Operation planning for heat pump in a residential building

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Abstract
In an effort to tackle environmental problems, sustainable policies that have a low environmental impact on the local community are being implemented in many countries, including Japan. One approach is the smart community, which is a policy to evaluate the cost of the entire community, considering each interaction while dividing society into seven fields: power, gas, water, railway, industry, business, and home models. In this study, we evaluate and optimize the home model. We develop an optimization model for the operation plan of energy storage equipment in a residential building as part of a smart community. The purpose of this model is to improve electricity costs from the demand profile and provide stable power supply from the supply profile. Therefore, this model controls the operation of energy storage equipment and also performs load leveling. It is intended to reduce the total power consumption during peak hours by operating the energy storage equipment at night, when the usage of other electrical appliances is low. A stochastic programming model is formulated using scenarios that represent the uncertainty of power and heat demand. This formulation assumes continuous operation in a residential building. We demonstrate the usefulness of the stochastic programming model by comparing it with the deterministic model. As an economic assessment, we compare the daily beneficial expense of the existing model with our new model of daily operations by following the improvement factors. Our model not only lowers peak total power consumption but also achieves load leveling. The total operating time of energy storage equipment is also reduced.

Keywords: Energy storage, Smart community, Load-leveling, Unit commitment, Stochastic programming

1. Introduction

In recent years, the reduction of CO\(_2\) emissions has become a priority owing to environmental issues and other factors. Sustainable policies that have a low environmental impact on the local community are being implemented in many countries, including Japan. The sustainability aspect includes the use of renewable energy, while the low environmental load aspect includes the reduction of the total operating time of equipment. Load leveling of demand is necessary to address uncertain demand. The concept of smart community emerged in response to this situation. The smart community is a policy to evaluate the cost of the entire community, considering each interaction while dividing society into seven fields: power, gas, water, railway, industry, business, and home models.

This study develops an optimization model for the operation plan of energy storage equipment in a residential building that is part of a smart community. On the demand side, we formulate an operational planning model for a heat pump water heater using the stochastic programming method to minimize the electricity cost. This model performs load leveling to determine the operational pattern of the heat pump water heater so that the sum of the fixed cost incurred by the peak demand and the operational cost is minimized. By leveling the load, this model allows the supply side to perform stable supply.
2. Previous studies

Demand-side management (Momoh (2012)) is a method of reducing overall supply costs by controlling customer demand. In this study, we consider controlling the operation of a heat pump. This shows that the same effect can be obtained without directly performing demand side management.

Tokoro and Fukuyama (2017) outlined the basic model that can quantitatively evaluate the energy cost of the smart community and introduced the research case regarding the optimization of the model. This study evaluates the energy cost of the entire smart community, considering the interactions among the seven fields. It calculates only the energy cost of the entire community, based on certain decision variables regarding the operation plan of the energy equipment input by the decision maker of the basic model; thus, there is no optimization function.

Tokoro et al. (2014) introduced a tool for identifying the optimal equipment configuration and operation pattern of the hybrid hot water supply system, in which the supply cost of hot water is minimized for a given level of hot water demand. This system consists of three elements: a heat pump water heater, a combustion water heater, and a tank. EcoCute is used as a heat pump water heater; it is a water heater that recovers the heat in the air by using electricity and generates hot water. The advantage of this water heater is its high efficiency in that it can generate hot water with thermal energy more than the input energy. However, it also has a disadvantage in that a large amount of hot water cannot be generated instantly. In order to satisfy the demand for hot water, it is necessary to store hot water in the supply tank in advance and operate the EcoCute and the combustion-type hot water heater systematically.

Vardakas et al. (2015) surveyed demand response programs comprehensively and classified the optimization models into five categories. They mainly deal with deterministic models. These classifications are as follows: a) minimization of electricity cost, b) maximization of social welfare, c) minimization of aggregated power consumption, d) minimization of both electricity cost and aggregated power consumption, and e) both the maximization of social welfare and minimization of aggregated power consumption. Agamah and Ekonomou (2017) introduce an optimization algorithm for load leveling of power demand using a storage battery. In this study, load leveling was achieved by distributing the use of all appliances. As a result, the demand in a residential building approaches a constant value in each time period. Therefore, the heat pump water heater can be operated with a constant output. The algorithm also enables the demand side to reduce the power consumption and consequently, lower the electricity cost. This study was only an approximate solution to the optimization problem under deterministic conditions. Zhu et al. (2011) introduced a demand-side schedule management method with a smart meter. The system model is shown in Fig.1. It consists of smart meters, a user interface, two types of appliances, and central control. The smart meters can be managed in residential buildings, and the central management unit can perform overall management. It is possible to level the load for residential buildings with this system. This study was also an optimization that was considered under deterministic conditions. In addition, the problem applied in the numerical example is based on virtual data, and a realistic analysis is desired. Furthermore, the objective function was to minimize the maximum power and did not consider the overall cost. In this paper we consider the control of the operation of heat pumps in a residential building, not the control by a smart meter. Mohsenian-Rad and Leon-Garcia (2010) introduced load...
control problems in a residential building considering real-time power prices. Real-time power prices are presented by retailers to consumers through a local area network. This problem aims to minimize the tradeoff of the power consumption and the operation waiting time of the appliance. Although the study focuses on forecasting electricity prices, it did not optimize for fluctuations in demand. Baniasadi et al. (2020) proposed a new framework for optimal sizing design and real-time operation of energy storage systems in a residential building equipped with a PV system, heat pump (HP), thermal and electrical energy storage systems.

The following studies deal with applications of optimization under uncertainty. Good et al. (2015) presented a two-stage stochastic programming model for provision of flexible demand response (DR) based on thermal energy storage. Ceseña et al. (2016) proposed a unified operation and planning optimization methodology for distributed multienergy generation (DMG) systems. Majidi et al. (2017) evaluated cost-efficient operation problem of photovoltaic/battery/fuel cell hybrid energy system in the presence of demand response program. Schwarz et al. (2018) studied a residential quarter using photovoltaic systems in combination with multistage air-water heat pumps and heat storage units. Zhang et al. (2020) presented the model to quantify uncertainty of water source heat pump and its impact on the system performance.

The differences of this research from Tokoro et al. (2014) are as follows.

1. Omitting the temperature distribution model in the tank
2. Introduction of the minimum up time \( L_i \) and the minimum down time \( l_i \)
3. Introduction of the minimum heat storage amount \( C_{\text{min}} \)

The operating rule presented by Tokoro et al. (2014) turns the water heater on and off checking the values of multiple thermometers. For this reason, it was necessary to model the temperature distribution in the tank in order to optimize the operation rules. We will extend this model to consider optimization under uncertainty. Based on the model that considers the temperature distribution in the tank, it is necessary to optimize complicated operation rules. Therefore, instead of optimizing the operation rules, we first consider optimizing the basic start and stop schedule. It is not necessary to model the temperature distribution in the tank because the schedule of hot water heater is decided independently of the temperature distribution.

Since the water heater has a start-up loss when it starts up, it is economical to operate it for a certain period of time without stopping immediately. Also, if we start and stop it frequently, the service life of the HP water heater will be shortened and it will be economical to extend the down time. In this paper, in order to find the optimal operation plan considering start-up loss and equipment life, the constraints of minimum up and down time as used in the unit commitment were introduced. Furthermore, in this paper, the parameters, outside air temperature, water input temperature to tank and boiling temperature are assumed to be constant. In this paper, outside air temperature was set to constant for simplification, but to be precise, it is necessary to change the value of air temperature within a day. We would like to consider the optimization considering the change of outside air temperature as a future issue. The shipment volume of heat pump water heaters is increasing, and it is expected that 14 million units will be popular by 2030. The feature of this research is that the developed method is applied to the problems of general households in Japan. This method can be used in virtual power plants in Japan.

3. Problem description

The purpose of this problem is to determine the operation pattern of the heat pump considering uncertain power and heat demand by the electric appliances in the residential building. The electricity cost is minimized to meet the constraints of the equipment and the operation constraints. We also compare it with the conventional system model and demonstrate the effectiveness of our new model.

3.1. Notations

The following symbols are defined to formulate the mathematical model.

