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A Study on the Effect of Energy Storage Systems and Distributed Generators on Reliability

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***Abstract*—Recently, as many researchers introduced various methods and factors for distributed renewable energy resources and energy storage systems to the grid, the need for verification on their performance and effect to the grid is emerging. So, in this paper, we predict system marginal price (SMP) by using long short-term memory (LSTM) based on empirical data published by the Korea Power Exchange and the Korea Meteorological Administration. After then, this paper suggests an optimal energy storage system (ESS) operation strategy based on the predicted data and the dynamic programming (DP) algorithm. To verify the impact of the proposed operation strategy on power grid, a grid fault is simulated through OpenDSS to consider the power system reliability. As a result, the proposed algorithm was able to interpret the effect on the system when the ESS operator shows selfish behaviors to the system.**

Keywords—Energy Storage System (ESS), Dynamic Programming (DP), Long Short-Term Memory(LSTM), Reliability

Nomenclature and Abbreviations

DG = Distributed Generator

ESS = Energy Storage System

LSTM = Long Short-Term Memory

DP = Dynamic Programming

PV = Photovoltaics

I. INTRODUCTION

As our modern society becomes complex and diverse, the modern power grid also becomes complex. So, the classical power grids are not able to solve problems made by the modern power grid enhanced by various types of renewable energy resources and energy storage systems. To solve the problem considering social requirements, academics and industries are trying to connect renewable energy-based distributed generators (DGs) with distribution systems. However, due to the inherent characteristics (e.g., the intermittent output) of the renewable energy resources, the power generation amount of renewable energies is not stable and may become probabilistic in their output. To solve this problem, energy storage systems (ESSs) were promoted [1, 2]. Furthermore, in order to overcome the weakness of distributed generators based on renewable energy resources with uncertainties in their output, there have been efforts to reduce the uncertainty by using prediction techniques.

Looking at the efforts for this from the perspective of wind farms, in [3], the prediction was performed as a case study through a method based on the neural network for Tamil Nadu in India. As a result, the prediction algorithm showed the possibility of accurate prediction of the output of wind farms. In [4], five prediction methods were tested through data mining in various prediction horizons. And support vector machine (SVM) and multiple perceptrons were shown to be suitable for prediction. However, when the power curve model of the wind farm generator and the predicted wind speed are given, the accuracy of the prediction was lowered.

On the other hand, in terms of photovoltaic (PV) prediction, as an early study, it was suggested that the neural network could show better prediction performance compared to the multiple regression model [5]. In addition, [6] was conducted as follow-up research. In this research, even though the prediction of the output is made through the support vector regression model, it is suggested that the prediction error problem can be solved by correcting the error between the actual and the prediction through the ESS.

Preliminary studies [3-6] showed that the generation amount of DGs based on renewable energy sources could be sufficiently predicted, but it was disappointing to utilize them. It is also regrettable that it did not reflect economic feasibility.

Due to the characteristics of the power grid, reliability is a significant factor. Therefore, to confirm the change in reliability, [7] showed how reliability changes in the distribution system according to the operation characteristics of DGs. Based on this research, [8] was conducted as a follow-up study to confirm the effect on reliability and suggest a control strategy when DGs and ESS are linked together. However, [8] also did not reflect that economic feasibility remains a disappointment.

Therefore, in this paper, when PV, which has entirely random power generation characteristics [2], and ESSs are connected to the grid together, the effect on the system is considered in the point of view of reliability. For this purpose, this study focuses only on economic efficiency. The system marginal price (SMP) is predicted by long short-term memory (LSTM) using empirical data published by the Korea Electric Power Research Institute and the Korea Meteorological Administration. After establishing an ESS operation strategy by dynamic programming (DP) based on this predicted value, simulation is performed on the Roy Billinton's test sytsem (RBTS) to find out the effect of the proposed operation strategy on the distribution system.

