Deep Reinforcement Learning-Based Optimal Building Energy Management Strategies with Photovoltaic Systems

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Abstract
Because of the spread of solar photovoltaic (PV) systems, a significant amount of research has been conducted on the development of efficient energy management methods. Significantly, the energy operation strategies are essential for residential buildings due to the difference between peak demand and solar power generation time. Therefore, we proposed a novel deep reinforcement learning-based model considering both, direct use of the generated energy to the buildings and selling to utilities to minimize the building's total energy operating cost in a residential building with PV-energy storage system (ESS) installed. To verify the performance of the proposed model, case studies such as rule-based, selling-only case, and consumption-only case were conducted, showing that the proposed model minimized energy operating costs.

Key Innovations
• Deep Reinforcement Learning-Based Model
• Energy Efficient Strategy for PV/ESS
• Energy Management System

Practical Implications
This study supports a deep reinforcement learning-based optimal PV-ESS management system for residential facilities considering economic efficiency based on several energy management strategies. Furthermore, this study can provide proper guidelines for deriving the optimal energy management methods of residential buildings equipped with PV-ESS systems, according to various operation strategies, energy policies, and building types.

Introduction
Global warming and energy security problems are caused primarily by the environmental destruction from fossil fuels' reckless use. In particular, the global oil crisis that occurred in the 1970s, and fossil fuels are no longer considered uninterrupted energy sources available at affordable prices.

Renewable energy systems have attracted significant attention as an alternative to reducing the dependence on fossil fuel and greenhouse gas emissions. The renewable energy system sector has been growing substantially over the past decade, in particular the photovoltaics (PV), making PV one of the fastest-growing industries (IEA, 2017). Moreover, PV systems are being promoted worldwide owing to the increased efficiency of the systems and the reduction in the cost of the materials because of the technological advances (Gul, Kotak, and Muneer, 2016).

However, climate factors such as atmospheric humidity and fine dust greatly influence the power generation, limiting the immediate use of the generated power (Kim and Suh, 2020). Furthermore, the peak demand times are in the evening. In contrast, because the PV systems are generating power during the day, solar power generation is not been used efficiently, especially in residential buildings.

To overcome these limitations many countries, including South Korea, are implementing several energy policies to support the PV-energy storage system (ESS) linked system.

ESS refers to a device that converts electrical energy from power systems into a form of energy that can be stored and converted back into electrical energy when needed. Thus, it can improve power safety by securing reserve power from the generation of unstable renewable energy systems. ESS is also used to arbitrarily adjust the sales and the time of use by charging and discharging to save operating costs (Teleke et al., 2010). Hong (2014) has proposed an optimal renewable energy system for educational facilities, considering the economic and environmental effects. Additionally, Nascimento and Rüther (2020) revealed that the efficiency of ESS is higher than past through the PV-ESS linked system economic analysis; but, the economic efficiency is still low because of the high initial investment cost.

However, the initial cost of ESS is expected to decline owing to the expansion of the electric vehicle market (Beetz, 2015). Therefore, it is considered a more critical matter the efficient use of the renewable energy system’s power. Previous studies have been reported on efficient energy management strategies of the systems.

Wang et al. (2017) optimized economic and occupant comfort by defining the power generated in building-integrated PV as a linear objective function. Hossain et al. (2019) performed particle swarm optimization (PSO) for optimal battery control, reducing operating costs by 12% compared to the original cost function through a case study.
Dehimi, Keshavarz Zahed, and Iravani (2016) proposed a scheduling algorithm of ESS for efficient operation management of microgrids to increase reliability and quality of energy supply. The performance was also verified by comparing the performance with algorithms previously used such as multi-objective PSO and normal constraint algorithms. Hemmati, Saboori, and Siano (2017) determined the optimal location and size of wind power systems, PV, and ESS via long-term planning and proposed a plan cost reduction method through optimal scheduling for 24 hours short-term planning.

Furthermore, studies using reinforcement learning by the advent of machine learning can consider the uncertainty of the amount of renewable energy generation and utility price showing good performance. The study on the optimal operation of buildings using reinforcement learning can be divided into two goals.