**Sets:**

- \( I \) The set of heat pump water heaters
- \( T \) = \{0, 1, …, 23\} The set of time periods in a day
- \( S \) The set of uncertain scenarios

**Variables:**

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3.2. Overview of the model

The heat pump water heater system model operates the water heater to satisfy the demand for heat and optimizes the electricity cost at each time period. The operation of the water heater is determined in consideration of the electricity cost generated through the use of all electric appliances except the heat pump water heater in the residential building. This model consists of a residential building, heat pump water heater, and tank components. All appliances in the residential building consume electric power. The heat pump water heater uses electric power and generates hot water by boiling the incoming water. The tank preserves heat by storing hot water generated by the water heater. The model is shown in Fig.2. This shows the flow of power consumption and heat in the residential building, heat pump water heater, and tank. At time \( t \), when the heat pump water heater is operating, hot water of \( M_{\text{kWh}} \sum_{i} x_{i} u_{i} / e \) is generated as thermal energy and stored in the tank. The hot water stored in the tank meets the residential heat demand \( h_{t} \). As the hot water cannot be generated when the water heater is not operating, the process from generation to storage is omitted and the heat demand is satisfied with the hot water stored in the tank. All these processes are performed under the condition that the heat generated can be consumed in the same period because power flow and heat flow are performed within unit time.

In the tank in this system model, changes in heat storage occur due to heat release over time. The flow of the reduction is shown in Fig.3. There are two types of constraints on this event. The first involves capacity constraints. The capacity restriction of the tank does not consider the water storage volume capacity, but the upper and lower limits of heat storage volume that can be stored in the tank are \( C_{\text{min}} \) and \( C_{\text{max}} \). The capacity constraints include the constraint of the initial heat storage, the heat storage after heat generation by the heat pump water heater, and the heat storage after the reduction. The second constraint is heat decay restriction. The tank loses heat over time. When time elapses from \( t \) time to \( t + 1 \) time, the heat storage reduction constraint is inevitable. This restriction applies only to the period between the end heat storage at \( t \) and the opening heat storage at \( t + 1 \). In general, the rate of decrease of heat per day of the tank installed in the residential building is 10%.

In this model, as the electricity cost depends on the maximum power consumption, it is affected by the on/off decision of the heat pump, which is denoted by binary variables. Fig.4 shows the relationship between the amount of power consumption by electric appliances excluding the heat pump water heater, and the power consumption of the water heater.
Fig. 2 Heat pump water heater system model

Fig. 3 Reduction of heat storage in the tank due to heat release

Fig. 4 Power consumption and θ relationship
3.3. Formulation

The optimization problem is formulated as follows. The operational patterns of the heat pump water heater are determined to minimize the expected electricity cost.

\[
\text{(Stochastic programming model): } \min f \theta + \frac{1}{|S|} \sum_{s \in S} \sum_{t \in T} \text{cost}
\left( d_t^s + \frac{\sum_{i=1}^{N} x_{it} u_{it}}{e} \right)
\]

s.t. 
\[
I_t^s + \frac{M_{\text{Wh}} \sum_{i=1}^{N} x_{it} u_{it}}{e} = h_t^s + G_t^s \quad \forall t \in T, \forall s \in S
\]
\[
\left( 1 - \frac{\text{cut}}{100} \right) G_t^s = I_{t+1}^s \quad \forall t \in T, \forall i \in I, \forall s \in S
\]
\[
C_{\text{min}} \leq I_t^s \leq C_{\text{max}} \quad \forall t \in T, \forall s \in S
\]
\[
C_{\text{min}} \leq G_t^s \leq C_{\text{max}} \quad \forall t \in T, \forall s \in S
\]
\[
G_{t+1}^s \geq I_t^s \quad \forall s \in S
\]
\[
0 \leq I_t^s + \frac{M_{\text{Wh}} \sum_{i=1}^{N} x_{it} u_{it}}{e} \leq M_{\text{cal}} V_{\text{BT}} \quad \forall t \in T, \forall s \in S
\]
\[
d_t^s + \frac{\sum_{i=1}^{N} x_{it} u_{it}}{e} \leq 0 \quad \forall t \in T, \forall s \in S
\]
\[
 u_{it} - u_{i,t-1} \leq u_{\tau} \quad \tau = t, \ldots, t + L_t - 1, \forall t \in T, \forall i \in I, \text{if } t + L_t - 1 \leq 23
\]
\[
 u_{i,t-1} - u_{it} \leq 1 - u_{\tau} \quad \tau = t, \ldots, t + l_i - 1, \forall t \in T, \forall i \in I, \text{if } t + l_i - 1 \leq 23
\]
\[
 u_{it} - u_{i,t-1} \leq u_{\tau} \quad \tau = t, \ldots, 23, 0, \ldots, t + L_t - 25, \forall t \in T, \forall i \in I, \text{if } t + L_t - 1 \geq 24
\]
\[
 u_{i,t-1} - u_{it} \leq 1 - u_{\tau} \quad \tau = t, \ldots, 23, 0, \ldots, t + l_i - 25, \forall t \in T, \forall i \in I, \text{if } t + l_i - 1 \geq 24
\]
\[
C_{\text{min}} = M_{\text{cal}} V(K_{\text{min}} BT + (1 - K_{\text{min}}) WT)
\]
\[
C_{\text{max}} = M_{\text{cal}} V(K_{\text{max}} BT + (1 - K_{\text{max}}) WT)
\]
\[
e = a_1 AT - a_2 WT - a_3 BT + a_4
\]
\[
G_t^s, I_t^s \geq 0 \quad \forall t \in T, \forall s \in S
\]
\[
\theta \geq 0 \quad \forall t \in T, \forall s \in S
\]
\[
u_{it} \in \{0, 1\}
\]

