Exploring New Building Energy Saving Control Strategy Application under the Energy Internet of Things

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Abstract. This paper makes innovative research on developing a data-driven control strategy under the Energy Internet of Things architecture. On the one hand, the platform aims to provide data representation and interpretable analysis for different stakeholders (end users, construction operators or managers) to realize the flexibility and scalability of the platform; on the other hand, it can improve the thermal comfort and also reduce the power consumption of buildings. However, to process vast amounts of data, it is critical to select appropriate control methods and design optimization issues. Data-driven predictive control (DPC) is a control technology that replaces model-based predictive control (MPC). When applied to complex building operations, MPC is implemented by using the control-oriented data-driven model. The key to DPC technology is the use of CatBoost algorithm, which is highly interpretable and easy to be operated by stakeholders. This paper chooses TDNN, LightGBM, and CatBoost to compare and analyze building energy consumption. Numerical simulation results show that the CatBoost algorithm's performance is better than other algorithms, and the complexity and implementation cost is significantly reduced.

1. Introduction
In the face of the growing energy crisis, one of the enormous challenges is to reduce energy use and CO\textsubscript{2} emissions from existing and new buildings [1]. In recent years, the construction industry has significant great progress in managing construction systems [2]. This development aims to mitigate the industry’s significant environmental impact (30% of the world’s energy consumption and one-third of its associated CO\textsubscript{2} emissions [3]).

To reduce these impacts by controlling resources, the Building Energy Management System (BEMS) provides a sustainable and efficient solution [4]. However, most of the building energy management systems are in the "supervision but not control".

Therefore, it is necessary to set up an energy management system in combination with the Internet of Things (IoT), to monitor, analyze and manage the energy efficiency of building ground equipment, and to set up a building energy consumption model in order to achieve the purpose of energy-saving truly. With the Internet of Things technology, a large amount of data can be collected and integrated into a unified energy management platform. However, there are some challenges. On the one hand, big data needs to be managed: transfer, store, preprocess, mine, optimize, and control in robust network infrastructure within an appropriate IoT framework. On the other hand, providing useful information to different stakeholders based on their use is another challenge [5,6]. Some related open source software is available, such as Open-Ended Energy Management, Freedomotic, Open Remote, and openHAB, etc. However, these software are not suitable for implementing demand response. Based on
a large number of practical projects in the early years, it is found that the problems of the current energy management platform mainly focus on the following aspects:

1) The poor platform interaction interface makes it difficult for stakeholders to use the platform;
2) Many platforms only collect and store data, but lack data mining capabilities;
3) There are deviations between platform design and customer requirements, which can not fully meet customer needs.

At present, a large number of building control strategies adopt fixed logic and rules and only have limited energy-saving capacity [7,8]. Many studies have shown that replacing current RBC-based controllers with buildings can benefit from more advanced control strategies such as MPC [9]. In recent years, MPC has become one popular solution to solve building energy-saving problem. However, MPC is time-consuming to establish the first-principles building system dynamics model [10,11]. Moreover, it usually requires domain experts to adjust models to match building measurements manually [12]. An alternative to MPC is Data Predictive Control (DPC), which has the advantages of low cost, fast response, and strong real-time performance. As one kind of DPC-like algorithms, the regression tree (RT) method has the advantages of accurate prediction and interpretability. In [13], the authors developed and a multiple-output regression tree as a prediction model for peak power reduction. In [9], an approximate model for predicting building control performance through machine learning has been developed based on two multivariate regression algorithms, including deep-delay neural network (TDNN) and regression tree (RT). The advantage of the method mentioned above is that the controller developed can be easily used in the underlying microprocessor for real-time implementation.

In this article, we first propose a hierarchical framework for the energy Internet of Things (IoT) and help introduce the energy optimization system for the IoT that has been developed. Our system provides an excellent solution for building energy optimization problems. Secondly, under the above framework, we have developed a reasonable energy optimization control strategy based on DPC optimization technology and machine learning (ML-CatBoost) technology, which not only improves the comfort of residents but also reduces energy consumption. This work contributes as follows:

1) This paper explores a new architecture that combines the four-tier architecture of the Energy Internet of Things with optimal energy consumption control. The architecture can be used to manage data from IoT devices and build energy management systems by using a cloud-based user-friendly human-computer interaction interface. The platform aims to provide data analysis for different stakeholders (end-users, building operators, or managers) to improve work efficiency.
2) The CatBoost algorithm is used to increase the building model's interpretability, thereby reducing the complexity without loss of accuracy. At the same time, the optimization problem is considered carefully by incorporating the best index of human comfort into the optimization constraints.

