

Automatic Voltage Stabilization System for Substation using Deep Learning

Jiyong Moon¹, Minyeong Son², Byeongchan Oh³, Jeongpil Jin⁴, and Younsoon Shin⁵

¹ Department of Business Administration, Dongguk University,
30, Pildong-ro 1-gil, Jung-gu, Seoul, Korea
asdwldyd@dongguk.edu

² Department of Medical Biotechnology, Dongguk University,
30, Pildong-ro 1-gil, Jung-gu, Seoul, Korea
smya0930@dongguk.edu

³ Department of Statistics, Dongguk University,
30, Pildong-ro 1-gil, Jung-gu, Seoul, Korea
oxox97@dongguk.edu

⁴ Department of Industrial System Engineering, Dongguk University,
30, Pildong-ro 1-gil, Jung-gu, Seoul, Korea
chin9510@dongguk.edu

⁵ Department of Computer Science, Dongguk University,
30, Pildong-ro 1-gil, Jung-gu, Seoul, Korea
ysshin@dongguk.edu

Abstract. The operating voltage in the substation must be maintained at its rated voltage within the specified standard because a voltage outside the specified range may cause a malfunction of the power facility and interfere with the stable power supply. Therefore, the voltage regulation process to maintain the rated voltage of the substation is essential for the stability of the power system. However, the voltage regulation process is currently performed manually by resident staff. Voltage regulation based on human judgment increases the uncertainty of voltage stabilization and makes efficient operation in consideration of the economic feasibility of power facilities difficult. Therefore, this paper proposes an automatic voltage stabilization system that can automatically perform voltage regulation. Instead of predicting the electrical load or overvoltage conditions studied so far, we focus on more direct, scalable input capacity prediction for an automatic voltage stabilization system. First, the proposed system predicts the input capacity required for a given situation through a trained stacked LSTM model. Second, an optimal regulation plan is derived through an optimization process that considers the economic feasibility of power facility operation. Additionally, the development of the user interface makes it possible to visualize the operation of algorithms and effectively communicate the models' predictions to the user. Experimental results based on real substation data show that the proposed system can effectively automate the voltage regulation process.

Keywords: automatic voltage stabilization system, energy system, input capacity prediction, deep learning, optimal regulation plan

1. Introduction

The operating voltage in the substation must be maintained at its rated voltage within the specified standard for the stability of the power system. If the voltage exceeds (**overvoltage**) or falls below (**undervoltage**) the rated voltage range, it may cause a malfunction of the power facility and interfere with the stable power supply. Therefore, the voltage regulation process to maintain the rated voltage of the substation is essential. The voltage regulation process is done through a voltage stabilization system (VSS). The voltage stabilization system refers to a system that can sequentially control the operating conditions of reactors constituting a substation [16]. A reactor is an absorber of reactive power, therefore compensating for high voltage transmission [14]. When the reactor is operated, the voltage decreases due to the consumption of reactive power, and when the reactor is stopped, the voltage increases.

However, most of existing voltage stabilization systems are manually operated by resident staff. In other words, various decisions for voltage regulation, such as deciding whether to operate a reactor, are made solely according to the personal judgment of the resident staff. There are two main problems with the voltage regulation process performed by humans. First, continuous monitoring is difficult. In the case of manual work, real-time response may be difficult due to breaks or shift hours, and inconsistent response may occur because each employee has a different handling method [24]. Second, efficient operation considering economic feasibility is difficult. In general, the more a reactor is used, the more likely it is to fail. When the reactor is operated at a high frequency, very fast transient overvoltage (VFTO) occurs more frequently, and when the voltage exceeds the basic impulse insulation level (BIL), it leads to the failure of the reactor [16]. Therefore, when performing voltage regulation, it is necessary to distribute the frequency of use of each reactor. Still, if the voltage regulation process is done manually, it isn't easy to properly consider this by personal judgment.

In order to solve the above problems, automation of the voltage stabilization system is required. Therefore, in this paper, we propose a prediction-based automatic voltage stabilization system using a stacked long-short term memory (stacked LSTM) model. Beyond statistical or mathematical methods [26,6,2,27], many prediction-based methods have been proposed for the stability of the power system. Recently, machine learning or deep learning-based methods have been mainly proposed. The main object of prediction is to predict the overvoltage situation for voltage stabilization [5,4,11,37], electrical loads [36,19,13], and reactive power [14]. Overvoltage situations, electrical loads, and reactive power are all important for the stability of a power system. However, developing an automatic voltage stabilization system requires a different approach. Overvoltage situations, electrical load, and reactive power can be used as indicators of the stability of a power system, but in terms of automatic voltage regulation, their purpose is different. This is because even with predictions for overvoltage situations, electrical load, and reactive power, it is not known how to adjust the power facility for a given situation. In other words, to implement automatic voltage stabilization, an additional prediction process is inevitable. In order to automatically regulate the reactors to the situation through an automatic voltage stabilization system, it is necessary to predict a more direct value to regulate. Therefore, we developed a model to predict the input capacity required for a given situation. Input capacity means the maximum amount of reactive power that one reactor can consume, but it can be used as a standard to regulate the reactor. For example,

if the model predicts that an input capacity of 400 Mvar is needed in a given situation, it can respond by operating two shunt reactors (Sh.R) with an input capacity of 200 Mvar. Predicting the input capacity indicates information about the level of danger expressed by overvoltage situations, electrical load, and reactive power. Predicting the input capacity also makes it easy to infer how to adjust the power facility in a given case. This is because input capacity is the most basic and direct basis for power facility operation. Therefore, the task of predicting input capacity is more suitable for implementing an automatic voltage stabilization system than simply predicting overvoltage, reactive power, and electrical load. In addition, this method does not require a prior definition of the applied system. This is because the required input capacity is fixed regardless of what kind of power facility the system consists of or the number of reactors constituting the system. This means that predicting input capacity is also beneficial for expansion and application.

In this study, we design an input capacity prediction model that is more suitable for automatic voltage stabilization systems and propose a solution that can be directly applied to the actual work site. The model was evaluated based on the data extracted from the actual substation to ensure reliability. We develop not only the algorithm but also the user interface and integrate them into one system so that it can be applied easily in the actual field.

2. Related Works

2.1. