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BISCUIT: Building Intelligent System Customer Investment Tools

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Abstract

Smart buildings as human-cyber-physical systems (h-CPSs) are capable of providing intelligent services, such as indoor positioning, personalized lighting, demand-based heating ventilation and air-conditioning, and automatic fault detection and recovery, just to name a few. However, most buildings nowadays lack the basic components and infrastructure to support such services. The investment decision of intelligent system design and retrofit can be a daunting task, because it involves both hardware (sensors, actuators, servers) and software (operating systems, service algorithms), which have issues of compatibility, functionality constraints, and opportunities of co-design of synergy. This work proposes a user-oriented investment decision toolset aimed at handling the complexity of exploration in the large design space and to enhance cost-effectiveness, energy efficiency, and human-centric values. The toolset is demonstrated in a case study to retrofit a medium-sized building, where it is shown to propose a design that significantly lowers the overall investment cost while achieving user specifications.

Keywords: smart building; intelligent system retrofit; mixed integer programming; energy efficiency; cyber-physical systems

1. Introduction

Smart buildings are human-cyber-physical systems (h-CPSs), which engage physical infrastructure with cyber computation to promote energy efficiency, grid reliability, and human-centric values such as comfort, productivity and well-being of occupants [1]. In the past decade, remarkable progress has been made in aspects of sensing technology [2,3], data-analytics and learning [4,5], and advanced control strategies [6,7], enabling intelligent buildings to have contextual awareness and make personalized response. Emerging smart building services include indoor positioning [8,9], occupancy detection [10,11], automated environmental monitoring [12], demand-based and personalized heating ventilation and air conditioning (HVAC) control [13], and human-building interactions [14,15],

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just to name a few. While these technologies have been demonstrated in research labs and few selected buildings, their public access in the majority of real-world buildings is still limited. One key bottleneck is that an intelligent system of sensing, learning, decision-making, and control capability is required to support these applications. Take occupancy detection as an example. To infer how many people are in the room, one reliable approach is to continuously monitor indoor environmental parameters, such as temperature, humidity, and CO_2 concentrations [16]. The measurement data are then uploaded wirelessly to a local/cloud server for analytics, and the results are forwarded to a building operation system (BOS) to further control HVAC and lighting systems [8]. If the building owner were to enable this intelligent service, he/she needs to ensure the availability of both physical infrastructures (i.e., sensors, servers, HVAC and lighting network-enabled actuators) and compatible software (i.e., occupancy detection algorithm, BOS).

Due to the numerous choices of sensors and actuators, and the rich set of software and control strategies, the design space is exponentially large to explore. The investment decision making is a complicated process, involving *estimation* of capital expenditure (HVAC, lighting retrofit, access control system, server, etc.) and operation cost (electricity, heating annual consumption, system maintenance), *satisfaction* of user specifications (e.g., privacy concerns, human-building interaction features), device compatibility (e.g., vendor system inter-operability) and functional requirements (e.g., sensing modalities for different applications), and *optimization* of device/function sharing (e.g., environmental sensing suit for both indoor environmental monitoring and occupancy detection) and control strategies (e.g., rule-based or model-predictive control).

1.1. Related work

Whole building design is an integrated approach to address multiple performance metrics, such as cost effectiveness, efficiency, functionality, sustainability and safety [17, 18]. It is a conceptual framework to meet the need for a building through planning, design, construction, and operation [18]. Several aspects have been discussed in [17], including low-energy building strategy, indoor environmental quality, and green building assessment. Critical factors to achieve green building have been categorized into technical, managerial and behavioral aspects [19]. A comprehensive review of existing computational methods for sustainable building design is conducted in [20], which include envelope design, configuration and control of building systems, and renewable energy generation. The key difference of these methods with the present study is that the optimization variables are limited to traditional building components, such as windows, shading, HVAC and lighting mechanical systems, water supply, and distributed energy resources, which do not take into account infrastructures/components (e.g., sensors, networked actuators, computational units, wireless networks, advanced analytics and control algorithms etc.) required to enable intelligent services (e.g., indoor positioning, demand-based ventilation, human-building interactions, etc.). A conceptual framework of smart building design automation has been proposed in [21], where a platform-based design approach has been investigated. This work provides an algorithmic framework and solution to the problem similar to [21].