Through this study, from the perspective of the system operator, it is expected that the influence on the system can be identified when the prosumer operates the ESS only for their benefit. Through this, it is also expected to help establish the system operation policy. In particular, in the current situation where many electric vehicles are being introduced [9], electric vehicles are treated as portable ESSs, which is expected to help establish a charge/discharge strategy for electric vehicles.

II. Problem Formulation

The operation strategy suggested by this paper is maximizing the profit of prosumers by deciding charge/discharge of ESSs connected to DG in hourly intervals. SMP is set differently every hour by Korea Electric Power Corporation (KEPCO), the profit of the prosumer may vary depending on the timing of selling power. That is, prosumers can earn the high profit when the SMP is high. For this, the prosumer needs to wait until the SMP is high by storing the generated power in the ESS. However, the capacity of the ESS is fixed, and there is a problem that the capacity more than the predefined value cannot be stored. Therefore, if the ESS is not discharged to wait for the upper limit of the SMP, the power not stored during the standby time becomes a sunk cost. The strategy of waiting for the SMP to record the highest price is not a good strategy for prosumers. That is, it is essential to establish an appropriate ESS operation strategy for maximizing profits.

To formulate the problem, the variables are defined as follows: Let N^{period} be defined as the period for establishing the operation strategy, and E_t^{gene} will be defined as the amount of electricity generated at $t\left(t=1,\ \cdots,\ N^{period}\right)$. Such then, X_t is defined as the operation of ESS at time t. That is, it means charge/discharge of ESS, and it is expressed as a binary variable as follows:

$$X_t=\begin{cases}0, \text{ the ESS charges energy } E_t^{gene} \\ 1, \text{ the ess discharges all the energy stored}\end{cases} \tag{1}$$

Let E_t^{store} be the amount of electricity stored in the ESS at time t when the ESS operates. At this time, E_t^{store} cannot exceed C^{limit}. For example, if the power stored in the ESS starts at 0, E_t^{store} becomes zero at $t=1$. Thus, the amount of power stored in the ESS at time step t is defined as follows:

$$E_t^{store}=\begin{cases}E_{t-1}^{store}+E_{t-1}^{gene},\ X_{t-1}=0 \\ 0,\ X_{t-1}=1\end{cases} \tag{2}$$

Let SMP at time step t be P_t^{price}, -the total gain at t - is defined as follows:

$$P_t^{bene}=P_{t-1}^{bene}+X_tP_t^{price}\left(E_t^{store}+E_t^{gene}\right) \tag{3}$$

From this formulation, we can define the ESS benefit maximize problem (EBMP), it is formulated as follows:

$$\begin{aligned}&\text{Maxmize : } P_{N^{period}}^{bene} \\ &\text{Subjected to : for } \forall t,\ E_t^{store}\le C^{\text{limit}}\end{aligned} \tag{4}$$

So, an EBMP is defined as a sequential decision-making problem for ESS operation, and since the ESS storage amount E_{t+1}^{store} at the next time step $t+1$ depends only on the values $\left(E_t^{store}, E_t^{gene} \text{ and } X_t\right)$ at the current time step t, values up to $t-1$ are not necessary. With this logic, based on equation (3), P_{t+1}^{bene} (i.e. the profit at $t+1$) also depends only on the current time step. Therefore, EBMP can be defined as a Markov Decision process (MDP).

III. ESS Opeartion Scheduling

MDP is defined as a 5-tuple parameter (S, A, P, R, γ). S is the state set and A is the action set. P is transition function that defines a state, transitions of which depend on the selected action. R is a reward function that calculates the value of reward of a given state. γ is the discount factor, and is a value between 0 and 1.

The purpose of the MDP is to find the policy with the greatest reward for decision makers. A policy π is a function that maps a given state selecting each possible action from that state, and is expressed as $\pi: S\rightarrow A$.

To solve the proposed EBMP, we have mapped the parameters to components of MDP as shown below:

1) State : The state at time t, s_t is the amount of electrical energy stored in the ESS at time t, which is expressed as: $s_t=E_t^{store}\in S$.

2) Action : The action at time t, a_t is the ESS operation X_t at time t, which is expressed as : $a_t=X_t\in A$.