The objective function (1) minimizes expected electricity cost. The equation (2) is the conservation of heat storage amount. The equation (3) represents a decrease in heat storage over time. The inequalities (4) and (5) indicate capacity constraints of initial and final heat storage, respectively. Constraint (6) shows the continuity of heat storage. This means that the heat storage at the end of the day will be the initial heat storage. Constraint (7) restricts the heat storage capacity constraint during heat generation. In constraint (8), maximum power consumption \( \theta \) is defined. Constraints (9) and (10) represent the minimum up-time and the minimum down-time constraint, respectively. Once the heat pump starts operation, it keeps on for at least \( L_t \) periods. If it stops, it must stop for more than \( l_i \) periods in a row. Constraint (11) and (12) represent the continuity of the operational constraint. Equations (13) and (14) define heat storage capacity. Assuming that \( BT \) is constant, the upper and lower limits of heat storage are defined as (13) and (14). Equation (15) defines the coefficient of performance. Constraint (16) represents nonnegativity of initial and final heat storage. Constraint (17) represents nonnegativity of maximum power consumption. Constraint (18) represents the definition of the binary decision variable. In this model, the lower limit of the heat storage capacity is 10% and the upper limit is 90%.

We then consider the operation of the existing system. The operational pattern is determined such that the heat storage amount is maximized as much as possible in early morning. This model simulates an existing hot water supply system.

\[
\text{(Model for existing system): } \max g_t
\]
The objective function (19) maximizes heat storage amount at 6 a.m. Constraint (20) represents the heat storage amount at 6 a.m. Constraint (21) represents the lower bound of heat storage.

4. Numerical experiments

4.1. Setting conditions for experiments

We demonstrate the effectiveness of the proposed model using numerical experiments. The computer used for this experiment is Core i7-7700 and 32GB memory using AMPL-CPLEX version 12.6.2.0 on Windows 10 Pro. Based on the data of Tokoro et al. (2014), we conduct numerical experiments to make a one-day operation plan. The lower limit of the heat storage capacity is 10% and the upper limit is 90%. The numerical values $a_1, a_2, a_3, a_4$ in (15) are as follows.

|   | $a_1$ | $a_2$ | $a_3$ | $a_4$ |
|---|-------|-------|-------|-------|
|   | 0.0598| 0.0254| 0.0327| 5.44  |

Scenarios representing the uncertainty of power and heat demand are generated using the power demand in May, August, October, and December 2003 from the data (Kanto Residential Building 02) of the Architectural Institute of Japan (2006). The average monthly temperature is used as the outside temperature and is obtained from the Japan Meteorological Agency (2003). In the daily operation plan, the basic charge and electricity charge are taken from the data of smart life of the Tokyo Electric Power Company (2019). The number of scenarios is set to 30, and the probability of each scenario is 1/30.