The first is to minimize the building's operating cost through electricity trading. For example, Lee and Choi (2019) minimized all appliances' total consumption and satisfied thermal comfort through energy management algorithms for smart homes equipped with PV, ESS, and intelligent home appliances. Kim and Lim (2018) minimized building operating costs using energy management algorithms in smart energy buildings by exchanging energy between distributed energy resources and external grids. Guan et al. (2015) proposed a storage control algorithm based on reinforcement learning that minimizes electricity bills by reducing the grid's power demand profile in residential-level PV-ESS systems. Hau et al. (2020) proposed automation of energy trading that maximizes monetary benefits when the maximum microgrid price maintains the contingency reserves of ESS in a PV-ESS linked system. Shin, Choi, and Kim (2020) reduced operating costs by 30% through an energy management scheme of a distributed electric vehicle charging station equipped with a PV system and an ESS.

The second is the indoor temperature range control method, in which the temperature is controlled within a specific range to maintain occupant comfort or to reduce energy consumption. Moriyama et al. (2018) proposed a plan to improve the existing cooling system control algorithm to reduce the electricity consumption of the data center. Nagy et al. (2018) proposed a space heating control algorithm that reduces energy consumption and maintains occupant comfort, showing 5%–10% better performance than rule-based control.

Although many previous studies have dealt with the building's optimal operation, the operating costs have been reduced by considering only each aspect, such as utility sales, indoor temperature control, and peak demand load reduction. Because both the electricity and the utility prices tend to be high in the peak demand load of residential buildings, it is necessary to reduce the energy operation cost by carefully considering both. Therefore, this paper aims to minimize the building's energy operation cost by utilizing the PV-ESS linked system in residential buildings. We propose an ESS optimal management operation model based on deep reinforcement learning (DRL) using PV power generation by comparing electricity and utility prices in the peak demand load section. Moreover, simulation-based case studies are conducted to verify the performance of the proposed model.

**System Description**

PV power generation is considered for the purpose of reducing the total operating cost. Figure 1 describes the energy management and operation scenario of the building studied in this paper. The building is connected by a grid that can be sold, including PV systems and ESS systems, as shown in Figure 1.

**Figure 1: Composition of a building with PV, ESS, and grid.**

The components of Figure 1 are described as follows.

PV systems directly convert solar energy into electricity through solar panels to reduce the peak demand load on the building or reduce energy operating costs by selling it to the grid.

ESS is an energy storage system able to charge and discharge energy as needed. In this study, discharge is performed when the utility and electricity prices are high, and the energy conversion efficiency is assumed to be 100%.

The grid represents a utility that supplies energy, and the buildings can buy and sell electricity energy by trading energy in real-time at a determined price.

Energy prices are composed of various price policies. The price policies include various form that gives incentives to EV users (Qian et al., 2011) and an approach that gives weight to a specific period (Sivaraman and Horne, 2011). However, most price policies show low prices at night and high prices during the day.

Therefore, the purpose of this study is to minimize operating costs through charging/discharging energy management scheduling of ESS that learned the price characteristics. It is also assumed that the environment satisfies the Markov decision process (MDP), and the agent state transition depends only on the present state.

In the next section, we use MDP to formulate the state space, action space, and reward function.

**State space**

The implemented Q-learning algorithm runs 24 hours per hour, and the state space is expressed as follows:

\[
S_t = [E^p_{t}, E^{Bldg}_{t}, S_P, C_P, SOC_t, S_{t}^{avg}, E_{t}^{peak}] \tag{1}
\]

where \(E^p_{t}\) is the PV power generation, \(E^{Bldg}_{t}\) is the total building electricity demand load, \(S_P\) is the energy utility price, \(C_P\) is the electricity price of the building, \(SOC_t\) is the state of charge (SOC) of the ESS, \(S_{t}^{avg}\) is the average electricity energy utility price, \(E_{t}^{peak}\) is the peak demand load, at time \(t\).
**Action space**

The operation strategy of ESS affects the overall performance, and the action space consists of 11 steps of charging and discharging. A negative number indicates discharge, and a positive number indicates charging.

\[ A = \{-1, -0.8, -0.6, -0.4, -0.2, 0, 0.2, 0.4, 0.6, 0.8, 1\} \]  

Discharging considers consumption and selling and compares the prices of \( CP_t \) and \( SP_t \) to choose the large value between the direct use of generated energy to the buildings or selling to utilities.

