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# An explanatory parametric model to predict comprehensive post-commissioning building performances

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ABSTRACT

Existing building commissioning (EBCx) is a promising approach to save energy and improve indoor environmental quality (IEQ) without sufficient attention yet. However, the uncertainty of building performance post-retrofit leads to a low adoption rate of EBCx, as the commissioning outcomes are dependent on various factors and difficult to model. To facilitate decision-making on EBCx, this paper introduces PECCO, a parametric mathematical model enriched with years of commissioning engineering experience to predict comprehensive EBCx outcomes for various types of public buildings, along with a mobile-based tool to automate the prediction process. An 8-min questionnaire is used to collect building parameters regarding general, management, HVAC, smart system, IEQ, electrical, water supply, and building envelope. Then, a mathematical model predicts commissioning outcomes including energy-saving potential, annual cost saving, asset value increase, comfort-improvement potential, operation risk, commissioning cost, simple payback period, and difficulty in commissioning, and provides overall commissioning strategies, specific commissioning suggestions, and benchmark figures compared with other buildings. Three case studies suggested that PECCO's prediction on the simple payback period achieved a mean absolute percentage error (MAPE) of 15.47%, which is acceptable and comparable to other related studies. By providing various perspectives of information to building owners and managers, PECCO is helpful to foster the industry to undertake EBCx, leading to a more energy-efficient, low-carbon building industry.

## 1. Introduction

### *1.1. Background*

Despite years of technology development, the building sector still consumes over one-third of global final energy. The energy-related $CO_2$ emissions from buildings account for almost 40% of the global carbon emissions, and the $CO_2$ emissions of the building sector hit a record high in 2019 [1], which is detrimental to global warming mitigation. Therefore, it is imperative to accelerate efforts on reducing building-related energy consumption. Meanwhile, as people spend up to 90% of their time indoors [2], indoor environmental quality such as thermal comfort, light, noise, and air quality has a great impact on human health, well-being, and productivity [3–6]. A comfortable indoor environment will lower the complaint rates in the office, hotel, and shopping malls, attract rentals and reduce costs on sick leaves and insurance. Keeping a high-quality indoor environment is, therefore, a fundamental requirement for building managers. However, in most cases, there is a performance gap between the intended performance in design and the actual performance in operation [7,8]. This is when building commissioning plays a role.

Generally speaking, there are two forms of commissioning: new building commissioning and existing building commissioning (EBCx). New building commissioning is a quality assurance process to ensure the new building operates initially as intended. EBCx seeks to improve the building equipment and systems function together or solve operation

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problems after the building has been built for a while. Statistics of 1500 North American buildings demonstrate that new building commissioning can achieve a median 13% whole building energy savings at a simple payback of 4.2 years, while an EBCx targeted to not only save energy but also improve comfort and maintenance can achieve an energy-saving range from 0 to 54% with a median saving of 14% at a median simple payback of 1.7 years [9].

New building commissioning has become a mandate for buildings. The American Society of Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE) published a set of standards and guidelines on commissioning [10–12]. The U.S. General Services Administration (GSA) and National Aeronautics and Space Administration (NASA) utilize whole building commissioning to ensure the quality delivery of building functionality in new construction and major modernizations [13]. Fundamental Commissioning and Verification is also a required prerequisite in the Leadership in Energy and Environmental Design (LEED) Building Design + Construction (BD + C) Rating System [14]. The recently published Chinese standard GB 55015-2021 mandates that centrally conditioned public buildings of over 100,000 square meters have to commission their HVAC systems [15].

However, EBCx is still a voluntary process and far from mainstream. Existing research on EBCx focused mainly on the implementation of EBCx. As the energy savings achieved from the implementation EBCx will be degraded over time if no follow-up were to be conducted [16,17], ongoing commissioning has become a hot topic that integrates machine learning with data collection systems of the Internet of Things (IoT) or uses calibrated energy models for fault detection and diagnosis of HVAC equipment and load prediction [18–21]. For example, use a sub-metering system for continuous fault detection and diagnostics (FDD) and automated commissioning analysis [22,23]; use temperature sensors and air quality sensors integrated with the building management system to speed up the building control commissioning and maintenance [24,25]; apply a Quantile Regression Neural Network (QRNN) model to improve load prediction accuracy for predictive control of cooling systems [26], etc. A continuous commissioning guidebook by Liu et al. discussed various commissioning measures in detail, each with estimated savings, costs, and payback periods [27].

Despite its high energy-saving potential, EBCx is rarely taken as a priority due to the building owner's lack of awareness, invisible deficiencies to the end-users, and the lack of a financial business case [28]. In practice, an energy audit is informative to decide whether to take commissioning. However, an energy audit requires a professional team to conduct a series of technical tests which are costly and labor-intensive. Although there exist some self-evaluation tools as an initial energy audit, such as a scoring system to evaluate the performance condition and smartness level of building automation and control systems [29], there still lacks a tool to picture the costs and benefits of an EBCx before the investment, as the EBCx is a holistic campaign and the commissioning outcomes are dependent on various variables and thus hard to predict. Therefore, this paper will shed light on the decision-making phase to foster the uptake of EBCx.

### 1.2. Related studies

Energy saving is the most prominent outcome of building commissioning. However, most studies focused on the prediction of energy consumption rather than energy savings. A study of 30 commercial office buildings in Hong Kong created a backpropagation neural network model using information from energy audit reports to predict the annual electricity consumption and the mean absolute percentage error (MAPE) was 3.1%, which is better than the MAPE of the multiple linear regression model (20.5%) [30]. Similarly, a study of an administration building located in London tested five techniques to predict daily electricity consumption based on measured weather data, and the ANN model achieved the lowest MAPE of 6% [31]. In the case of ongoing commissioning, hourly prediction of electricity consumption is required. Wang et al. derived five data-driven models based on outdoor weather conditions and hourly whole building electricity consumption to predict the next-hour whole building electricity consumption. The results show that Gaussian mixture model regression (GMMR) outperformed other algorithms with the maximum relative errors being 14.5% and 22.3% for the analyzed two buildings [32]. On a broader scale, researchers also tried to understand influential factors to whole-building energy consumption. Awan and Knight drew linear regression models based on 4597 survey responses and identified that the occupancy, floor area, conditioned rooms, appliances, lights, and power rating have predictive power for annual household electricity consumption [33]. For secondary school buildings, building characteristics, energy use profile, and occupants' behavior turned out to be predictive factors for annual electricity consumption [34].

In terms of the prediction of energy savings, most studies focused on predicting post-retrofit savings of equipment, building, or city, but less focused on post-commissioning energy savings. Both commissioning and retrofit are ways to improve the energy efficiency of existing buildings, but commissioning is the optimization of existing facilities while retrofit sometimes involves adding new equipment or replacing existing facilities. To gather inspiration for predicting commissioning outcomes, here we reviewed the methods for predicting post-retrofit energy savings—energy simulation models, machine learning techniques, and mathematical models. In the cost-benefit analysis or optimization of retrofit measures, the energy savings of each measure are usually calculated through an energy simulation model [35–37] or just determined arbitrarily by the researchers [38]. Whereas machine learning algorithms can be used to predict the overall energy savings after a retrofit. For example, Yalcintas used ANN to predict post-retrofit equipment power consumption based on the measured dry bulb temperature, wet bulb temperature, and time (representing building-occupancy and equipment-operation schedule), and the MAPE in two hotel cases varied from 5.31% to 9.95% [39]. As for building scale, Deb et al. collected pre- and post-retrofit information from energy audit reports of 56 office buildings and created ANN models based on gross floor area (GFA), air-conditioning energy consumption, operational hours, and chiller plant efficiency to predict the change in energy use intensity (EUI, measured in kWh/m$^2$year) between pre- and post-retrofit conditions with a MAPE of 14.8% [40]. Another method is a bottom-up mathematical model. Zheng et al. proposed a set of equations to calculate annual energy savings from seven types of retrofit measures: envelope, cooling, lighting, elevators system, boiler system, renewable energy, management, and control. With the information collected from energy audits, literature surveys, manufacturer data, and engineering experience, they provided an energy-saving potential map to indicate for each type of public building, what kind of retrofit measure would save more energy [41].