This paper proposed that the combination of the Internet of Things and building energy management system, we use CatBoost method to optimize building energy consumption while maintaining a good comfortable environment for the human body. This paper is organized as follows: Section 2 discusses the Architecture of Building Energy Internet of Things System, and section 3 briefly describes the building model. Then, the control optimization layer is described in detail in section 4. Section 5 presents the simulation results and discussion. At last, section 6 states the conclusion of this paper.

2. The architecture of building energy internet of things system
This paper's overall architecture is based on the four-layer architecture of the Internet of things, as shown in Figure 1. The system contains four layers: perception control layer, network transmission layer, data intelligence layer, and human-computer interaction-information layer.

1) Perception Control Layer: In building automation systems, the purpose of this layer is to collect indoor and outdoor environmental parameters and power load measurement data. Under the
guidance of the optimal control strategy, the output signal is supplied to the frequency converter to adjust the frequency of power supply to the refrigerated water pump, and to adjust the amount of water and cooling delivered.

(2) Network Transmission Layer: By using the Internet of things communication technology such as NB-IoT, 5G, etc., to ensure the sensor data upload and control signal U transmission.

(3) Data intelligence layer: This layer consists of two sublayers: information aggregation and modeling, control, and decision. 1) Error elimination and fusion of data, storage. 2) Modeling buildings and building control-oriented building models. 3) Use CatBoost algorithm to complete the control decision to ensure the control requirements of the indoor environment. Ultimately, the building’s energy consumption is minimized.

(4) Human-Computer Interaction-Information Layer: Human-computer interaction is the embodiment of human in the loop, which includes the target setting of environmental parameters, the display of real-time monitoring data, the PMV evaluation of human comfort and the prediction of energy consumption.

Figure 1. The overall architecture of the energy optimization system

3. Building description and modeling
The data set used in this paper is a single office building floor, which collects information about the floor and occupancy measurements, load level consumption curves, and weather observations.

3.1. Building description
The dataset is collected from an office building floor located in the southwest city of Borås in Sweden [14]. Although the climate environment in Sweden is not very similar to that in China, the control strategy method is universal, and this paper validates the proposed algorithm through the Swedish office building dataset.

The building consists of 47 single offices, a conference room, and other joint areas such as the kitchen and bathroom. The office floor is 790 m², out of which 470 m² is single-occupancy office rooms. This room was surveyed in 2013 for specific house information: Thermal transmittance of the roof uses \( U_{\text{roof}} = 0.2 \text{W/m}^2\text{°C} \); thermal transmittance of the ground is designed to be \( U_{\text{ground}} = 0.4 \text{W/m}^2\text{°C} \). Thermal transmittance of the wall uses \( U_{\text{wall}} = 0.3 \text{W/m}^2\text{°C} \); Three-layer glass window uses \( U_{\text{window}} = 1\text{W/m}^2\text{°C} \).

The Modbus energy counter is used for energy metering in residential buildings. Collect information about these energy counters every 10 minutes. The information collected includes energy consumption of heat recovery ventilation devices, domestic hot water heat pumps (COP of 3.0), electrical appliances, lighting, and electric floor heaters. There are four main categories of data collected: Appliance module, Domestic hot water module, Energy storage equipment, and environmental information. Energy information is collected through the NB-IoT energy monitoring system and stored in a network MySQL database. Figure 2 shows consumer’s electricity consumption proportion statistics. According to statistics on the electricity consumption of consumers in five months, appliances accounted for the largest proportion, more than 70% per month.
3.2. Modeling office building
At the beginning of building the model, the Modelica building envelope model is implemented by using ideas library, but its complexity can not be directly used as a state-space model. A large number of collected data are nonlinear. For example, the heat generated by solar radiation: the equation of sunlight transmission and absorption through windows is highly nonlinear, so a nonlinear filtering algorithm is needed to deal with it. For these unprocessed data, to remove the burr, the processing algorithm is extended Kalman filter [15]. After linearization, the state space expression can be constructed. Please read the literature [16] for details. The sampling interval for humidity, temperature, and other sensors is 10 minutes. Therefore, the discrete space expression is constructed as follows:

$$x_{k+1} = Ax_k + Bu_k + Ed_k$$

(1.1)

$$y_k = Cx_k + Du_k$$

(1.2)

In the above equation, $x_k$, $u_k$ and $d_k$ respectively represent the state, input and interference variables at time $k$; $y$ is the output variable; the sampling frequency of the model is $T_s = 600$sec. The interference signal $d_k$ presents the heat absorbed and the direct and diffuse solar radiation transmitted by each window such as radiation temperature of ambient and sky temperature, ambient temperature, and ground temperature. Table 1 summarizes the dimensions of the building model variables used.

| Notation | Description                  | Values |
|----------|------------------------------|--------|
| $n_x$    | Number of states             | 269    |
| $n_y$    | Number of inputs             | 47     |
| $n_y$    | Number of outputs            | 47     |
| $n_r$    | Number of output references  | 47     |
| $n_d$    | Number of measured disturbances | 36     |

4. Controller design and energy optimization
This section designs the controller while minimizing house energy consumption. In section 4.1, to achieve a good energy-saving effect, an optimization function is designed to achieve the optimal energy consumption under the conditions that the human body is suitable for living. In section 4.2 and 4.3, the controller is designed according to this optimization function.

4.1. Control optimization design for comfort objective
It is necessary to ensure that the output temperature meets the requirements, to minimize the $s_k$ and room energy consumption. However, the ideal comfort and energy consumption are contradictory. To
solve this problem, the control problem is transformed into an optimization problem. Table 2 lists the symbols and meanings of variables frequently used in this section.

Table 2. Notation and meaning of the variables used in control

| Notation | Units | Description                                      | Control setup |
|----------|-------|--------------------------------------------------|---------------|
| $x$      | [K]   | Building temperatures                            | States        |
| $y$      | [K]   | Controlled temperature                           | Outputs       |
| $r$      | [K]   | Reference temperature                            | References    |
| $u$      | [W]   | Radiators heat flows                             | Inputs        |
| $d$      | [K, W]| Temperatures, heat flows, and radiation gains    | Disturbances  |
| $s$      | [W]   | Comfort band violations                          | Slack variables|

In summary, in order to achieve maximum human comfort and lowest energy consumption. Equation 2 builds the optimized function model.

\[
\min_{u_0, \ldots, u_N} \sum_{k=0}^{N-1} \left( Q_s \| \delta \|_2^2 + Q_u \| u_k \|_2^2 \right) \quad (2.1)
\]

\[
s I x_{k+1} = A x_k + B u_k + E d_k, k \in N_0^{N-1} \quad (2.2)
\]

\[
y_k = C x_k + D u_k, k \in N_0^{N-1} \quad (2.3)
\]

\[
x_0 = x(t) \quad (2.4)
\]

\[
d_0 = d(t) \quad (2.5)
\]

\[
\frac{59 + 3 \cdot 2 \sqrt{v} - 32 - 0.143 + 0.143RH}{0.81 + 0.143 + 0.143RH} \leq y_k \leq \frac{70 + 3.2 \sqrt{v} - 32 - 0.143 + 0.143RH}{0.81 + 0.99RH} \quad (2.6)
\]
Where, \( N^b = \{a, a+1, \ldots, b\} \) is a set of integers, and \( x_k, u_k, y_k \) and \( d_k \) represent state, input, output, and disturbance variables, respectively. The prediction range is \( N \), and \( k \) is the \( k \)-th moment in the prediction range. (2.2) and (2.3) are the time-invariant state-space expressions of the building. (2.6) is the introduction of the more popular Comfort Index of Human Body (CIHB) in 1999 [17], and divides it into 9 levels to evaluate comfort Table 3. The index also considers the effects of average temperature, average relative humidity, and wind speed on human comfort. Equation 3 is shown below,

\[
CIHB = 1.8y - 0.55(1.8y - 0.26)(1 - RH) - 3.2\sqrt{V} + 32
\]  

(3)

Where, \( y \) is the average temperature \(^\circ C\), \( RH \) is the average humidity (\%), and \( V \) is the wind speed (m/s). According to Table 3, comfort level 0 is the most liveable environment for the human body. The CIHB index should be the most reasonable at 59~70, which is converted into an inequality (2.6) about temperature, so as to construct a constraint. (2.4) Limit the maximum and minimum boundaries of the control signal \( u_k \). (2.4) and (2.5) set the initial parameters. (2.1) indicates that the objective function finally constructed by the optimization problem outputs a sequence \( u_0, H_1, \ldots, u_{N-1} \) under the influence of 6 constraints, so that the output control amount is minimized, and the objective function \( \| \| \) represents the square of the second norm, \( s_k \) is a slack variable, \( u_k \) is a control variable, and \( Q_s, Q_u \) represent the weight of human comfort and energy consumption, respectively. Set it to \( Q_s/Q_u = 10^7 \). The first term in the objective function is the square with the lowest degree of comfort violation, and the second term is the square with the lowest energy consumption.

| CIHB       | Level | Corresponding to human feeling                      |
|------------|-------|-----------------------------------------------------|
| > 85       | 4     | Very hot and uncomfortable;                         |
| 80~85      | 3     | Need to Protect against heatstroke                  |
| 76~79      | 2     | Too hot;Need to heatstroke prevention               |
| 71~79      | 1     | Hot;uncomfortable;Needs to be cooled                |
| 59~70      | 0     | The most comfortable & acceptable feeling           |
| 51~58      | -1    | Warm;Comfortable                                    |
| 39~50      | -2    | Very cold ; Keep warm & Cold protection             |
| 26~38      | -3    | Cold and Uncomfortable.                             |
| <25        | -4    | Extreme cold;Prevent frostbite                      |

4.2. Analysis of CatBoost prediction algorithm

Boosting [18], as a representative of the integrated algorithm, can reduce bias and variance in supervised learning. It is a machine learning algorithm that converts weak learners into strong learners. CatBoost algorithm can better handle Categorical features based on GBDT [19]. The main improvements of the algorithm are:

1. CatBoost improves Greedy TBS by adding a priori distribution term to reduce the effect of noise and low-frequency data on the data distribution as shown in Equation 4.

\[
\hat{x}_k = \sum_{j=1}^{m_k} \left[ x_{\sigma_j,k} = x_{\sigma_j,k} \right] Y_{\sigma_j} + a * P
\]

where, \( P \)-a prior term; \( a \)-weight coefficient. For features with a small number of categories, the addition of a priori is conducive to the reduction of noise data. In solving regression problems, the mean of the data set is usually taken as prior. CatBoost uses the oblivious tree as a base learner. This method of calculating node values avoids the problem of directly calculating overfitting.

2. Prediction offset is often a problem that plagues modeling it leads to the problem of inaccurate prediction of the model. CatBoost replaces the gradient estimation method in the traditional algorithm...
by using ordered boosting, thereby reducing the deviation of the gradient estimation and improving the generalization ability of the model. CatBoost uses the minimum error square as the loss function at the tree split nodes. Explain that the CatBoost model is shown in Figure 4.

\[ y_{M}(x) = \text{sgn}\left( \sum_{m} \alpha_m y_m(x) \right) \]

**Figure 4.** CatBoost algorithm structure

### 4.3. Control strategy

Based on the existing collected data, the temperature of the house is controlled based on the thermodynamic method. The variables used in this section are shown in Table 4. Mainly through controlling the heat output of the electric heating system to maintain the predetermined indoor reference temperature \( T_{ref} \). The indoor temperature \( T \) will deviate due to the following interference signals: (1) outdoor temperature \( T_{out} \); (2) solar radiation \( Q_{sun} \); (3) presence of occupants \( Q_{occ} \); (4) use of electrical appliances and hot water \( appT \).

