Enerbrain System

Tailor made monitoring

Intuitive Dashboard
Advantages of the Enerbrain Solution

- Technology Enabler
- Simplicity
- plug & play
- Fast Installation
- Short Payback Period

Expected Results

Reducing energy consumption by at least 9%
Install everything in a couple of days to test scalability

Tested for the first time: Algorithm to act for demand side management for peak shaving and peak shifting
Installation of the Enerbrain System

Installation was done remotely and it took a total of 2 working days, where the local electrician was coordinated remotely by Enerbrain technical team.

Sigfox Antenna

*Typically not needed, in this case was used to boost the received signal.
POC on 4 rooms in EPRI Headquarter

Installation*

31 Aug  
8 Sep  
13 Sep  
20 Sep

Week OFF  
Week ON  
Week OFF

27 Sep  
4 Oct  
11 Oct  
15 Oct

Week ON  
Week OFF  
Week ON  
End of POC

Testing “Cost profile”
Testing “Demand Response Actions”
Focus on results on Unit 4

Enerbrain OFF:
- Internal T: 20.5 °C to 21.8 °C
- External T: 30.9 °C to 14.2 °C

Enerbrain ON:
- Internal T: 19.9 °C to 21.9 °C
- External T: 31.0 °C to 17.1 °C
Focus on results on Unit 4

With Enerbrain OFF:
- Total consumption in 4 days = 8.08 KWh

With Enerbrain ON:
- Total consumption in 4 days = 3.11 KWh

From this moment Enerbrain Algorithm is bypassed
Deep dive on the control logics, standard setpoint

**IMPORTANT NOTE!**

The Daikin Unit is not a modulating unit, but it can only be controlled as ON-OFF or with a set-point on the temperature, that will trigger an ON-OFF.

Therefore, this is a very different condition on a normal large size Air Handling Unit, where Enerbrain Algorithm can modulate each different component.

![Energy consumption graph](chart)

**Enerbrain ON**

Algorithm control signal calculated by our cloud system

resulting ON-OFF trigger from the algorithm

Threshold of 40% to turn On-Off the Daikin Unit, calculated by AI

When Algorithm signal goes over threshold, turn on the Daikin unit
Deep dive on the control logics, changing setpoints

Energy consumption

External & internal temperature

K Parameter Index of the Enerbrain Algorithm, variable according to external conditions and reinforcement learning training

Monday

Temperature

Monday

Tuesday

Wednesday

21.66 °C
71 °F

21.11 °C
70 °F

20.55 °C
69 °F

20 °C
68 °F
Reinforcement learning

Deep reinforcement learning to optimise indoor temperature control and heating energy consumption in buildings

Silvio Brandi a, Marco Savino Piscitelli a, Marco Martellacci b, Alfonso Capozzoli a,∗

aDepartment of Energy “Galileo Ferraris”, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy
bEnervitrin s.r.l., Strada Villa d’Aglì 26, 10132 Torino, Italy

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ABSTRACT

In this work, Deep Reinforcement Learning (DRL) is implemented to control the supply water temperature setpoint to terminal units of a heating system. The experiment was carried out for an office building in an integrated simulation environment. A sensitivity analysis is carried out on relevant hyperparameters to identify their optimal configuration. Moreover, two sets of input variables were considered for assessing their impact on the adaptability capabilities of the DRL controller. In this context a static and dynamic deployment of the DRL controller is performed. The trained control agent is tested for four different scenarios to determine its adaptability to the variation of forcing variables such as weather conditions, occupant presence patterns and different indoor temperature setpoint requirements. The performance of the agent is evaluated against a reference controller that implements a combination of rule-based and climatic-based logics. As a result, when the set of variables are adequately selected a heating energy saving ranging between 5 and 12% is obtained with an enhanced indoor temperature control with both static and dynamic deployment. Eventually the study proves that if the set of input variables are not carefully selected a dynamic deployment is strictly required for obtaining good performance.

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Reinforcement learning architecture

Fig. 1. Double Deep Q-Learning structure.
A typical control of a VFD in an AHU

In an environment different from the Daikin Unit, for example controlling a VFD, it is possible to use the Algorithm to modulate the control in a more refined way, resulting in a modulating command and not in a simple ON OFF.

In a similar environment, like the AHU in the image on the left, **Enerbrain can control dynamically:**

- VFD speed of the ventilation
- Opening of heating coil valves
- Opening of cooling coil valves
- Recirculation dampers

In this way it would be possible to improve enormously the existing PID control of the machines, typically programmed by the vendors and BMS integrators.
A typical control of a VFD in an AHU

In an environment different from the Daikin Unit, for example controlling a VFD, it is possible to use the Algorithm to modulate the control in a more refined way, resulting in a modulating command and not in a simple ON OFF.