The aforementioned studies predict either the absolute electricity consumption or the energy savings after building retrofits. Very few studies coped with the prediction of energy savings after building commissioning. A study with the same purpose is that Wang et al. developed an EnergyPlus simulation model to estimate the energy savings of commissioning measures such as adjustment of room temperature setpoints, direct expansion cooling control, outdoor air damper control, and optimal start. Simulation of taking eight commissioning measures together was predicted to save 15% energy, but in the real case, only four of the eight measures were conducted and the actual commissioning achieved an overall energy saving of 10% [42]. The drawback of this method is that creating a calibrated energy model for simulation is very time-consuming and resource-consuming—it is hard to generalize this method to quickly identify commissioning benefits for a number of buildings. Moreover, stakeholders care about not only energy savings but also performance regarding economic, environmental, and human health [43]. Yet, there does not exist a light-effort tool or model to predict all types of benefits after a building commissioning.

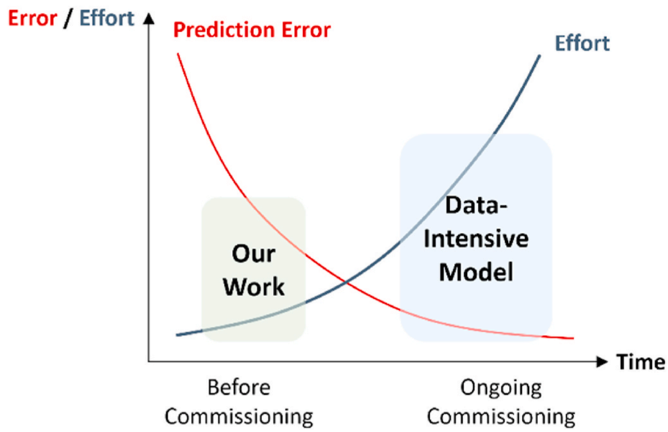


**Fig. 1.** Comparison of our work with other work.

### 1.3. Motivation and objectives

In light of the research gap, we intended to create a low-cost, low-effort tool to provide a more comprehensive prediction of EBCx outcomes for public buildings. Existing research on commissioning mostly devoted efforts to collecting measured data and creating data-intensive models with the aim to accurately predict energy consumption for ongoing commissioning. The data collection methods such as energy audit and model creation process such as energy simulation and data training are usually associated with a high investment in cost and labor. Differently, our work focuses on the pre-commissioning decision phase, aiming to use little effort to collect data and predict commissioning results with a bit higher but acceptable error rate (Fig. 1). This work can help the decision-makers such as building owners and managers to visualize and understand the benefits of EBCx and therefore enhance their interests in taking an EBCx to save energy and improve IEQ.

This project aims to develop a smart tool for predicting energy-saving potential and other benefits of building commissioning to foster its adoption. The specific objectives of this paper include:

1) Identify factors that may influence the results of building commissioning,
2) Design a mathematical prediction model based on engineering experience,
3) Develop a computerized tool to achieve automated building diagnosis, and
4) Exemplify and validate the prediction accuracy of the model.

## 2. Methods

This research follows a design science method, which consists of three phases: conceptual design, tool development, and application and validation (Fig. 2).

In the conceptual design phase, we identified both the influential factors of commissioning outcomes and the predictors that decision-makers are concerned with based on a literature review and years of commissioning experience. The influential factors, in another word, the parameters, will form the questions of the data collection survey, and the predictors will be the commissioning results presented by the tool. Rich engineering experience then formed the basis for calculation rules of the prediction model, determining how the parameters impact the commissioning results. Rounds of expert interviews were conducted to provide advice on the mathematical model. Finally, the calculation rules were tuned via testing the model with an actual project that had been commissioned.

In the tool development phase, a data collection survey is used as the input interface, and then the input information is processed by the embedded mathematical rules to predict the commissioning outcomes automatically. Aside from the predicted results in numbers, the tool also provides comparison figures to visualize the building performance.

Lastly, the developed tool was validated both quantitively and qualitatively. Three public buildings that had undergone a commissioning process were used as the case studies. Their information before the commissioning was used as the input to the tool, and the predicted commissioning outcomes were compared to the actual commissioning results to calculate the prediction accuracy. On the other hand, we also interviewed a building manager who used this tool to provide qualitative feedback.

The following sections will introduce the design concepts and framework, the mathematical model, and the developed tool in detail.