The only factor which can drain energy from the house is factor (1). If the outdoor temperature is below the reference temperature, power will flow through the building envelope (walls, windows, etc.) to the external surroundings. This is called the transmission losses of heat and is captured by the insulation coefficient \( \Lambda_{trans} \). \( \Lambda_{trans} \) is defined by:

\[ \Lambda_{trans} = \sum U_j A_j \] (5)

where \( U_j \) is the thermal transmittance of each building component \( j \), and \( A_j \) is the total area of that component. In addition to the transmission losses, there will be power losses when the heated air is exchanged with fresh outside air, i.e. ventilation losses (labeled as \( \Lambda_{vent} \)). This parameter is given by:

\[ \Lambda_{vent} = V_b N_{vent} C_p \alpha_{rc} (1 - \alpha_v) \] (6)

where \( V_b \) is the total internal volume of the building, \( C_p \) is the heat capacity factor of air, \( N_{vent} \) is the exchange rate of the air, and \( \alpha_{rc} \) is the heat recycle factor of the ventilation system.

The control strategy algorithm is shown in Algorithm 1.
Algorithm 1. The control strategy algorithm

**Input:** \( T_{\text{ref}}, T_{\text{out}}(t), Q_{\text{sun}}(t), Q_{\text{occ}}(t), Q_{\text{app}}(t), \) Slack variable \( \beta \)

**Output:** Indoor temperature \( Y(t) \)

Initialize \( Y(t) = T_{\text{ref}} \)

For \( t = 1, 2, \ldots, n \):

1. Calculate heat loss \( Q_{\text{loss}}(t) = (T(t) - T_{\text{out}}(t))(\Lambda_{\text{trans}} + \Lambda_{\text{vent}})[W] \)
2. Calculate solar radiant heat \( Q_{\text{sun}}(t) = \alpha_{\text{red}}A_{\text{window}}P_{\text{sun}}(t) \)\ [W]
3. \[ Y(t+1) = Y(t) + \frac{Q_{\text{sun}}(t) + Q_{\text{occ}}(t) + Q_{\text{app}}(t) + Q_{\text{loss}}(t)}{\tau(\Lambda_{\text{trans}} + \Lambda_{\text{vent}})} \Delta t \]
4. \[ Q_{\text{heat}}(t+1) = \frac{(T(t) - Y(t+1))(Q_{\text{heat}}(t) - Q_{\text{heat}}(t+1))}{\tau(\Lambda_{\text{trans}} + \Lambda_{\text{vent}})} \]
5. If \( |Y(t+1) - Y_{\text{ref}}| \geq \beta \):
   - Heat change of electric heating system
     \[ \Delta Q_{\text{heat}} = \frac{1}{Y(t+1) - Y_{\text{ref}}} (Q_{\text{heat}}(t) - Q_{\text{heat}}(t+1)) \]
   - \( Q_{\text{heat}}(t+1) = Q_{\text{heat}}(t) + \Delta Q_{\text{heat}} \)

End

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Table 4. Control strategy related variables

| variable   | description                                      |
|------------|--------------------------------------------------|
| \( Q_{\text{sun}}(t) \) | heat gain from solar radiation at time t [W] |
| \( Q_{\text{occ}}(t) \) | heat gain from occupancy at time t [W]         |
| \( Q_{\text{app}}(t) \) | heat gain from appliance usage at time t [W]   |
| \( Q_{\text{loss}}(t) \) | total heating power loss due to the outdoor temperature at time t [W] |
| \( Q_{\text{heat}}(t) \) | the heating power from the electric heating system at time t [W] |
| \( P_{\text{sun}}(t) \) | the solar radiation against a vertical object for time slot t |
| \( A_{\text{window}} \) | the total window area per building side          |
| \( \alpha_{\text{red}} \) | the reduction factor.                           |
| \( Y(t) \) | the indoor temperature at time t [°C]           |
| \( \Lambda_{\text{trans}} \) | the transmission coefficient of the building envelope [W/°C] |
| \( \Lambda_{\text{vent}} \) | the heating loss coefficient due to ventilation in the building [W/°C] |

5. Simulation and verification

5.1. Simulation analysis of house electricity consumption and control

This paper uses CatBoost data prediction control method to control and optimize the power consumption of a building. Control the temperature of the room to achieve a suitable living environment. Figure 5 shows comparisons of room temperatures by predicting and controlling TDNN, LightGBM, and CatBoost energy consumption for ROOM1 rooms.
Figure 5. Controlling temperature in ROOM1 with multiple methods

The above illustration shows that the room temperature is set to $T_{\text{ref}}=21$ degrees Celsius. Expect a constant temperature environment. In addition to the system itself, considering the influence of external temperature on the room temperature inside the system, the outdoor temperature is set as interference, which improves the system’s anti-jamming ability.