1.2. Contributions

Motivated by the tremendous success of design automation in the integrated-circuit industry, which shares considerable similarities in both challenges and opportunities with the building intelligent system design, we proposed and developed the Building Intelligent System Customer Investment Tools (BISCUIT). The goals of BISCUIT are **(1)** to facilitate smart building retrofit by providing a comprehensive framework based on mixed integer programming (MIP), **(2)** to save investment costs for building owners by exploiting potential infrastructure sharing and advanced control strategies, and **(3)** to promote energy efficiency and human-centric designs through occupancy and control co-simulation. To the best knowledge of the authors, this is also the *first* work to propose and develop an *algorithmic framework* for *building intelligent system design automation*.

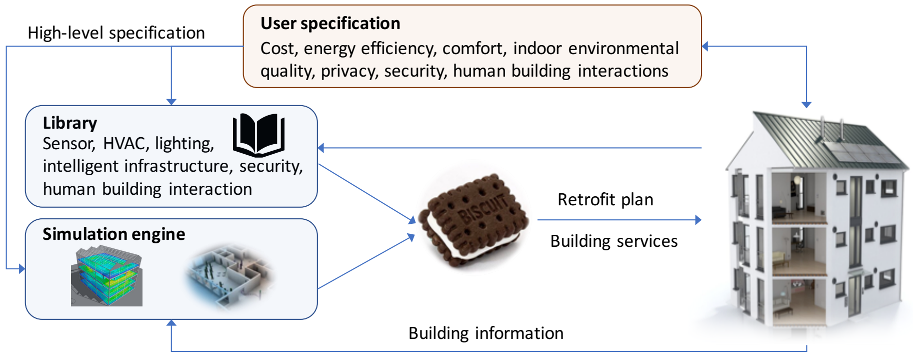


Fig. 1. Illustration of BISCUIT for smart building retrofit design.

2. Methodology

2.1. Optimization framework

The optimization problem is formulated as an MIP. The intelligent system design and retrofit is naturally a multi-objective optimization, which involves cost, energy efficiency, privacy, comfort and security; however, except for cost and energy efficiency, there is no clear way to compare other factors on the same scale (i.e., dollars). Thus, we set a simple goal to reduce cost, while satisfying the constraints of other factors set by the users.

The overall procedure of BISCUIT is described below:

1) User specifications, which includes **(1)** building meta information: building areas, occupancy levels, usage, and weather; **(2)** functional requirements: privacy, comfort, and security; and **(3)** specifications for components such as HVAC, lighting and sensors (to be specified in Sec. 2.4).
2) Simulation of building occupancy profiles and energy consumptions based on user-provided information and supported control strategies (to be specified in Secs. 2.2 and 2.3).
3) Recommendations of optimal investment plan by solving the corresponding MIP.

For the optimization problem, the objective function is given by the sum of the investment cost (i.e., additional components needed for HVAC, lighting, sensors, computing server and security systems), the annual operation cost (i.e., electricity and thermal energy cost consumed by HVAC and electricity used by lighting), and the annual maintenance cost (i.e., personnel employed to maintain HVAC, lighting, and subscription fees for computing server and security). Because the infrastructure such as HVAC and sensors can have various life spans, we use the capital recovery factor (CRF) to convert the present value to annual payment.

The constraints of the optimization problem encode preference and technological information to tailor the treatment of individual cases, and can be grouped into the following categories:

- *User specification constraints* take into account user preferences. For instance, if the user requires a high-level of privacy, then some sensors such as camera and sound might be excluded from selections. If the user expresses the need for security or human building interaction, then the corresponding infrastructures and software should exist in the optimized plan.
- *Device compatibility and sharing constraints* ensure that the selected components are interoperable according to vendors' standards (e.g., whether the intelligent HVAC control box is BACnet compatible), and also indicate which components can be shared among the subsystems (e.g., a sensor that can measure environmental parameters can be used for occupancy detection, and thus, can be shared by intelligent HVAC and lighting systems; however, a camera can be used for occupancy detection for HVAC control, but not lighting control because it might not operate in the darkness).
- *Functional constraints* are imposed for proper operation of intelligent services, which can be categorized into **(1)** sensor instrumentation: intelligent building services require contextual awareness (e.g., indoor positioning,

occupancy detection, activity recognition, thermal comfort, etc.), enabled by sensors which can measure a variety of environmental parameters; **(2)** control algorithms: advanced building operation strategies such as model-predictive control (MPC) require both real-time sensing, computation and actuation capabilities supported by respective infrastructures (i.e., sensor, server, and intelligent HVAC/lighting); and (3) infrastructure investment: this captures the interdependent operation of subsystems; for example, the operation of intelligent HVAC, depends on the availability of computational unit and building operating systems, so they need to be all present to enable cooperative services.

From an optimization perspective, the variables to be optimized include both continuous variables, such as hourly HVAC energy consumption and maintenance costs, and predominantly, binary variables (i.e., 0 or 1 value), such as the decision to install equipment and employ certain control algorithms (e.g., MPC, reactive or rule-based control [22]). In the same vein as [Fig. 1, ref. 20], the optimization variables and simulation parameters are summarized in Table 1. To streamline the presentation, we omitted the technical MIP formulation in this article, and refer the readers to [23] for details.

Table 1. Summary of the computation engine of BISCUIT.

Method	Objective	Variables	Simulated system	Simulation method	Program
MIP	Annual operation and maintenance cost, investment cost (adjusted by CRF)	Installation of infrastructure, building operation strategy (control algorithms)	Occupancy profile, HVAC/lighting energy consumption	Annual hourly (2 days per month with proper weight adjustment: 21 weekdays and 9 weekends)	Gurobi

Because the building retrofit/design problem has multiple objectives, some of which cannot be easily quantified, we encode them as constraints, as discussed above for privacy related constraints for sensor instrumentation.

2.2. Building occupancy simulation and control strategies

Building occupancy profile is critical to evaluate energy consumptions [25]. We use an occupancy dataset collected from real-world buildings and then simulate occupancy measurements for different types of occupancy sensors. For instance, PIR sensor measurements are simulated by binarizing the actual occupancy data; further, we flip the binary occupancy state with fixed probability at each time step in order to mimic sensor noise. Occupancy counter measurements are simulated by adding Gaussian noise to the actual measurements. The generated occupancy profiles are then used to simulate energy consumptions of HVAC [26] and lighting, using both traditional PID-based setpoint control [27] and intelligent methods such as occupancy-responsive setpoint control [27] and MPC [26]. The control performance depends on both the efficiency of the system, and the precision of the sensors in the case of occupancy-driven control; thus, we associate each combination with a corresponding simulation trace. Furthermore, requirements such as comfort level and energy efficiency are incorporated in the simulation by adjusting corresponding control parameters based on occupancy profiles, which is equivalent to constraining the set of appropriate building operation modes.