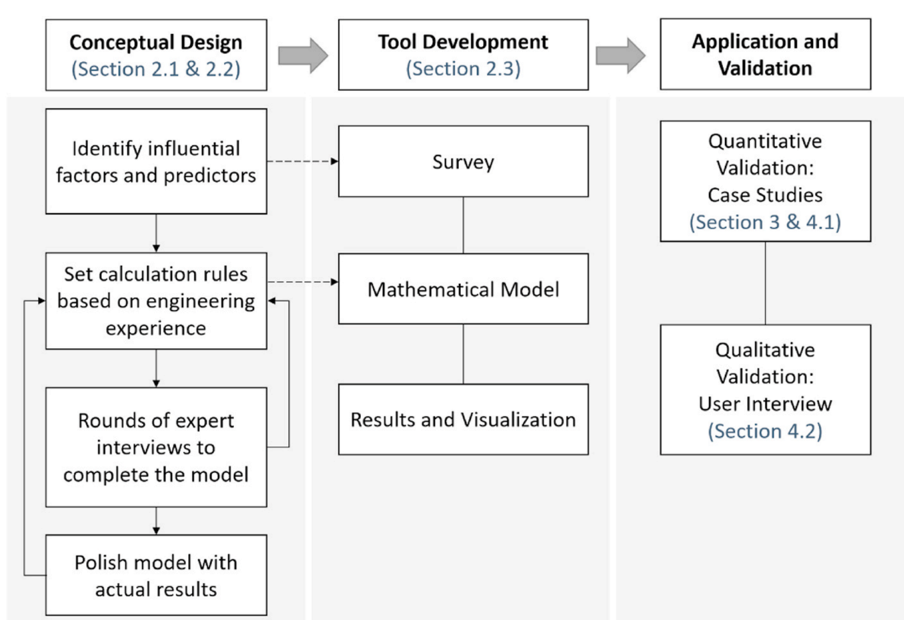


**Fig. 2.** Overall methodology.

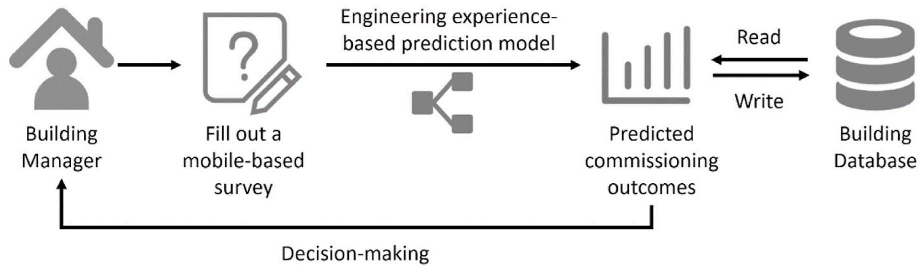


**Fig. 3.** Workflow of the proposed work.

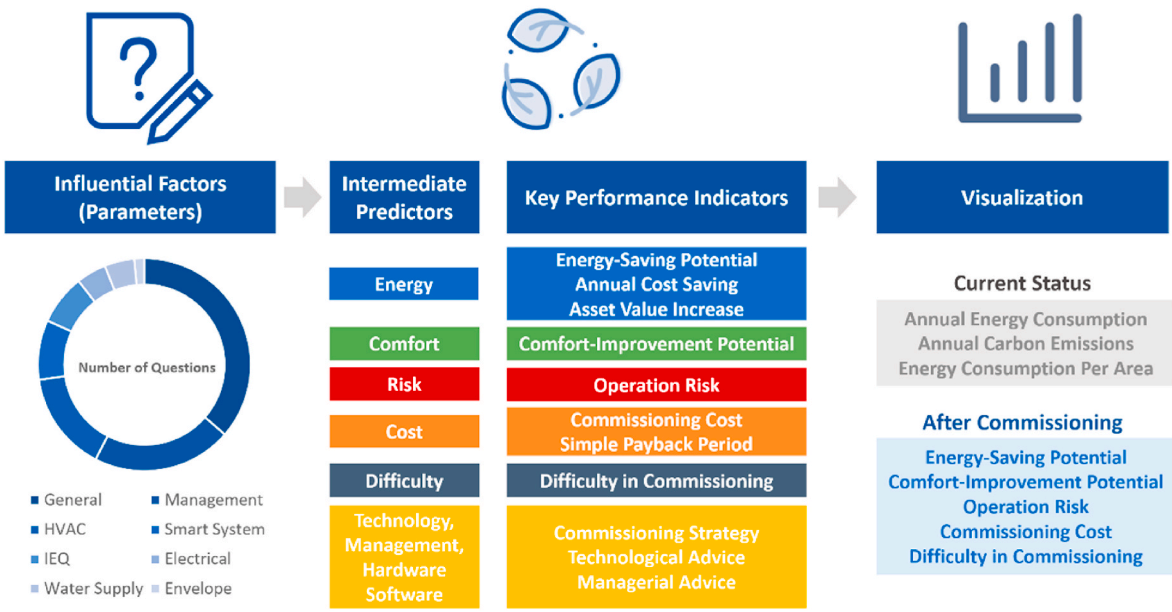


**Fig. 4.** Input and output of the tool.

### 2.1. Design principles and framework

At the outset, we set three principles to guide the tool design. First, comprehensives. The tool should be able to predict not only energy-saving potential but also other important results such as comfort improvement potential and risk potential that may influence the final decision-making on whether or not to undertake an EBCx. Second, practicability. Normal building managers should be able to use the tool and fill in information within a short time. Third, user-friendly. The output of the tool should be easy to understand to solicit support from the executives.

Following the three design principles, it is decided that the tool uses a mobile-based survey questionnaire with questions written in plain language to ensure practicability. It should be noticed that this tool is not simply a survey that reports statistical results. The survey is used to collect information, and then a mathematical model based on years of commissioning experience will apply complicated calculation rules using the input information to predict energy-saving potential and other results. All the calculation rules are embedded in the tool so that once the user submits their questionnaire, they will be directed immediately to the report page where fruitful diagnosis results including numbers, suggestions, and comparable figures will be displayed. The predicted results will be saved to our database to enable comparisons—the comparable figures will compare the performance of the user's building with other buildings in our database to provide further interpretation of the predicted results. Fig. 3 summarizes the overall workflow.

Fig. 4 shows the input and output of our tool in detail. The input, namely, the collected data using the questionnaire, involves eight groups of factors that may influence the effect of building commissioning. The eight groups are General, Management, HVAC (Heating, Ventilation, and Air-Conditioning), Smart System, IEQ (Indoor Environmental Quality), Electrical, Water Supply, and Envelope. Each factor group contains several questions. The full questionnaire contains over 60 questions, most of which are single-choice or multiple-choice questions and the others are completion question that requires number filling. The exact number of questions depends on the inputs from the users. Some of the questions are only applicable to a certain type of building and thus these questions will be hidden if other types of buildings were designated. Some questions are interdependent that if a certain choice was selected for a certain question, several other questions will pop up. On average, there will be around 60 questions in a questionnaire. The donut chart in Fig. 4 presents the relative number of questions of each factor group. It is worth noticing that the number of questions is not proportional to the score of each factor group. Section 2.2 will display the score weights of each factor group. The full list of questions can be found on the developed website in Chinese (https://drbuilding.cn/questionnaire).

To ensure the principle of comprehensiveness, the predicted results not only include the energy-saving potential, which is a percentage of annual energy saving, but also include outcomes regarding human comfort, operation risk, commissioning cost, commissioning strategy, and specific commissioning advice. To ensure the principle of user-friendly, some of the key performance indicators are compared with other buildings of the same type via intuitive visualizations.

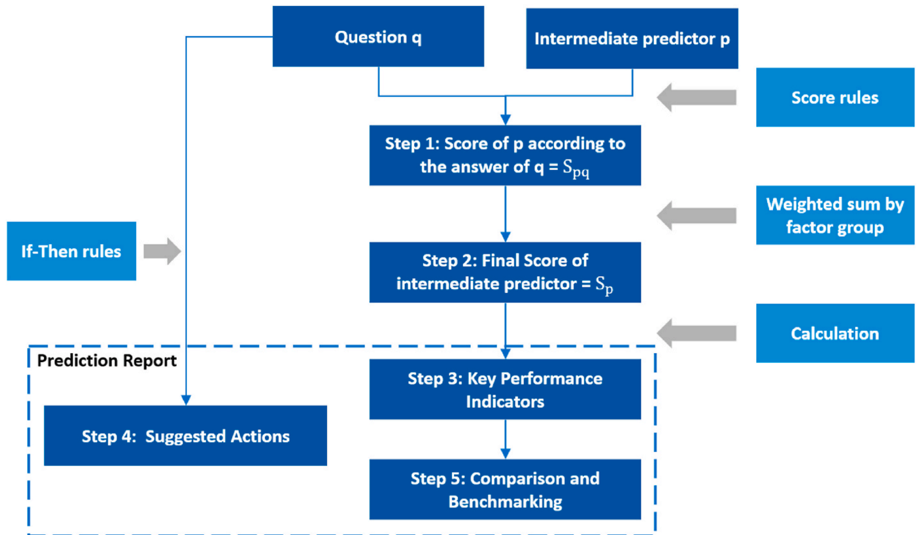


**Fig. 5.** The flowchart of the mathematical model.

**Table 1**
Questions included in each factor group.

| Factor Group | Specific Factor (Parameters) |
|---|---|
| General | building age, floor area, building type, previous energy consumption, utility price, electricity bill payment method, green building certification, energy-saving measures and effects, the relationship between the facility management team and the building owner, the overall status of HVAC, lighting, and BAS |
| Management | Energy-saving performance appraisal system, facility management manual, main equipment meter intervals, previous comfort problems and their solutions, energy audit results/plan, maintenance plan, retrofit plan |
| HVAC | Cooling/heating source, air-conditioning type, inverter, natural cooling in transition seasons, HVAC maintenance |
| Smart System | Automated control of air-conditioning and lighting, electricity sub-metering, data storage, control software, sensor calibration |
| IEQ | Indoor temperature, airspeed, humidity, indoor air quality, noise, and vibration |
| Electrical | Lighting control, declaration of maximum demand, infrared inspection |
| Water Supply | Hot water source, inverter, water leak detection |
| Envelope | Dew and mold |

**Table 2**
Explanation of the intermediate predictors.

| Predictors | Meaning |
|---|---|
| Energy | The worse the current condition, the higher the energy score, and the higher potential for energy-saving via commissioning. |
| Comfort | The worse the current condition, the higher the comfort score, and the higher potential for improving human comfort via commissioning. |
| Risk | Risk refers to the possibility of equipment problems during operation. A higher risk score means it is more likely to encounter problems during building operations. |
| Cost | A higher cost score means it requires more investment for building commissioning. |
| Difficulty | Difficulty refers to the resistance to the building commissioning from the management team or technical problems. A higher difficulty score means harder implementation of commissioning. |
| Technology | Higher technology score means that the building should be improved from the perspective of technology. |
| Management | A higher management score means that the building should be improved from the perspective of management. |
| Hardware | A higher hardware score means that the building should be improved from the perspective of hardware. |
| Software | A higher software score means that the building should be improved from the perspective of software. |

**Table 3**
Question types and their corresponding score rules.

| Question Type | Score Rules |
|---|---|
| Normal single-choice | Each option directly gives a score of one or more intermediate predictors. |
| Normal multi-choice | The number of selected options influences the score of one or more intermediate predictors. |
| Special multi-choice | Each option corresponds to a different score. The largest score among the selected options will be used as the score. |
| Normal single-blank completion | Fill in a number. The number will be used in the final calculation of KPIs. |
| Special single-blank completion | Fill in a number. The numerical value influences the score of one or more intermediate predictors. |
| Multi-blank completion | Fill in numbers. The numbers are associated with the weights for multiplication with the data from other questions. |

### 2.2. *Mathematical model*

We created a **P**arametric, **E**xperience-based model for **C**omputerized prediction of building **C**ommissioning **O**utcomes with the nickname “PECCO”. PECCO can be summarized into five steps (Fig. 5).

#### 2.2.1. *Step 1: Get $S_{pq}$*

First, the answer to each question $q$ from the data collection questionnaire gives a score to one or more intermediate predictor $p$, that is, $S_{pq}$. As mentioned above, questions are categorized into eight factor groups. Table 1 listed the specific factors included in each factor group. Each specific factor may need one or more questions to collect information. Therefore, the number of listed specific factors in Table 1 is not equal to the number of questions in each factor group. Meanwhile, the mathematical model requires nine intermediate predictors: Energy, Comfort, Risk, Cost, Difficulty, Technology, Management, Hardware, and Software. Table 2 describes the score meaning of the intermediate predictors. The determination of $S_{pq}$ is based on a set of preset rules inspired by years of building commissioning experience of the authors. For example, experience shows that building age normally affects the energy-saving performance, operation risk, commissioning cost, and commissioning difficulty; thus, the question of building age will assign a score to the intermediate predictors: energy, rick, cost, and difficulty. Due to the paper’s length, the detailed hundreds of score rules are omitted here. Nevertheless, Table 3 summarizes all the types of score rules to shed light on the complexity of the mathematical model.

**Table 4**
Preset weights of factor groups.

| Factor Group | Energy Score Share | Comfort Score Share | Cost Score Share |
|---|---|---|---|
| General | 20% | 8% | 30% |
| Management | 15% | 25% | 10% |
| IEQ | 0% | 30% | 0% |
| HVAC | 35% | 17% | 30% |
| Electrical | 8% | 0% | 5% |
| Water Supply | 2% | 0% | 0% |
| Envelope | 0% | 5% | 0% |
| Smart System | 20% | 15% | 25% |
| **Sum** | **100%** | **100%** | **100%** |

#### 2.2.2. Step 2: Get $S_p$

The second step is to calculate the final score for each intermediate predictor, that is, $S_p$. $S_p$ is not a simple sum of $S_{pq}$, considering the following two reasons. First, the number of questions of each factor group and their scores are not in a linear relationship with their magnitude of influence on the predictors. Second, the influential magnitude of certain factor group is different for different predictors. For example, the water supply may affect the energy-saving after commissioning but does not affect commissioning cost and comfort improvement. Therefore, $S_p$ should be the sum of $S_{pq}$ weighted by factor group, illustrated by Eq. (1):

$$S_p = \sum_{f=1}^{8} S_{pf} \times \frac{Rw_{pf}}{Cw_{pf}} \tag{1}$$

where $p$ denotes intermediate predictor listed in Table 2, $f$ denotes factor group listed in Table 1, $S_{pf}$ is the sum score of factor group $f$ on intermediate predictor $p$, $Rw_{pf}$ is the rational weight of factor $f$ to predictor $p$, $Cw_{pf}$ is the current weight of factor $f$ to predictor $p$.

$S_{pf}$ is calculated by summing up all the achieved scores in factor group $f$ with regard to intermediate predictor $p$, as shown in Eq. (2):

$$S_{pf} = \sum_{q=1}^{n} S_{pf,q} \tag{2}$$

where $q$ denotes questions, $n$ is the number of questions in factor group $f$. $n$ is dynamic and dependent on the user input as explained before.

$Rw_{pf}$ in Eq. (1) was set according to the authors' experience on the influential magnitude of certain factor group to predictors. Table 4 shows the used $Rw_{pf}$ in PECCO—the current version only adjusted the scores of Energy, Comfort, and Cost by factor groups. In the future, more data of the actual commissioning results can help to tune the values of $Rw_{pf}$.

$Cw_{pf}$ is calculated using Eq. (3):

$$Cw_{pf} = \frac{A_{pf}}{\sum_{f=1}^{8} A_{pf}} \tag{3}$$

where $A_{pf}$ is the total applicable score of factor $f$ to predictor $p$. Applicable score is the largest score of each question that applies to the target building. For example, a question has three options and their corresponding scores to Energy are 0, 2, and 5. Then, the applicable score of this question to predictor Energy is 5. Since a larger energy score means higher room for improvement (explained in Table 2), the applicable energy score can be regarded as the maximum room for energy saving.

#### 2.2.3. Step 3: Calculate predicted KPIs

The KPIs presented to users (as shown in Fig. 4) are calculated from the scores of intermediate predictors.

(1) Energy

**Table 5**
Classification rules for Comfort-Improvement Potential and Operation Risk. $p$ is comfort or risk.

| $KPI_p$ | Category shown to the users |
|---|---|
| <40% | Relatively Small |
| 40%–60% | Ordinary |
| 60%–80% | Relatively Big |
| 80%–100% | Very Big |

The **Energy-Saving Potential *ES*** is a percentage calculated as the achieved energy score divided by the total applicable energy score (Eq. (4)), and it is artificially scaled to a range to account for the uncertainty of calculation (Eqs. (5) and (6)). The 31% used in Eq. (4) is the largest possible energy savings according to the statistics of 643 commissioned buildings in the U.S [44].

$$ES = \frac{S_{energy}}{\sum_{f=1}^{8} A_{energy\,f}} \times 31\% \tag{4}$$

$$ES_{max} = ES + 2\% \tag{5}$$

$$ES_{min} = ES - 4\% \tag{6}$$

With the user input of their energy bills in the previous years, the average annual energy cost (sum of electricity, gas, and municipal heating/cooling source) is calculated as ***EB***. Then, the **Annual Cost Saving *CS*** is predicted using Eqs. (7)–(9).

$$CS_{max} = ES_{max} \times EB \tag{7}$$

$$CS_{min} = ES_{min} \times EB \tag{8}$$

$$CS = (CS_{max} + CS_{min}) / 2 \tag{9}$$

**Asset Value Increase *AVI*** can be estimated using the capitalization rate. As the tool is used mainly in Shanghai, China, at this stage, the capitalization rate in Shanghai is taken as 5%.

$$AVI_{max} = \frac{CS_{max}}{5\%} \tag{10}$$

$$AVI_{min} = \frac{CS_{min}}{5\%} \tag{11}$$

$$AVI = (AVI_{max} + AVI_{min}) / 2 \tag{12}$$

(2) Comfort and Risk

The **Comfort-Improvement Potential** and **Operation Risk** are calculated using Eq. (13):

$$KPI_p = \frac{S_p}{\sum_{f=1}^{8} A_{pf}} \times 100\% \tag{13}$$

where $p$ is comfort or risk. Then, the result is presented to the end-users as a category to increase the understandability (Table 5).

(3) Cost

The **Commissioning Cost *CC*** is predicted using Eqs. (14)–(16). First, calculate the upper and lower bounds of $CC$ by the following equation

$$CC_{upper\ or\ lower} = CS_{max\ or\ min} \times \mu_{upper\ or\ lower} \times \theta \tag{14}$$

where $CS$ is previously calculated Annual Cost Saving, $\mu$ is a coefficient based on the authors' experience (here $\mu_{upper} = 2.5$, $\mu_{lower} = 1.5$), and $\theta$ is an adjustment coefficient determined by the building floor area entered by the users.

Second, calculate *CC* based on the bounds, and then multiply *CC* with the coefficient $\beta$ to provide an uncertainty range that will be presented to the users (here $\beta_{max} = 1.0$, $\beta_{min} = 0.9$).

$$CC = CC_{lower} + \left(CC_{upper} - CC_{lower}\right) \times \frac{S_{cost}}{\sum_{f=1}^{8} A_{cost\,f}} \tag{15}$$

$$CC_{max\ or\ min} = CC \times \beta_{max\ or\ min} \tag{16}$$

Lastly, calculate the **Simple Payback Period *SPP*** using Eqs. (17)–(19).

$$SPP_{max} = \frac{CC_{max}}{CS_{min}} \tag{17}$$

$$SPP_{min} = \frac{CC_{min}}{CS_{max}} \tag{18}$$

$$SPP = (SPP_{max} + SPP_{min}) / 2 \tag{19}$$

(4) Difficulty in Commissioning

The **Difficulty in Commissioning *DC*** is calculated using Eqs. (20) and (21):

$$DC = \frac{S_{difficulty}}{\sum_{f=1}^{8} A_{difficulty\,f}} \times \alpha \times 10 \tag{20}$$

$$\alpha = \begin{cases} 0.8, & \textbf{SPP} < 2 \\ 1.0, & 2 \le \textbf{SPP} < 3 \\ 1.2, & \textbf{SPP} \ge 3 \end{cases} \tag{21}$$

where $f$ denotes the factor group and $\alpha$ is a coefficient to suggest the influence of a simple payback period on the commissioning difficulty. *DC* is a decimal number between 0 and 10, and the report page presents the user with the rounded integer between 0 and 10, with 10 being the most difficult.

(5) Commissioning Strategy

Commissioning strategy indicates that if the user plans to start a building commissioning, what kind of strategy should be considered—more technological or more managerial, focusing more on hardware renewal or software update. $\frac{S_p}{\sum_{f=1}^{8} A_{pf}}$ is calculated for Technology, Management, Hardware, and Software. The larger the $\frac{S_p}{\sum_{f=1}^{8} A_{pf}}$ is, the more attention should be given in building commissioning. For example, if $\frac{S_{techonology}}{\sum_{f=1}^{8} A_{technology\,f}}$ is greater than $\frac{S_{management}}{\sum_{f=1}^{8} A_{management\,f}}$, then the building owners should take more technological measures than managerial measures in a building commissioning campaign. The results will be presented as relative percentages, for example, 60% technology and 40% management.

### 2.2.4. Step 4: Provide commissioning suggestions

Following the overall commissioning strategy, specific commissioning actions are automatically driven using preset If-Then rules based on the users' answers to some questions, i.e., if option a to question A is selected, then suggest action x.

### 2.2.5. Step 5: Compare results with other buildings in the database

Comparison and benchmark are essential to help users position the performance of their buildings. Aside from the predicted KIPs after commissioning, PECCO also presents the current status of the building,

**Table 6**
Conversion rates between energy units.

| Energy source | Entered unit | Conversion Rate | | |
|---|---|---|---|---|
| | | kWh | kgce | $kgCO_2e$ |
| Electricity | kWh | 1 | 0.288 | 0.7035 |
| Natural Gas | $m^3$ | 7.148 | 1.33 | 2.184 |
| Municipal cooling/heating | kWh | 1 | 0.12276 | 0.4729 |

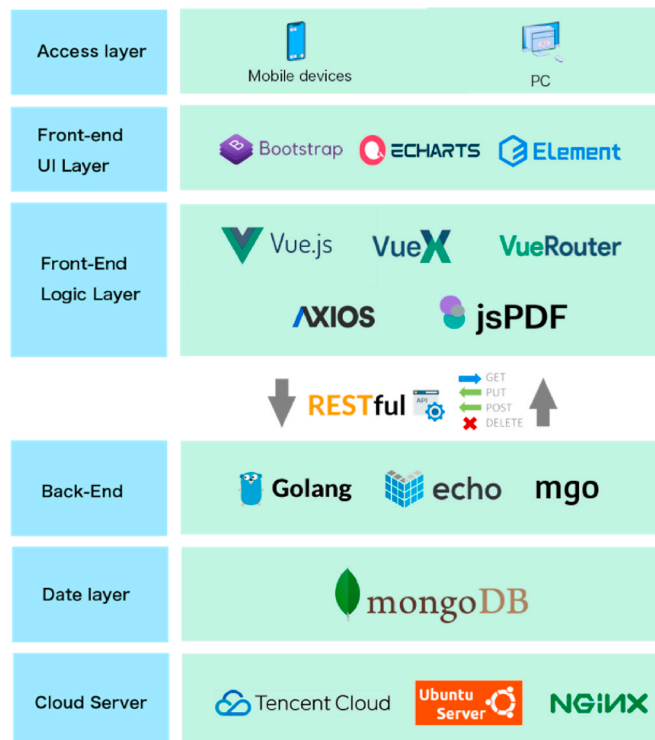


**Fig. 6.** Tool framework.

that is, the **Annual Energy Consumption** and **Annual Energy Consumption Per Area**. The "Energy" here is a general term accompanied with three units: kWh, tce, and $tCO_2e$, that users can choose from. Table 6 displays the conversion rates used to calculate the consumption of standard coal equivalent and carbon emissions.

## 2.3. Tool interface

The tool was developed using Python and other tools listed in Fig. 6. It can be accessed on mobile devices or computers with the URL www.drbuidling.cn. The mobile interface is prepared for individual users while the web interface is mainly used by the admin to manage the database. Fig. 7 shows the use cases. Users should first register an account to manage their projects and then fill out the data collection survey (Fig. 8). After submitting the questionnaire, they will be able to view the prediction results in a few seconds and they can save the results in a PDF format locally (Fig. 9). They can also revisit the filled questionnaires and prediction results online with their account at any time. Whereas the admin account can modify and publish the questionnaire, view all the projects in the database, and manage user accounts.

# 3. Results of case studies

As of December 2021, the PECCO database contains 43 public buildings in Shanghai. This section will exemplify the usage of PECCO using three of them. The selected three buildings are the only ones that


**Fig. 7.** Use case diagram.


**Fig. 8.** Screenshots of the tool: input process.

have been commissioned by Harvency Building Commissioning Ltd. over a year ago, and therefore yearly energy bills after the building commissioning are available to be used as the ground truth for later quantitative validation.

Located in Shanghai, China, the three buildings are of different types and attributes as Table 7 shows. Project 1 is a medium-size office building with Chinese green building certifications, Project 2 is an old 5-Star hotel, and Project 3 is a newly built complex composed of an office and shopping mall. Fig. 10 shows the exteriors of the buildings.

The major results of the three cases are summarized in Table 7. As the tool was developed in Chinese, Fig. 11 to Fig. 13 show the screenshots of Project 1's results with English annotations. The results of Project 2 and


**Fig. 9.** Screenshots of the tool: Prediction results (see Section 3 for complete results).

**Table 7**
Description of the case buildings and the predicted results.

| | Project 1 | Project 2 | Project 3 |
|---|---|---|---|
| Basic Information | | | |
| Building Type | Office | 5-Star Hotel | Complex (office + shopping mall) |
| Building Age | Over 5 years | Over 5 years | 0–2 years |
| Floor Area ($m^3$) | 23,000 | 51,094 | Office 39,000 $m^3$; Shopping mall 30,000 $m^3$ |
| Certification | Chinese 2-Star for design and operation | None | None |
| Energy Source | Electricity | Electricity and Gas | Electricity |
| Predicted Commissioning Outcomes | | | |
| Annual Cost Saving | RMB 280,000 | RMB 1,370,000 | RMB 980,000 |
| Energy-Saving Potential | 17.30% | 18.90% | 20.1% |
| Asset Value Increase | RMB 5,680,000 | RMB 27,300,000 | RMB 19,660,000 |
| Commissioning Cost | RMB 610,000 | RMB 2,660,000 | RMB 1,740,000 |
| Simple Payback Period | 2.2 years | 1.9 | 1.7 |
| Comfort-Improvement Potential | Ordinary | Ordinary | Relatively Big |
| Operation Risk | Relatively Big | Relatively Big | Relatively Big |
| Difficulty in Commissioning | 5/10 | 4/10 | 4/10 |

Project 3 were described in text.

For project 1 (Fig. 11), it is anticipated that after an EBCx, the building could save RMB 280,000 per year and save 17.30% of the energy consumption. The commissioning may cost about RMB 610,000 and therefore the simple payback period will be 2.2 years. Meanwhile, there was an ordinary room for comfort improvement, which corresponds to the users' input saying there are some problems with the indoor environmental quality. The operation risk was relatively big, indicating some problems with the existing building systems. The difficulty in commissioning achieved a middle score of 5 out of 10. In terms of the commissioning strategy, the tool suggested taking more managerial measures than technological measures and focusing more on the software rather than the hardware. The specific technological advice includes upgrading the building automation system (BAS), applying free cooling in the swing seasons, testing and adjusting the hydraulic balance, etc. The managerial advice includes incorporating energy management into the annual Net Operating Income (NOI) targets, developing a manual for energy-efficient equipment operation and maintenance under the guidance of a professional commissioning company, inviting professionals to support BAS maintenance, etc.

When comparing project 1's current status (before commissioning) with other office buildings in our database, the left plot in Fig. 12 shows that the annual carbon emission of project 1 was relatively small—it was only greater than 28.6% of the office buildings and lower than both the mean and median levels. The right plot in Fig. 12 compares the annual energy consumption per area among buildings—project 1 was in the middle area, lower than the reasonable value in Shanghai, and higher than the advanced value in Shanghai. The above results suggested that the energy performance of project 1 before commissioning was acceptable but still had a large room to improve.

Fig. 13 compares the predicted commissioning outcomes of project 1 with those of other office buildings in our database. It shows that the energy-saving potential of project 1 was greater than one-third of the office buildings, and the comfort-improvement potential was larger than 47.6% of office buildings. The operation risk was relatively big (the risk score was between 60% and 8's 0%), but since most of the buildings had a relatively big operation risk, project 1risk was just greater than 42.9% of office buildings. Compared with other buildings, project 1's commissioning cost was quite low, but the difficulty in commissioning was relatively high. All the information above could inform comprehensive decision-making on whether to take an EBCx.

For project 2, commissioning could help save 18.9% energy and lead to an annual cost saving of RMB 1.37 million. This would increase the asset value by RMB 27.3 million. The commissioning of project 2 was projected to cost RMB 2.66 million with a simple payback period of 1.9 years. Project 2's comfort-improvement potential and operation risk were at the same level as project 1, but the difficulty score was a bit lower. The tool suggested the commissioning of project 2 to consider more from the perspectives of management and software. From the management perspective, the building management team should


**Fig. 10.** Pictures of the case buildings. (a) Project 1 (b) Project 2 (c) Project 3.

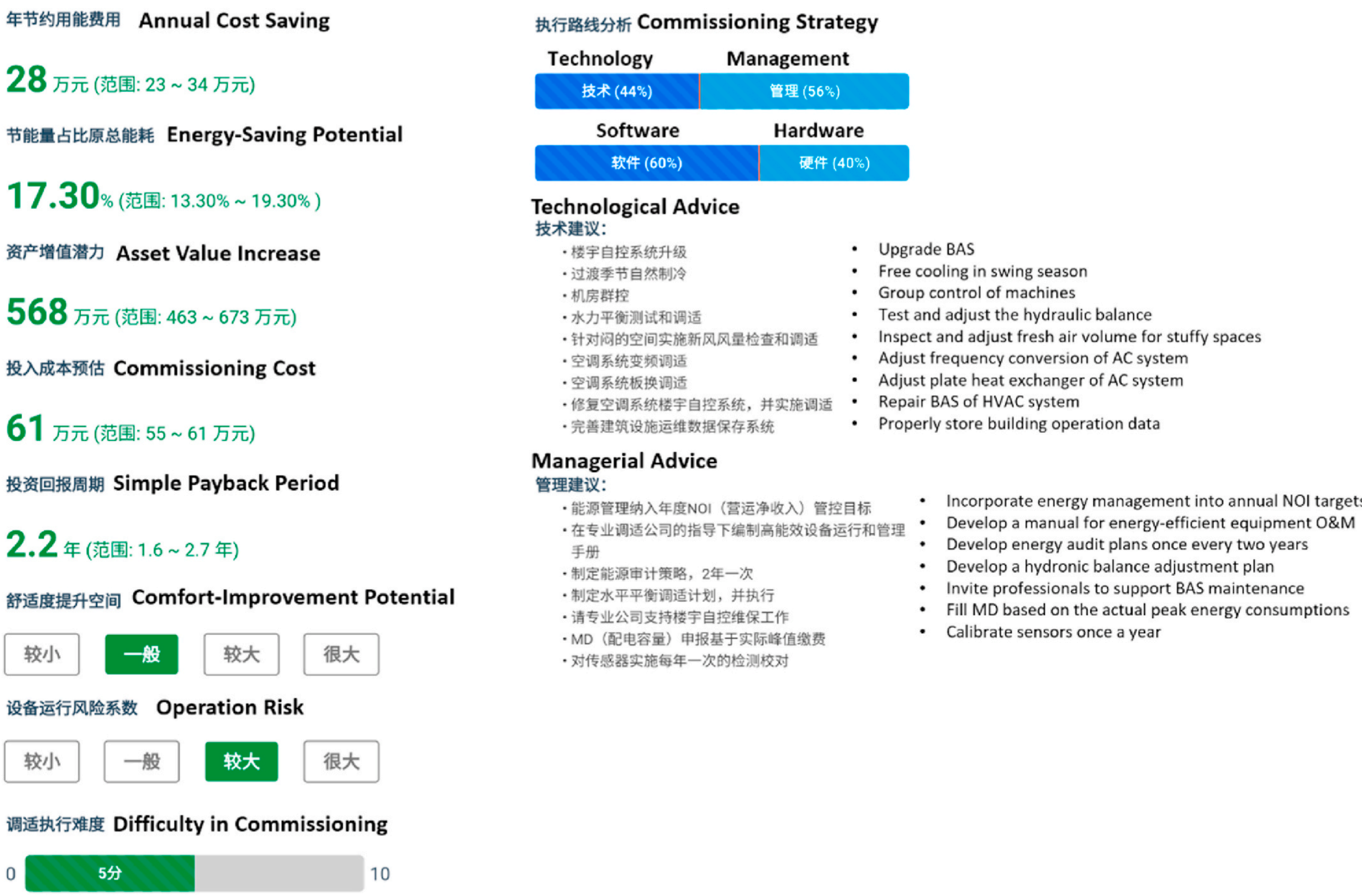


**Fig. 11.** Prediction results of Project 1: Commissioning outcomes and strategies.

develop and implement a hydronic balance adjustment plan, fill the Maximum Demand (MD) based on the actual peak energy consumptions, and calibrate the sensors once a year. From the technological perspective, the building should consider repairing and commissioning the BAS, properly storing the building operation data, etc.

There are currently five 5-star hotels in PECCO's database. When comparing the current energy performance (before commissioning) of project 2 with that of other 5-star hotel buildings, project 2's annual carbon emissions and annual energy consumption per area were greater than three other 5-star hotels. Compared with the benchmarks in Shanghai, the annual energy consumption per area in kgce/m$^2$ was between the reasonable value and the advanced value, meaning a quite good energy performance of project 2 with some potential to improve.

When comparing the predicted commissioning outcomes with other 5-star hotels, the energy-saving potential of project 2 turned out to be the largest in the database, but the predicted commissioning cost was also the greatest. The room for improving human comfort and the commissioning difficulty were at a median level, and the operation risk of project 2 was above the average level.

For project 3, an EBCx may save 20.2% energy and reduce energy bills of RMB 980,000 per year, leading to an asset value increase of approximately RMB 20 million. The commissioning would cost RMB 1.74 million with a simple payback period of 1.7 years, which equals the median simple payback period of the American study [5]. The room for improving human comfort and the operation risk of the existing building systems were relatively big, indicating serious problems of the building. The difficulty of commissioning scored 4 out of 10, which is a good sign for undertaking an EBCx. Similar to the other two cases, project 3's commissioning strategy should consider more management than technology and more software than hardware. Specific technological advice includes fresh air volume inspection and adjustment for stuffy spaces, frequency conversion adjustment of air conditioning system, plate heat