Power consumption is also of concern to us. In order to achieve the effect of optimal control, CatBoost simulates and analyzes the data collected for 5 months. The proportion of training set, validation set and test set partitioning is 90%, 5%, 5%. After 1600 iterations, the test set achieves the best training result in 1599, bestTest_RMSE = 0.5669463264, R2 score: 83.8%, RMSE score: 35.29. To verify the degree of power savings, we analyzed TDNN, CatBoost, LightGBM by comparison. At the preset temperature, the power consumption comparison is shown in Figure 6.

Figure 6. Comparison of energy consumption predicted by multiple methods

Compared with these results above, CatBoost consumes less power, TDNN consumes the highest energy, and CatBoost consumes close and lower energy than LightGBM. The diagram shows that the CatBoost method is used to reduce the peaks and optimize power consumption. Table 5 highlights CatBoost's advantages more intuitively from the five dimensions of Total power consumption, R2 Score, RMSE Score, Training time (s), Test time (ms). However, the CatBoost column of Training time in the table does not perform well because the algorithm uses Ordered Mode during training, which solves the problem of prediction offset and makes the prediction more accurate than other algorithms.
Table 5. Multi-dimensional contrast analysis of multiple algorithms

| Algorithm   | Total power consumption (KWH) | R2 Score | RMSE Score | Training time(s) | Testing time(ms) |
|-------------|-------------------------------|----------|------------|------------------|------------------|
| LightGBM    | 19420.102794975               | 76.1%    | 101.22     | 1034             | 9.8              |
| TDNN        | 16524.917965227               | 67.2%    | 69.38      | 895              | 6.9              |
| CatBoost    | 13183.79304                   | 83.8%    | 35.29      | 980              | 3.4              |

5.2. Interpretability analysis

From an explanatory point of view, the influence of the characteristic variable on the power consumption is analyzed. Because the CatBoost algorithm is well interpretable, the sensitivity analysis provides useful information for the research system. This study fitted a CatBoost model to 100,000 random building samples to generate a better empirical distribution of signature importance, as shown in Figure 7. The results show that the influence on power consumption mainly depends on room humidity characteristics such as Pbase, Papp, and room temperature. Among them, Pbase is base load consumption in the other room area. Besides, indoor temperature and electrical use have a significant impact on room power consumption.

Figure 7 shows that the base, Papp, and room temperature of the room have a large impact on power consumption, but it is not clear how they will be affected. Therefore, the SHAP value can decompose the predicted value into the contribution of each feature. It then compares the impact of baseline predictions (the average of the target values of the training dataset) and characteristics on individual predictions [20]. Based on this, the analysis in Figure 8 shows that the feature of Pbase in a room has a great impact on the power consumption of a house. When people live in a room, Pbase has a positive correlation with the power consumption of the whole room, while the higher the Pbase, the higher the overall power consumption.

Figure 7. The importance of features

Figure 8. SHAP value of overall features
6. Conclusion

This paper makes novel research on the combination of data-driven control strategy and cloud platform of four-story building energy Internet of Things architecture. The platform can manage data from IoT devices and BMES, which uses a cloud-based user-friendly human-computer interaction interface, making the different stakeholders (users, building operators, or managers) easy to get started.

In the context of demand response, we apply CatBoost to reduce building power consumption. The performance of CatBoost is evaluated by simulation. The simulation results show that CatBoost can reduce power consumption while maintaining the thermal comfort required for each residential building room. TDNN, LightGBM, and CatBoost are used for comparison and analysis. The results show that buildings' peak power consumption using CatBoost can be reduced by 25.34% and 47.30% compared with LightGBM and TDNN under the same environmental comfort requirements. From the perspective of algorithm performance, four dimensions, Total power consumption, R2 Score, RMSE Score, Test time (ms), are used to highlight the advantages of CatBoost.

Future work will focus on the combination of IoT and DPC, which will apply to more complex buildings. Innovative and improved methods will be used to collect, model, and reduce real buildings' energy consumption. The IoT-DPC application is not limited to buildings and energy systems, but also includes industrial process control and large critical infrastructures such as water supply networks, local heating, and cooling. IoT-DPC has excellent value and prospects compared to the high cost of first-principles modeling.

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