3) Transition: In the EBMP, the policy π is a deterministic policy defined as a single optimal action per state. The transition function P performs deterministic transitions expressed as $S \times A \rightarrow S$. For example, if the case of charging E_t^{gene} to the ESS at time t receives the optimal reward, E_t^{gene} should be charged to the ESS and not discharged (i.e., $X_t = 1$ and $X_t = 0$). The transition probability at time t , p_t as follows:

$$p_t = \begin{cases} 1, & a_t \text{ is the optimal action} \\ 0, & \text{Otherwise} \end{cases} \tag{5}$$

It means that the transition probabilities of the optimal policy π^* are always 1.

4) Reward: The reward obtained at time t , r_t is expressed as: $r_t = X_t P_t^{price} \left(E_t^{store} + E_t^{gene} \right) \in R$.

5) Discount factor: The goal of EBMP is to maximize the sum of total future rewards, so $\gamma = 1$.

In order to solve EBMP, a policy that maximizes the cumulative sum of rewards is required. The optimal policy π^* and the benefits obtained by applying π^* can be calculated by Bellman optimality equation $Q^*\left(s_t, a_t\right)$ as follows:

$$Q^*\left(s_t, a_t\right) = r_t + \max_{a' \in A} Q^*(s', a') \tag{6}$$

where state s' and action a' are values at the next time $t+1$.

The maximum reward from time t to N^{period} can be calculated recursively through inequality (6). Thus calculating $Q^*\left(s_1, a_1\right)$ will solve the EBMP.

We simply solved the problem using top-down dynamic programming called memorization. Memoization is a technique that recursively solves a problem and reuses a saved result when the same input occurs again.

Fig. 1 shows the details of the ESS operation scheduling (EOS) algorithm.

Algorithm 1 The ESS operation scheduling (**EOS**) algorithm

function MEMOIZATION($t, e^{\text{curr}}, x^{\text{curr}}$):
  if ($e^{\text{curr}} \neq C^{\text{limit}}$) **then**
    return $-\infty$;
  end if
  if ($t > N^{\text{period}}$) **then**
    return 0;
  end if
  if ($D^{\text{bene}}_{t,e^{\text{curr}},x^{\text{curr}}}$ is none) **then**
    if (x^{curr}) **then**
      $e^{\text{next}} \leftarrow 0$;
    else
      $e^{\text{next}} \leftarrow e^{\text{curr}} + E_t^{\text{gene}}$;
    end if
    $D^{\text{bene}}_{t,e^{\text{curr}},x^{\text{curr}}} \leftarrow x^{\text{curr}} P_t^{\text{price}}(e^{\text{curr}} + E_t^{\text{gene}}) + \max_{x^{\text{next}} \in \{0,1\}} \text{MEMOIZATION}(t+1, e^{\text{next}}, x^{\text{next}})$;
    $D^{\text{arg}}_{t,e^{\text{curr}},x^{\text{curr}}} \leftarrow$ An argument x^{next} with highest benefit in the above line;
  end if
  return $D^{\text{bene}}_{t,e^{\text{curr}},x^{\text{curr}}}$;
end function
function SCHEDULING:
  $X_1 \leftarrow arg \max_{x^{\text{curr}} \in \{0,1\}} \text{MEMOIZATION}(1, 0, x^{\text{curr}})$;
  $E_t^{\text{store}} \leftarrow 0$;
  for $t = 1$ to $N^{\text{period}} - 1$ **do**
    $X_{t+1} \leftarrow D^{\text{arg}}_{t,E_t^{\text{store}},X_t}$;
    if (X_{t+1}) **then**
      $E_{t+1}^{\text{store}} \leftarrow 0$;
    else
      $E_{t+1}^{\text{store}} \leftarrow E_t^{\text{store}} + E_t^{\text{gene}}$;
    end if
  end for
  return The optimal schedule;
end function

Fig. 1 The ESS operation scheduling (EOS) algorithm

IV. LONG-SHORT TERM MEMORY

For predicting SMP, this research adopted the LSTM model. LSTM is the method suggested by Hochreite and Schmidhuber [10] to overcome the vanishing gradient problem of recurrent neural network (RNN). RNN has the characteristic of using previous information for prediction, when distance of information becomes so far, the learning ability of the model becomes low [11]. In the Fig. 2, LSTM has a structure in which the cell state is added to the hidden state of the RNN.