**Reward**

The purpose of this paper is to minimize the total operating cost of the building. In other words, to maximize the monetary benefit of energy stored in ESS (Equation 3).

\[ \text{max monetary benefit} = \sum (SP_t + CP_t)E_{PV}^t \]  

The reward function for the ESS agent is determined as follows.

\[ R = s c_a r_{trading} + sc_b r_{SOC} + sc_c r_{PV} \]  

where \( sc_{a,b,c} \) is the scaling factor, \( r_{trading} \) is formulated as the sum of trading costs, and it reduces the energy operating costs by comparing \( SP_t \) and \( CP_t \) and selling them at a larger value. Therefore, the reward function is defined as follows.

\[ r_{trading} = \begin{cases} CP_t \times \Delta SOC \times \text{capacity}, & \text{if } SP_t^{avg} < CP_t \\ SP_t \times \Delta SOC \times \text{capacity}, & \text{if } SP_t^{avg} > CP_t \end{cases} \]  

where \( r_{SOC} \) represents the physical constraint of the ESS and it is a constraint that limits the scope of the SOC. If it is less than 0 or more than 1, a penalty is given and can be defined as Equation 6.

\[ r_{SOC} = \begin{cases} \text{reward, if } 0 < SOC < 1 \\ \text{penalty, if } 0 > SOC, 1 < SOC \end{cases} \]  

where \( r_{PV} \) is also a physical constraint of ESS and prevents overcharging the PV power generation. Therefore, if there is an overcharging in the load at the time \( t \) and the remaining SOC, a penalty is given as in Equation 7.

\[ r_{PV} = \begin{cases} \text{reward, if } E_{PV}^t > \Delta SOC \times \text{capacity} + E_{t^\text{bidg}} \\ \text{penalty, if } E_{PV}^t < \Delta SOC \times \text{capacity} + E_{t^\text{bidg}} \end{cases} \]

**Deep reinforcement learning (DRL)**

Reinforcement learning, which is learned through trial and error, is a way to learn the optimal policy according to the state by trying various actions. Q-learning is the representative method of model-free reinforcement learning. In the current state, the agent learns the environment by learning the Q function as an optimal value by receiving a reward for action choice. The goal of reinforcement learning is to learn optimal action to maximize rewards. For this purpose, reinforcement learning uses the concept of an action-value function. The action-value function is given a time \( t \) and a policy \( \pi \), and when a selected action \( a \) is performed in a certain state \( s \), the value of the sum of future rewards applying the discount rate \( \gamma \) is obtained. This is expressed by the equation 8.

\[ Q_\pi (s, a) = E [R_{t+1} + \gamma R_{t+2} ... | S_t = s, A_t = a, \pi] \]  

When the agent learns the environment through MDP, it stores and updates the value of all states' action-value function. However, if the Q-learning based on reinforcement learning is used to solve complex real-world problems, it is impossible to manage this problem due to the increase in all states' size and actions. Therefore, Deep Q-Network (DQN), which integrates RL based on the DRL algorithm with deep neural networks, has been developed to resolve these problems (Mnih et al., 2015).

**Deep Q-Network**

DQN is a DRL algorithm proposed by Google DeepMind. It approximates the Q function of the existing Q-learning algorithm by learning through a Deep Neural Network (Mnih et al., 2015). It takes a state as input and calculates the reward that can be received to consider all possible actions according to the state, and learn the Q value that can receive the highest reward. The process of DQN is shown in Figure 2.

