, and (vi) internal temperature and humidity. In this way, we have realized the complete architecture, as presented in Fig. 1. The *anomaly detection* module was realized as a simple function to test its integration with the other parts of the system.

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