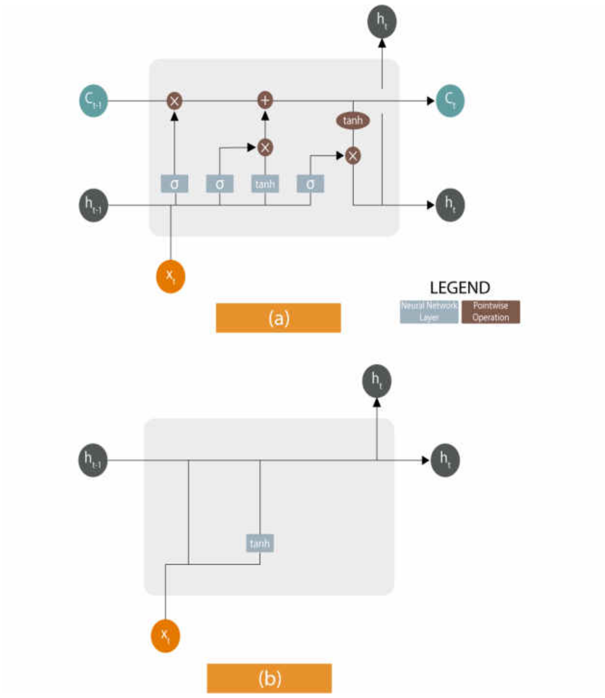

Fig. 2 (a) The basic cell structure of LSTM (b) The basic cell structure of RNN

By applying this structure, the model can predict the data and the previous data on bird-eye view.

In the Fig. 3, the cell state is consisted of 4 gates; forget, input, update, and output gate. From these gates, the model chooses the information throw away or save.

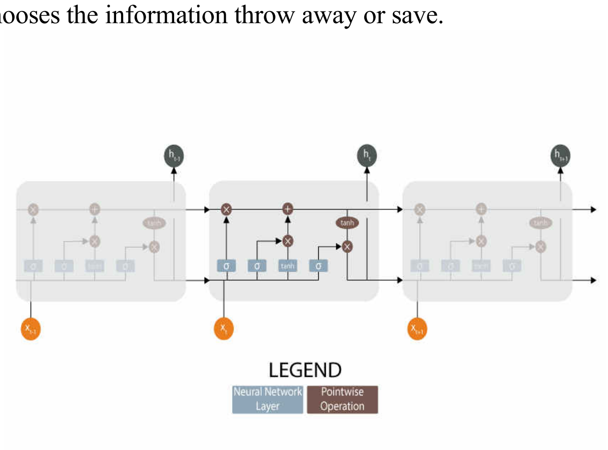

Fig. 3 The overall structure of LSTM

The forget gate is the process chooses that throws away previous data or not; the forget gate decides the last data, which will go to the current cell state by using the output of just before and current input. The process uses the sigmoid function as an activation function; if the function value becomes 0, outcomes from the previous cell don't affect the future results. However, if the sigmoid function value becomes 1, the gate sends previous work intact and affects future results. In other words, the forget gate plays a role in determining which value of the cell state deletes when considering the current input and previous output. The structure is visualized as Fig. 4 (a), and we can express it as the equation (7).

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{7}$$

The input gate is the process to decide whether to store the current information, and it determines what things to put into the cell state as new information through the tanh function. The structure is visualized as Fig. 4 (b), and we can express it as the equation (8).

$$\begin{aligned} i_t &= \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \\ \tilde{C}_t &= \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \end{aligned} \tag{8}$$

The update gate is the procedure to update the previous cell state as a new state. It is expressed as the sum of the amount of information deleted from the input gate and the data saved from the input gate. The structure is seen as Fig. 4 (c), and it is expressed as an equation (9).