The agent performs the selected action in its current state. It calculates the reward for the action and stores <state, action, reward, next state> in replay memory. The Q network is trained by randomly extracting <state, action, reward, next state> from the replay memory. By learning the above process iteratively, the Q network can select the action that will receive the highest reward.

![Figure 2: DQN process.](https://doi.org/10.26868/25222708.2021.30879)

**Case Study**

The case study verified the proposed model's suitability in a residential building on campus in South Korea. The rest of the spaces except for the fire escape stairs of the building and non-air conditioning zones were modeled using a dynamic energy simulation program, Design Builder & Energyplus, by grouping zones with similar purposes into one for simulation analysis.

In the air conditioning system, cooling is operated by an electric heat pump, and the setpoint temperature was 26°C. The heating has a boiler operating, and the setpoint temperature was 20°C. The operating scheduling was performed 12 hours per day for both the heating and cooling systems.
Table 1 shows the lighting input parameters and thermal properties related to the physical properties.

### Table 1: Thermal properties

<table>
<thead>
<tr>
<th>Lighting</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Target illuminance [lux]</td>
<td>125</td>
</tr>
<tr>
<td>Normalized power density [W/−100 lux]</td>
<td>2.5</td>
</tr>
<tr>
<td>Luminaire type</td>
<td>Suspended</td>
</tr>
<tr>
<td>Radiant fraction</td>
<td>0.42</td>
</tr>
<tr>
<td>Visible fraction</td>
<td>0.18</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>U-value</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>External wall</td>
<td>0.35 W/m²·K</td>
</tr>
<tr>
<td>Internal wall</td>
<td>1.639 W/m²·K</td>
</tr>
<tr>
<td>External floor</td>
<td>0.25 W/m²·K</td>
</tr>
<tr>
<td>Ground floor</td>
<td>0.25 W/m²·K</td>
</tr>
<tr>
<td>Roof</td>
<td>0.25 W/m²·K</td>
</tr>
<tr>
<td>Lighting Power Density</td>
<td>6.25 W/m²</td>
</tr>
</tbody>
</table>

The weather data for the simulation analysis was obtained from 2010 Daegu from the International Weather for Energy Calculations.

Weather data includes dry bulb temperature, dew point temperature, relative humidity, wind speed, air volume, diffuse radiation, and direct radiation data.

First, the total energy consumption was calculated by simulation analysis to determine the PV system’s installation capacity. The mandatory installation of renewable energy systems in Korea is more than 27% of the expected annual energy consumption. By the simulation analysis program, the annual energy consumption was 3,623,884 kWh, and 40 kW was installed for the PV system, which satisfies 28% of the yearly energy consumption. The simulation results of one year were extracted per hour using simulation.

Figure 3 shows the total annual energy consumption per month combined with cooling, heating, and lighting loads. The load is the highest consumption in January, because of the gas consumption in the winter. The demand load and PV power generation of an arbitrary day in January, when the demand load is the highest, are also shown in Figure 4. The occupancy in the daytime is low and the demand load in the morning and evening is high, because of the residential building characteristics.

Moreover, the efficiency is expected to be low when the energy is consumed immediately without ESS because the PV generation time and the load time do not match.

Electricity prices and utility sales prices are essential when trading electricity. This case study used the electricity price of high-voltage A and optional type II products for educational services, and electricity prices were divided by season and time. $C_{Pt}$ is composed, as shown in Table 2.

### Table 2: Electricity price

<table>
<thead>
<tr>
<th>Price of electricity ($/kWh)</th>
<th>Per</th>
<th>Summer</th>
<th>Spring/Fall</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Off-peak load</td>
<td>0.041</td>
<td>0.041</td>
<td>0.045</td>
<td></td>
</tr>
<tr>
<td>Mid load</td>
<td>0.082</td>
<td>0.054</td>
<td>0.081</td>
<td></td>
</tr>
<tr>
<td>Peak load</td>
<td>0.14</td>
<td>0.073</td>
<td>0.12</td>
<td></td>
</tr>
</tbody>
</table>

Table 3 shows the load timetable for each season. The demand load should be reduced during the morning and evening hours when the electricity prices are the highest.