The experiments are performed according to the following policy. First, operations of the proposed model and existing system are compared. In the proposed model, the total cost is calculated as the sum of the basic price of power and the expected value of power consumption. Operation of existing systems simply maximizes heat storage in the early morning. Comparing the costs of these operations, we find out which method of operation is better. We will also discuss where the difference comes from by comparing operating patterns of the heat pump. Second, mathematical programming models are compared. We discuss the benefits of using a stochastic programming model. In the stochastic programming model, a solution is calculated assuming that one month’s data extracted from real samples correspond to actual fluctuations. On the other hand, a deterministic model assumes that only one scenario corresponding to the expected value will occur. Expected value of cost is calculated by applying the solution obtained by the deterministic model to the scenario used in stochastic programming.

4.2. Comparison of operation methods

We compare the electricity cost of the stochastic programming considered in this study and the model for an existing system that simulates an existing hot water supply system. The months are May, August, October, December, which represent four seasons in Japan. The results for each target month are shown in Table 2. This table shows the difference in electricity cost.

| Month   | Daily electricity cost of the stochastic programming model(yen) | Daily electricity cost of the model for existing system(yen) | Difference (yen) |
|---------|---------------------------------------------------------------|-------------------------------------------------------------|-----------------|
| May     | 1110.29                                                      | 1252.76                                                    | 142.47          |
| August  | 1075.37                                                      | 1157.59                                                    | 82.22           |
| October | 1074.71                                                      | 1239.90                                                    | 165.19          |
| December| 1715.05                                                      | 1826.49                                                    | 111.44          |
Electricity cost is improved because the difference is positive in all months. Since we consider one-day operation, the values shown in Table 2 are the daily electricity costs and their differences. When converted to monthly expenses, the expected benefits of cost saving range from $82.22 \times 30 = 2466.6$ (yen) to $165.19 \times 30 = 4955.7$ (yen).

Next, the reasons for the difference in total costs are considered. Table 3 and Table 4 show the optimal operational patterns of the model, and Table 5 shows the maximum power consumption. From Table 5, it can be seen that the maximum power is suppressed in the stochastic programming model. That is, load leveling has been achieved.

Table 3  Optimal solution of operational pattern of the stochastic programming model

| t   | May | August | October | December |
|-----|-----|--------|---------|----------|
| 0   | 0   | 1      | 0       | 1        |
| 1   | 0   | 1      | 0       | 1        |
| 2   | 1   | 1      | 1       | 1        |
| 3   | 1   | 1      | 1       | 1        |
| 4   | 1   | 1      | 1       | 1        |
| 5   | 1   | 1      | 1       | 1        |
| 6   | 1   | 1      | 1       | 1        |
| 7   | 0   | 1      | 1       | 0        |
| 8   | 0   | 1      | 1       | 0        |
| 9   | 0   | 1      | 1       | 0        |
| 10  | 0   | 1      | 1       | 0        |
| 11  | 1   | 0      | 1       | 0        |
| 12  | 1   | 0      | 1       | 1        |
| 13  | 1   | 0      | 1       | 1        |
| 14  | 1   | 0      | 0       | 1        |
| 15  | 0   | 0      | 0       | 1        |
| 16  | 0   | 0      | 0       | 0        |
| 17  | 0   | 0      | 0       | 0        |
| 18  | 0   | 0      | 0       | 0        |
| 19  | 0   | 0      | 0       | 0        |
| 20  | 1   | 0      | 0       | 0        |
| 21  | 1   | 0      | 0       | 0        |
| 22  | 1   | 0      | 0       | 1        |
| 23  | 0   | 0      | 0       | 1        |
Table 4  Optimal solution of operational patterns of an existing system

| Model for existing system | May | August | October | December |
|---------------------------|-----|--------|---------|----------|
| 0                         | 1   | 1      | 1       | 1        |
| 1                         | 1   | 1      | 1(+)*   | 1        |
| 2                         | 1   | 1      | 1       | 1        |
| 3                         | 1   | 1      | 1       | 1        |
| 4                         | 1   | 1      | 1       | 1        |
| 5                         | 1   | 1      | 1       | 1        |
| 6                         | 1   | 1      | 1       | 1        |
| 7                         | 0   | 1      | 0       | 0        |
| 8                         | 0   | 1      | 0       | 0        |
| 9                         | 0   | 1      | 0       | 0        |
| 10                        | 0   | 1      | 1       | 0        |
| 11                        | 0   | 1      | 1       | 0        |
| 12                        | 1   | 0      | 1       | 0        |
| 13                        | 1   | 0      | 1       | 0        |
| 14                        | 1   | 0      | 1       | 0        |
| 15                        | 1   | 0      | 1       | 0        |
| 16                        | 1   | 0      | 1       | 1        |
| 17                        | 1   | 0      | 0       | 1        |
| 18                        | 1   | 0      | 0       | 1        |
| 19                        | 0   | 0      | 0       | 1        |
| 20                        | 0   | 0      | 0       | 1(+)*    |
| 21                        | 0   | 0      | 0       | 1        |
| 22                        | 1(+)*| 1      | 1       | 1        |
| 23                        | 1(+)*| 1      | 1       | 1        |