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{9}$$

The output gate determines how much to extract the current cell state value by using the tanh function, which is defined as the product of the output gate, and update the state, which is schematically shown in Fig. 4 (d) mathematically expressed as (10).

$$\begin{aligned} o_t &= \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right) \\ h_t &= o_t * \tanh\left(C_t\right) \end{aligned} \tag{10}$$

From (7)-(10), there are b_i, b_f, b_C, b_o -bias terms; to prevent deleting all information when the model starts learning [12]. Therefore, if we put these data together, the learning step proceeds with the structure as shown in Fig. 4.

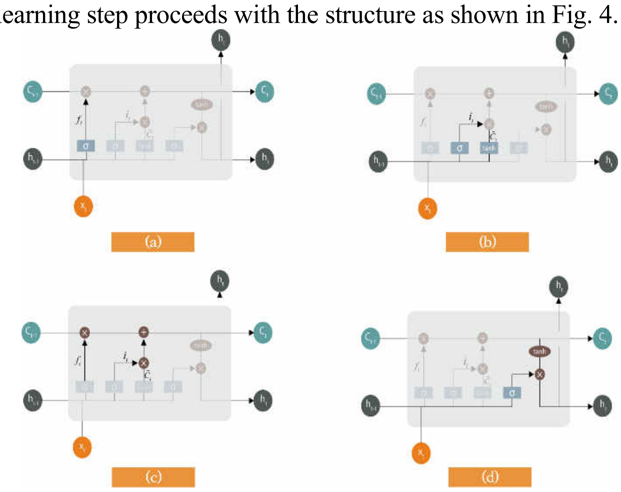

Fig. 4 The operation scheme of LSTM (a) the forget gate, (b) the input gate, (c) the update gate, (d) the output gate

V. Power System Reliability

The problem to be investigated in this paper is the reliability of the power system, and utilities are under pressure from consumers to provide power with appropriate the quality and reliability to remain competitive in the market. For this, the ideal case is when the power is continuously supplied without a grid outage in the power distribution system, but a power outage inevitably may occur. In this case, the power outage means a state in which the power supply is temporarily or long-term interrupted for internal, external factors, or preventive maintenance during the operation of the power system. The power utility uses several indicators to check the effect of such a blackout on the grid through the quality and reliability of power, and the indicators are as follows.

A. System Average Interruption Duration Index (SAIDI)

System average interruption duration index (SAIDI) is a general utility reliability indicator. It means the average time for each customer receiving power service to experience a power outage for one year and is defined as follows:

$$\text{SAIDI} = \frac{\Sigma\left(R_y N_y\right)}{N_t} \tag{11}$$

B. System Average Interruption Frequency Index (SAIFI)

System Average Interruption Frequency Index (SAIFI) indicates the frequency of user power outages within a specific area. And it is defined as follows:

$$\text{SAIFI} = \frac{\Sigma N_y}{N_t} \tag{12}$$

C. Customer Average Interruption Duration Index (CAIDI)

Customer Average Interruption Duration Index (CAIDI) is the average recovery time required to recover from a fault. It means the average recovery time required for the user to receive electricity again when a permanent power outage occurs. It is defined as follows:

$$\text{CAIDI} = \frac{\Sigma\left(R_y N_y\right)}{\Sigma N_y} = \frac{\text{SAIDI}}{\text{SAIFI}} \tag{13}$$

VI. Case Study

The RBTS is a test system proposed in 1989 by the power system research group of the University of Saskatchewan for education and research on reliability indices. It consists of transformers, switches, busbars, overhead and underground lines [13]. The test system used in this paper is the modified RBTS 2-bus system, and the system configuration is shown in Fig. 6. In this paper, distributed power and ESSs are respectively attached to nodes 6 and 44 of feeders 1 and 4, which run a lot of loads (Fig. 5), and the charging and discharging of the ESS is operated based on the solution presented in this paper. Then, the changing reliability indices are checked. The results are suggested as TABLE I.