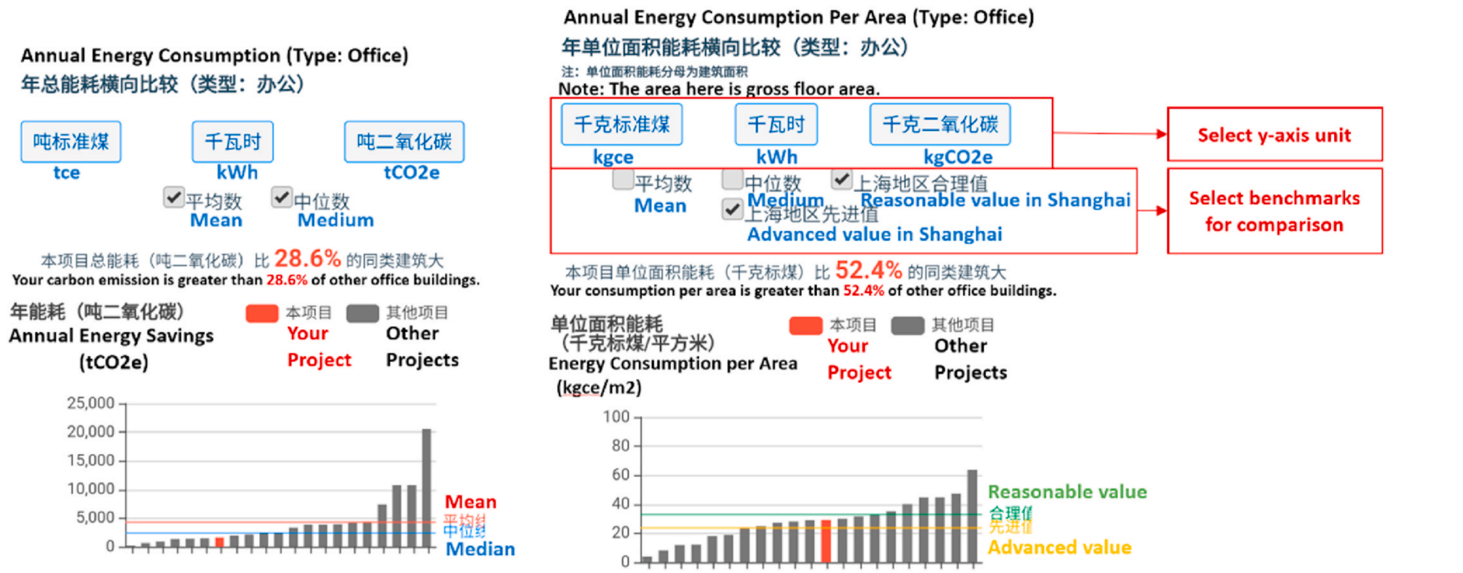


**Fig. 12.** Prediction results of Project 1: Current status (before-commissioning) compared with other buildings.

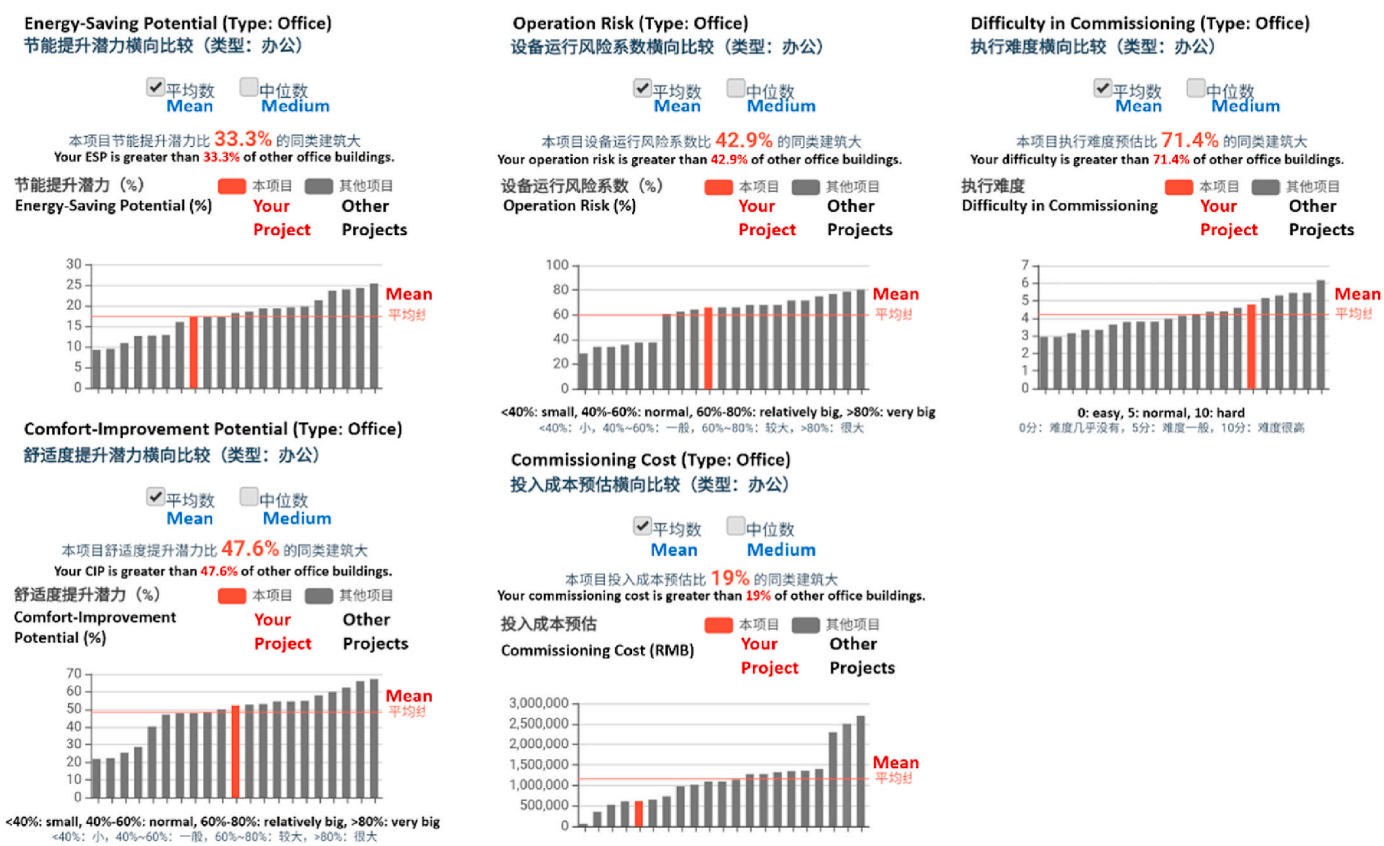


**Fig. 13.** Prediction results of Project 1: Commissioning outcomes compared with other buildings.

exchanger adjustment of air conditioning system, etc. From the management perspective, the building management team should develop energy audit plans once every two years, better implement an energy audit within a year, identify faulty equipment and schedule repair plans and budgets for them, etc.

When compared with other complex buildings, project 3's annual energy consumption was at a median level, and the energy consumption per area was relatively small—even below the advanced value in Shanghai. Although the energy performance of project 3 before commissioning was already quite good, there were still a high energy-saving potential and comfort-improvement potential. The operation risk was relatively high among complex buildings, and the commissioning cost was below the average level. Meanwhile, it would not be very difficult to apply commissioning in project 3 compared with other buildings. All the information above suggested a strong motivation to implement an EBCx for project 3.

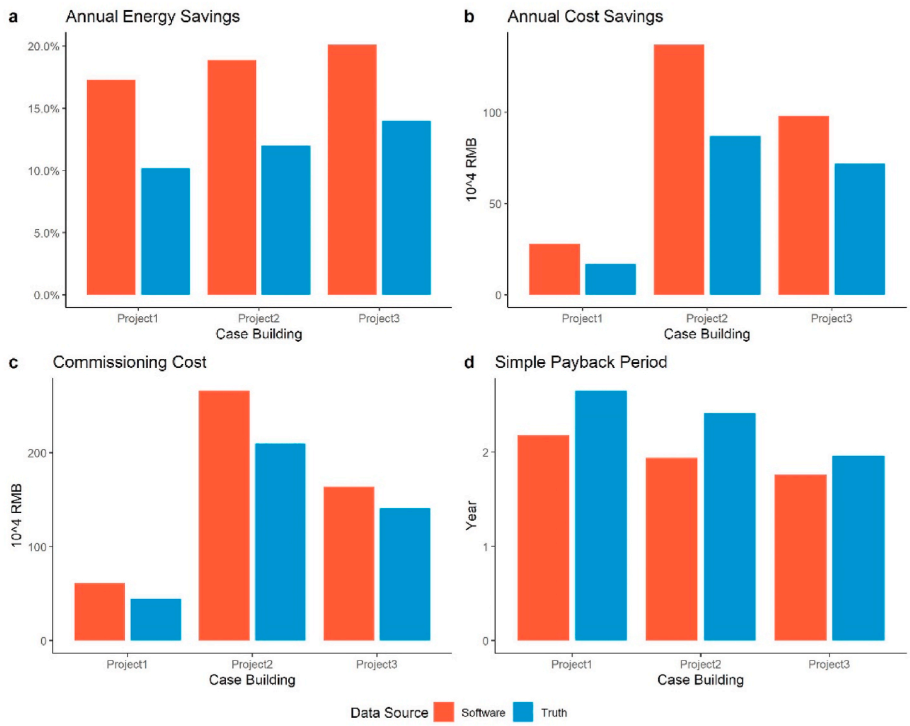


**Fig. 14.** Comparison of the predicted and the actual commissioning results.

**Table 8**
Comparison of the predicted and the actual Simple Payback Period.

| Case Building | Simple Payback Period | | |
|---|---|---|---|
| | Predicted | Truth | Error = (Truth – Predicted)/Truth |
| Project 1 | 2.18 | 2.65 | 17.73% |
| Project 2 | 1.94 | 2.41 | 19.50% |
| Project 3 | 1.78 | 1.96 | 9.18% |