The symbol (+) represents the time of maximum power consumption.

Table 5  Comparison of maximum power consumption amounts

| Month     | The stochastic programming model[kWh] | Model for existing system[kWh] |
|-----------|--------------------------------------|-------------------------------|
| May       | 3.26735                              | 3.47894                       |
| August    | 3.35076                              | 3.3631                        |
| October   | 2.81807                              | 3.2808                        |
| December  | 5.13747                              | 5.42652                       |

We can evaluate what is needed for the improvement of load leveling. Operational patterns are analyzed as follows. According to Table 3, the heat pump is always operated between 2 a.m. and 6 a.m. in all target months. On the other hand, the model for the existing system was operated to fill the heat storage as much as possible at 6 a.m.. Table 4 shows that the heat pump is always operated between 10 p.m. and 6 a.m. in all target months. And this table shows that power consumption was the largest during this period except in December. In December, the maximum power is generated at 8 p.m. In other time periods (07:00-21:00), differences in operational patterns are large in each season because the operation is optimized according to the heat demand.

Considering the results of stochastic programming, the heat pump water heater is halted during the peak time of total power consumption. It can be seen that the time periods marked with + in Table 4 is not operating in the stochastic programming model as shown in Table 3. To ensure adequate heat generation, the heat pump water heater must be operated at other time periods. For load leveling, the heat pump water heater is operated in the time period when the...
power demand is low. As a result, after satisfying the heat demand, the maximum power consumption is suppressed and load leveling is achieved.

The improvement in electricity cost is not only due to the decrease in maximum power consumption but also the decrease in the total operating time of the heat pump water heater. The total operating hours for the model of an existing system in May, August, October, and December are 16, 14, 16, and 15 hours, respectively. By contrast, the operating hours in the target months under the stochastic programming model were 12, 11, 12, and 13 hours, respectively. This indicates that the total operating time is decreasing in all target months under the latter model. The reduction of the total operating time implies a reduction in total power consumption, which further results in a reduction of the electricity cost.

| Month         | Existing system | Stochastic model |
|---------------|-----------------|------------------|
| May           | 16              | 12               |
| August        | 14              | 11               |
| October       | 16              | 12               |
| December      | 15              | 13               |

4.3. Comparison of optimization models

We evaluate the effectiveness of the presented model. We use the value of the solution of the stochastic programming problem (VSS: Birge and Louveaux (1997)) in the evaluation of the solution. VSS is defined as $VSS = EEV - RP$. EEV represents the expected cost of using an EV (expected value problem) solution, where the value of a random variable is replaced by its expected value in stochastic programming. RP is the optimal objective function value of the stochastic programming problem. Theoretically, the relationships $RP \leq EEV$ and $VSS \geq 0$ hold. Their values in this numerical experiment are shown in Table 7.

| Month         | RP(yen) | EEV(yen) | VSS  |
|---------------|---------|----------|------|
| May           | 1110.29 | 1126.38  | 16.09|
| August        | 1075.37 | 1385.74  | 310.37|
| October       | 1074.71 | 1127.37  | 52.66|
| December      | 1715.05 | 1739.92  | 24.87|

5. Conclusion

We developed an operation plan optimization model in a residential building that constitutes a smart community. In the smart community, it is important that demand leveling is achieved because it is essential to introduce distributed power sources. The effectiveness of the stochastic programming model considering the uncertainty of power and heat demand is shown by comparing it with the conventional deterministic model. Future research issues include the expansion of the scale for residential buildings and the expansion of the planning period. As the problem is large in scale, an efficient solution is required.

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