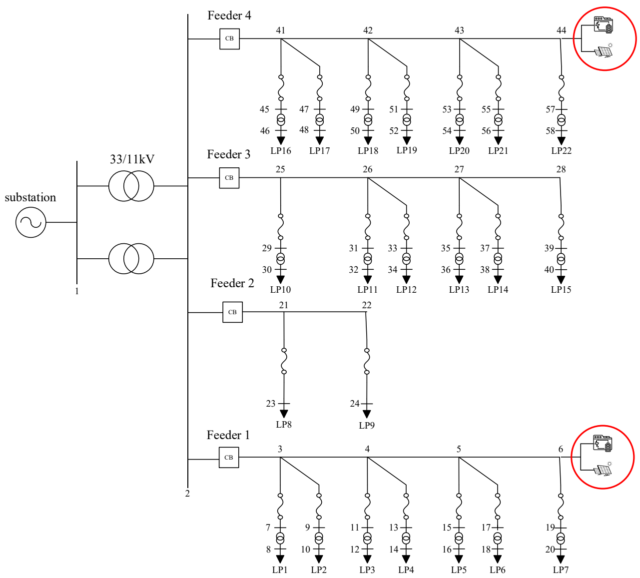

Fig. 6. Modified RBTS 2-bus system

VII. Results and Discussion

In this paper, without considering the interaction with the system, a case study was conducted to confirm the change in the reliability of the system when the prosumer operates the charge/discharge operation of the ESS only for prosumer's profit. Analyzing the data given from the case study, the overall reliability index of the system showed a tendency to improve overall. When interpreted based on the results of the case study, it was shown that the behavior of prosumers increases their own benefits and increases the system's reliability. However, it is regrettable that the verification of CAIDI convergence to a specific value was not carried out. Therefore, as a follow-up study, the selection of the optimal capacity of ESSs and PV in the distribution system and the re-establishment of the operation strategy, and the effect of the operation strategy on the change in system reliability should be conducted furthermore.

TABLE I. The Result of Reliability Indices

	Without DG & ESS			**With DG & ESS**		
	SAIFI	SAIDI	CAIDI	SAIFI	SAIDI	CAIDI
LP1	0.2400	3.5784	14.9100	0.192	0.576	3.0000
LP2	0.2530	3.6432	14.4000	0.1518	0.4554	3.0000
LP3	0.2530	3.6432	14.4000	0.1898	0.5693	2.9994
LP4	0.2400	3.5784	14.9100	0.1920	0.5760	3.0000
LP5	0.2530	3.6432	14.4000	0.1898	0.5693	2.9994
LP6	0.2500	3.6275	14.5100	0.1500	0.4500	3.0000
LP7	0.2530	3.6027	14.2400	0.2024	0.6072	3.0000
LP8	0.1400	0.5446	3.8900	0.0840	0.2520	3.0000
LP9	0.1400	0.5040	3.6000	0.1120	0.3360	3.0000
LP10	0.2430	3.5794	14.7300	0.1944	0.5832	3.0000
LP11	0.2530	3.6432	14.4000	0.1518	0.4554	3.0000
LP12	0.2560	3.6582	14.2900	0.1920	0.5760	3.0000
LP13	0.2530	3.5901	14.1900	0.2024	0.6072	3.0000
LP14	0.2560	3.6045	14.0800	0.1920	0.5760	3.0000
LP15	0.2430	3.5794	14.7300	0.1458	0.4374	3.0000
LP16	0.2530	3.6432	14.4000	0.1518	0.4554	3.0000
LP17	0.2430	3.5915	14.7800	0.1944	0.5832	3.0000
LP18	0.2430	3.5794	14.7300	0.1823	0.5468	2.9994
LP19	0.2560	3.6454	14.2400	0.2048	0.6144	3.0000
LP20	0.2560	3.6454	14.2400	0.1536	0.4608	3.0000
LP21	0.2530	3.5901	14.1900	0.1898	0.5693	2.9994
LP22	0.2560	3.6045	14.0800	0.1536	0.4608	3.0000

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