### Table 3: Seasonal load timetable

<table>
<thead>
<tr>
<th>Seasonal load timetable</th>
<th>Per</th>
<th>Summer</th>
<th>Spring/Fall</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Off-peak load</td>
<td>23:00 – 09:00</td>
<td>23:00 – 09:00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mid load</td>
<td>09:00 – 10:00</td>
<td>09:00 – 10:00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>12:00 – 13:00</td>
<td>12:00 – 17:00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>17:00 – 23:00</td>
<td>20:00 – 22:00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peak load</td>
<td>10:00 – 12:00</td>
<td>10:00 – 12:00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>13:00 – 17:00</td>
<td>17:00 – 20:00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>22:00 – 23:00</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The $S_{Pt}$ selling to a utility used South Korea’s 2019 system marginal price (SMP).

The electricity price and the price of SMP are compared in Figure 5. Although the average price has a high SMP, it can be seen that the electricity price is only high in a specific section. Therefore, it is necessary to consider which price is higher when selling electricity.
The training parameters of the DQN model for reinforcement learning are listed in Table 4.

Table 4: Parameter settings in DQN algorithms

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\epsilon$-greedy parameter</td>
<td>0.01</td>
</tr>
<tr>
<td>Batch size</td>
<td>20</td>
</tr>
<tr>
<td>Time steps</td>
<td>24</td>
</tr>
<tr>
<td>Discount factor</td>
<td>0.95</td>
</tr>
<tr>
<td>Episodes</td>
<td>2000</td>
</tr>
<tr>
<td>ESS capacity</td>
<td>500 kW</td>
</tr>
<tr>
<td>Initial SOC</td>
<td>0</td>
</tr>
</tbody>
</table>

In the policy of the DQN model, the $\epsilon$-greedy parameter is set to 0.01, and random behavior is performed with 1% probability. In other cases, the Q function performs with Max being the maximum.

The agent experience, $e_t = (s_t, a_t, r_t, s_{t+1})$, according to the policy is stored in Dataset $D_t = \{e_1, ..., e_T\}$ in units of 24-time steps, and learning is performed in 20 batch sizes through random sampling from this Dataset.

The DQN architecture is structured as follows. The input layer comprises seven nodes, which is the number of states, and two hidden layers are required with 50 and 150 nodes, respectively. The output layer consists of 11 nodes, which is the number of actions.

Also, the total ESS capacity was set to 500 kWh, and the initial SOC of the ESS was set to 0. The power dissipation generated during charging/discharging was not considered.

To verify the performance of the proposed model, we compare the proposed model, which considers both selling and consumption, with three different cases, including the rule-based control approach, Only considering selling, Only considering consumption in buildings. The three cases are defined in the next section.

Rule-based control approach

In the rule-based case, charging discharging times are determined. This system cannot utilize the system's performance and needs to be improved. It operates as follows in the case study.

Regardless of the electricity price or utility price, the ESS was discharged from 24:00 to 06:00 when the demand load was the highest and used to reduce the demand load of the building. Equation 9 shows the set charging/discharging time.

$$A = \begin{cases} \text{Charging, if 06:00–24:00} \\ \text{Discharging, if 24:00–06:00} \end{cases}$$ (9)

The rule-based approach discharges generation power during off-peak load times when electricity prices are the lowest. Therefore, annual revenue from the PV-ESS linked system is estimated to be $3,725.

Only considering selling

This case was designed only to consider selling. In this case, the SMP charges at a lower price and sells at a higher price. The proposed model and the state and action spaces are the same, and the reward is as shown in Equation 10.

$$R = S\Delta SOC \times \text{capacity}$$ (10)

In this case, the monetary benefit for the case study is calculated as $17,919. The efficiency was lower than that of the model considering both, consumption in buildings and selling to utilities, because the peak demand load time electricity price was not considered.