Achieved results with:
- Standard BMS with VFD control and CO₂ sensors
- AI optimised Enerbrain system

Extra Consumption
- When comfort takes precedence (only when it is relevant for the final users of the room), Enerbrain may consume more energy in limited moments
- Cloud Algorithm permits predictive control related to weather forecast, thermal dynamic of building, occupation profile history.

Standard VFD Control
In standard BMS, VFDs are controlled with correlation to CO₂ with normal PID relations

Advanced AI Algorithm
Thanks to Enerbrain AI, ventilation is controlled thanks to many additional advanced cloud logics

Extra Consumption
Thanks to the integrated weather forecast Enerbrain improves comfort
Testing “Cost Profile”

To be done on Room 1, on the 29th September 2021

WHY?
To test capabilities to reduce energy consumption when more expensive, using the building as part of a Virtual Power Plant ecosystem.

EXPECTED RESULTS
Reduce energy in peak hours, pre-cool the area and reduce overall cost use.

COST PROFILE

By using a cost profile, we can let the algorithm use less energy when energy is more expensive and vice versa, use more energy when it is cheaper (pre-cooling the building area).

This allows the client to save energy.

For the POC we can use a generic curve to simulate the effect.

NOTE: This has never tested by Enerbrain yet, and it is a great opportunity to test it together on Room 1

HOURLY COST

<table>
<thead>
<tr>
<th>Time</th>
<th>Cost ($/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-5</td>
<td>$60</td>
</tr>
<tr>
<td>5-9</td>
<td>$100</td>
</tr>
<tr>
<td>9-11</td>
<td>$80</td>
</tr>
<tr>
<td>11-17</td>
<td>$65</td>
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<tr>
<td>17-18</td>
<td>$90</td>
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<td>$150</td>
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<tr>
<td>21-22</td>
<td>$120</td>
</tr>
<tr>
<td>22-24</td>
<td>$70</td>
</tr>
</tbody>
</table>
Results of Cost Profile

First day: Activated

Second day: Deactivated

Comfort hourly

Hourly Consumption

**HOURLY COST**

- 0-5 = $ 60/MWh
- 5-9 = $ 100/MWh
- 9-11 = $ 80/MWh
- 11-17 = $ 65/MWh
- 17 = $ 90 /MWh
- 18 = $ 120 /MWh
- 19 = $ 200 /MWh
- 20 = $ 150 /MWh
- 21 = $ 120 /MWh
- 22-24 = $ 70 /MWh

**Total Cost of Energy hourly**

**TOTAL COST**

- **First day:** $0.1603
- **Second day:** $0.3097

Max T = 23°C (73,4 °F)

Max T = 22°C (71,6 °F)
Testing “Demand Response”

To be done on Room 1, on the 30th September 2021

DEMAND RESPONSE

A local aggregator or utility could send to the Enerbrain system a signal to ask to consume more energy or to consume less energy in any give time for a short period (30 minutes for example).

We can fake to receive a signal from the utility for 2 times during the day of the 30th September and simulate what will happen.

This operation has been already tested by Enerbrain in Estonia in September 2021 with great results!

WHY?
To test capabilities to reduce energy consumption when it is needed by the local utility / energy trader.

EXPECTED RESULTS
Reduce energy after receiving a signal from the grid with a reaction time that is less than 15 minutes.

Example on the left shows the consumption of one AHU with the effect of the signal received by Enerbrain from the Estonian Aggregator, generating a temporary reduction of energy consumption by 50%, without strong disruptions on comfort levels.
Results of the Demand Response

The test was an important part of the POC to demonstrate the ability of the system to predict and help the electric grid to balance the supply and demand during peak hours of using energy.
Next steps in USA

Enerbrain Solution for a worldwide energy problem

Research Project on the technical rooms of the EPRI office building in Charlotte, NC

Larger Applications on
- Commercial Buildings
- Shopping Malls
- Public Buildings
- Hospitals
- Theatres
Backup slides
Top customers in 13 countries

- Hospitals
- Offices & Schools
- Airports
- Museums
- Municipalities
- Shopping malls
- Supermarkets
- Retails
- Utilities
- Industries

And more…
IREN + Enerbrain for the city of Torino

Rollout on 89 public buildings in 4 weeks
- 49 schools
- 22 offices
- 18 recreational

24h/24 / remote control with AI and IoT
- 6,700 MWh / yearly energy saved
- 1,400 t / CO₂ not emitted per year
- 100,000 ca / trees equivalent
- 7,000 ca / car equivalent

Video Explainer