2.3. Building libraries

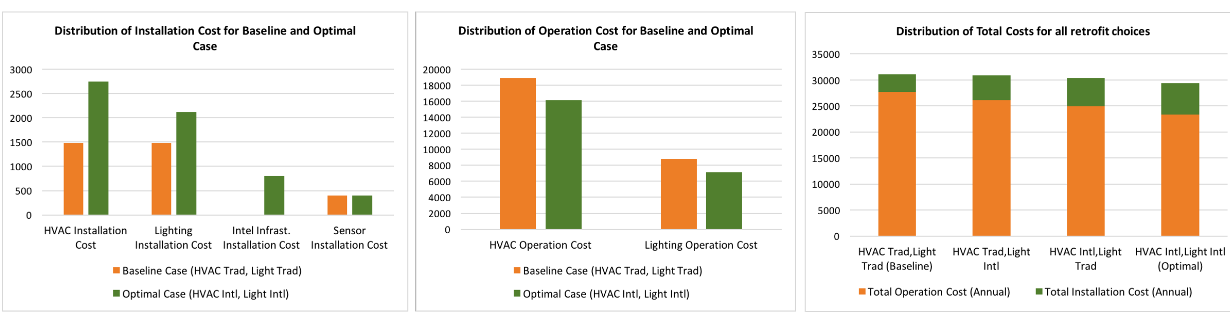
To facilitate optimal decision making, libraries of available equipment/components can be specified by the user. These libraries include high-level information about pricing, life span, rate powers, efficiency, maintenance cost, compatibility and functional requirements. A short description of each library is summarized in Table 2. While the default libraries have information about common off-the-shelf components, this organization is intended to facilitate users to specify their preferred brands, and the vendors to contribute their available products.

Table 2. Summary of building libraries supported by BISCUIT for building system design automation.

Library	Items	Information	Constraints
Sensors	Available sensor models	Sensing modalities (environmental parameters, sound, visual), functions (presence/occupancy/indoor position/identity detection), cost	User specifications (privacy, IEQ, etc.); compatibility with intelligent HVAC/lighting/infrastructure
HVAC	Intelligent/ traditional systems	Vendor, investment cost, maintenance cost, rate power, efficiency, lifespan, supported control strategies	User specifications (intelligence upgrade, safety), requirement on the existence of compatible sensors and intelligent infrastructures
Lighting	Intelligent/ traditional systems	Vendor, investment cost, maintenance cost, rate power, efficiency, lifespan, supported control strategies	
Security	Available systems	Vendor, investment cost, subscription cost, lifespan	
HBI	Available systems	Maintenance cost, lifespan, control strategies, efficiency	
Infrastructure	Available packages	Vendor, cost, maintenance cost, lifespan	User specifications

3. Case study

In this case study, we examine the retrofit of a medium-sized building (40 rooms, 100 occupants) in California, USA. Based on RSMeans cost manual [24] and market prices, we provide an estimate of costs for the components. The available HVAC and lighting system candidates (both traditional and intelligent types), in tandem with building meta data, are evaluated for annual consumptions. The user further specifies a high level of privacy requirements. The data was fed to the BISCUIT software and the optimal choice was found to be HVAC Intelligent Retrofit and Light Intelligent Retrofit. Controller for both HVAC and Lighting was selected to be a High Precision React Controller. Fig 2(a) and Fig 2(b) show the distribution of installation cost and operation cost respectively for baseline choice (Traditional HVAC retrofit + Traditional Lighting retrofit) and the optimal choice (Intelligent HVAC retrofit + Intelligent Lighting retrofit). Fig 2(c) shows the distribution of total costs for all retrofit choices. As apparent from Fig 2(c), the optimal choice has the lowest total cost. Another observation to note in Fig 2 is that, though the installation cost for optimal choice is more than the baseline choice, the difference between them can be recovered in approximately 3-4 years with the difference in operation cost which is less for optimal case than the baseline case.



(a) (b) (c)

Fig 2. Results of BISCUIT software run with retrofit data from the RSMeans cost manual [24].

4. Conclusion

To fulfill the potential of smart buildings, intelligent services such as indoor positioning, occupancy detection, and demand-based ventilation need to gain wider access to the public. A critical step is to equip buildings with the infrastructure to support these services, from sensing, actuation to control and learning. This work comprises of a key step towards this goal by focusing on the task of building design retrofit, with the aim of providing a cost-saving toolset to facilitate the selection of sensors, retrofit components and control algorithms. This toolset is able to further facilitate cost saving analysis, energy efficiency evaluation and early technology adoption.

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