## 4. Validation

### *4.1. Quantitative validation*

As mentioned above, the three buildings have been commissioned by Harvency Building Commissioning Ltd. for more than a year and thus it is possible to compare the predicted commissioning outcomes with the actual ones. Since the Annual Cost Savings, Commissioning Cost, and Simple Payback Period (SPP) are the three KPIs that the building owners and managers are mostly concerned with, Fig. 14 compares the predicted four KPIs generated by PECCO with the actual performances after an EBCx. The predicted annual energy savings, cost savings, and commissioning costs are generally higher than the actual ones. This is because our prediction model takes into account all the possible commissioning measures comprehensively, while in reality, due to the limited budget and many other reasons, the commissioning contract usually involves several major commissioning measures only. In light of this fact, SPP is a more reasonable and representative indicator to evaluate prediction accuracy. Table 8 lists the predicted SPP and the actual SPP. It shows that the predicted results were a bit optimistic with a lower SPP. The prediction error rates are 17.70%, 19.56%, and 9.34%, respectively, giving a mean absolute percentage error (MAPE) of 15.47%, which is acceptable given the fact that the data were simply collected by a survey without any professional energy audit.

Table 9 summarizes the differences between PECCO and other related studies. PECCO is designed for the prediction of more comprehensive results with easily obtained data. As expected, our prediction

**Table 9**
PECCO's prediction error compared with related studies.

| Goal | Ref. | Building type | Predictor | Data collection effort | Model | Error rate |
|---|---|---|---|---|---|---|
| Predict commissioning benefits | This paper | Public | Simple payback period and other commissioning outcomes | An 8-min questionnaire | Mathematical | SPP's MAPE 15.47% |
| | [42] | Office | Annual energy savings | Drawings, equipment specifications, control sequence, testing reports, and two-month-long monitored data | EnergyPlus Simulation | Estimated 15% savings with 8 measures, actual 10% savings with 4 measures |
| Predict retrofit energy savings | [41] | Public | Annual energy savings | Energy audits, literature surveys, manufacturer data, and engineering experience | Mathematical | – |
| | [40] | Office | Annual EUI change | Energy audits | ANN | MAPE 14.8% |
| | [39] | Hotel | Post-retrofit hourly equipment power consumption | Measured weather conditions, building-operation schedules, and 3-week-long monitored consumption | ANN | MAPE 5.31%–9.95% |
| | [37] | Primary school | Post-retrofit daily gas consumption | Estimate 48 parameters and calibrate them for simulation models | Simulation | <10% |

accuracy of SPP is higher than the ANN models which were fed with tremendous measured data, but our prediction accuracy is comparable to some of them. For example, the ANN model trained by energy audit reports for predicting change in EUI after a retrofit had a MAPE of 14.8% [40], our mathematical model for predicting the commissioning SPP achieved a slightly higher MAPE of 15.47% but with much less data collection effort.

### 4.2. Qualitative validation

Aside from the quantitative validation, we also interviewed a building manager to gather first-hand qualitative feedback. This target building is another 5-star hotel located in the Minhang district, Shanghai, China. It is a none-green hotel that has been built for over 5 years, with a gross floor area (GFA) of 63,705 $m^2$. The building is centrally-conditioned powered by electricity and the hot water comes from gas boilers. The building had taken some energy conservation measures such as using LED lighting, but the energy savings over the past two years was quite low—only 3–5%. Besides, the BAS has never been used since installation. The HVAC and lighting systems all rely on manual control. Furthermore, the metering system is not operated and the staff has to record energy and water consumption periodically. With the outdated hardware and software, the management team is striving to provide a comfortable indoor environment as the experience of consumers is crucially important for a 5-Star hotel. Therefore, the building manager was delighted to use PECCO to identify improvement potentials.

After using PECCO, the building manager commented that the predicted results are quite close to their estimates, especially the predicted commissioning cost of RMB 2.7 million is very close to a quote from an energy audit company. Since commissioning or retrofit will interrupt the hotel operation for a while, they are very careful about making this decision, especially in the pandemic period when business is hard-hitting. By providing a clear predicted benefit of the potential energy savings with a simple payback period, PECCO could strengthen their decision on taking commissioning or retrofitting.

Moreover, the building manager provided some suggestions. For example, he mentioned that although the HVAC systems used in different types of public buildings are similar, the operation strategies of hotels are distinct from those of offices or shopping malls. They would like the questionnaire to target more precisely each building type. This may form future research to derive more targeted versions of questionnaires. In addition, the building manager suggested the questionnaire to collect more detailed operation data. For example, if the water supply system is using variable frequency, collect the regional pressure setting to identify problems. For air-conditioning system, information about the centrifugal machine and screw machine and the maximum and minimum energy consumption may provide some insights on whether there exists energy waste. Since PECCO was designed for a broad audience, the current tool mainly includes general questions to enable easy filling. Too technical questions may be more suitable for case-by-case interviews or energy audits.

In general, the interview suggests that the tool can provide useful information for decision-making on EBCx, but a more pertinent evaluation of a building's existing systems is still needed to implement the commissioning.

## 5. Conclusion

Existing building commissioning (EBCx) is one of the top energy-saving measures to reduce a building's performance gap. However, it is rarely taken as a priority due to the uncertain benefits and costs. There were few studies on the prediction of commissioning results as the commissioning outcomes may be affected by various factors and therefore are hard to predict. This paper introduces a **P**arametric, **E**xperience-based model for **C**omputerized prediction of building **C**ommissioning **O**utcomes named "PECCO". PECCO is a mathematical model developed following a rigorous design science method, aiming to suggest potential benefits and costs of commissioning for public buildings such as offices, shopping malls, hotels, and complex buildings (combination of the above). A mobile-based tool was also created to realize automated prediction. Building information is collected in a questionnaire format with a dynamic number of questions. The parameters collected can be categorized into eight groups: general, management, HVAC, smart system, IEQ, electrical, water supply, and envelope. PECCO can predict commissioning outcomes such as energy-saving potential, annual cost saving, asset value increase, comfort-improvement potential, operation risk, commissioning cost, simple payback period, and difficulty in commissioning. PECCO also provides both the overall commissioning strategy and the specific technological and managerial advice according to the collected building information. Three public buildings that have been commissioned were used to validate the prediction accuracy of PECCO. It turned out that the mean absolute percentage error (MAPE) of PECCO's predicted simple payback period was 15.47%, which is acceptable for a diagnosis tool at the early stage with little data collection effort. An interview with a building manager of a 5-Star hotel suggested that the user was satisfied with the tool and thought that PECCO provided valuable information for their decision-making.

Different from previous related studies that predicted annual, daily, or hourly electricity consumption based on building characteristics, energy use profile, occupants' behavior, and weather conditions, PECCO is the first of its type that integrates fruitful engineering experience to predict comprehensive commissioning results including not only energy-saving potential but also commissioning cost, human comfort improvement potential, risk, and difficulty. Although the prediction accuracy is lower than data-intensive models like ANN, PECCO is a low-effort, user-friendly tool to quickly predict the costs and benefits of various types of public buildings. It is useful to provide a general idea on whether to take the next step for decision-makers, such as taking an energy audit, an EBCx, or a retrofit. This study not only provided a theoretical model for the prediction of commissioning outcomes to fill the research gap but also developed a mobile-based tool with reference cases to enable practical use.

Nevertheless, the current model is mainly based on engineering experience. The used default coefficients and weights in the model could be tuned by artificial intelligence (AI) in the future if more data of actual commissioning results are available. In addition, it may also be worth developing specific versions of PECCO to tailor for each type of public buildings.

## CRediT authorship contribution statement

**Peixian Li:** Writing – original draft, Validation, Software, Project administration, Investigation. **Yujie Lu:** Conceptualization, Funding acquisition, Supervision, Writing – review & editing. **Yingchu Qian:** Validation, Resources, Methodology, Data curation. **Yicheng Wang:** Software, Visualization. **Wanying Liang:** Validation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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