Only considering consumption in buildings

This case uses the energy stored in the ESS to reduce the demand load in the building. We compared only the operating cost aspect with the proposed model. State and action are the same as the proposed model, and the reward is calculated using Equation 11.

$$R = C_p \times \Delta SOC \times \text{capacity}$$ (11)

The monetary benefit from the direct use of generated energy to the buildings is estimated at $9,078. This is because the electricity bill was formed at a lower price than the average price of SMP, and this case can be used in the environmental aspect of reducing total energy demand.

Results

The hourly data for 2016 was used as training data, and the hourly data for 2017 was utilized as test data for the performance evaluation of the proposed model. As a result of the 2,000 episodes, the reward with a discount rate of 0.95 converges was observed, as shown in Figure 6. During the entire episode, the cumulative reward for the charge/discharge operation gradually increased. Moreover, it finally converged at 30,000 and learning was successfully implemented.

![Figure 6: Total reward results by episode.](image-url)
The proposed model which considers both selling and consumption was compared with three cases, including the rule-based approach, only considering selling, and only considering consumption in buildings. Figure 7 shows the SOC and action results for 10 days.

First, (a) is a proposed model to charge and discharge by grasping the price of SMP and electricity price based on the DRL model. (b) is a DRL-based output considering only selling to the utility, and the case predicts the price of SMP and perform action. (c) is also DRL-based output considering only consumption in the building and discharges the maximum when the building peak demand load. (d) is a rule-based approach that charges during the daytime when there is insolation and discharges during the high demand load period. Table 5 compares the monetary benefits of each one.

**Table 5: Monetary benefit from experimental results**

<table>
<thead>
<tr>
<th>Stragety</th>
<th>Monetary benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed model considering both selling and consumption</td>
<td>$21,209</td>
</tr>
<tr>
<td>Only considering the selling</td>
<td>$17,919</td>
</tr>
<tr>
<td>Only considering consumption in buildings</td>
<td>$9,078</td>
</tr>
<tr>
<td>Rule-based approach</td>
<td>$3,725</td>
</tr>
</tbody>
</table>

In the result of the derived experiment (a) is sold to the utility with $S_p$ in most cases, but it is confirmed that the generated power is discharged at higher values by comparing $C_p$ and $S$ in the time section close to the peak demand load. As a result, higher monetary benefits were achieved compared to other strategies, which seems to be the optimal operating strategy. (b) conducts charge during when the utility price is low and discharge primarily when the utility price is high. (c) discharge at the peak demand

Figure 7: Operating schedule according to SMP and electricity price for 10 days. (a) A proposed model based on DRL considering both selling and consumption in buildings; (b) DRL-based test case considering only selling; (c) DRL-based test case considering only consumption in buildings; (d) Rule-based control approach.
load, but it can discharge when there is a remaining capacity of the ESS and a building demand load, which has a constraint on consumption when the electricity price is peak load. Finally, (d) is a determined charging/discharging time approach, which used power generation at the off-peak load electricity price, showing the lowest monetary benefit among the four alternatives. As a result, it was possible to reduce energy operating costs by efficiently adjusting the charging/discharging scheduling of the ESS. Rule-based approach came out with the highest energy operating cost, and the proposed model had the best results from the aspect of monetary benefits.

**Conclusion**

This study proposes an optimal operational management model of PV-ESS system based on DRL to minimize the building's total operating costs in residential buildings where a difference between peak demand and solar power generation time is observed. The proposed model minimizes the operating cost of the building through the charging and discharging scheduling of ESS. In the proposed DQN-based model, the ESS agent learns actions until it maximizes the total cumulative reward while preventing overcharging and undercharging.

A simulation-based case study was conducted to verify the performance of the proposed model. The experimental results show that the proposed model reduced the energy operation cost by $17,484 compared to the rule-based approach, confirming the monetary benefits. Thus, the proposed model can provide a guideline for optimal energy management methods of residential buildings equipped with PV-ESS systems.

Further research is needed to improve the PV and ESS optimally linked energy management methods, considering several energy policies in the development of energy management techniques of the general-purpose PV-ESS system.

**Acknowledgement**

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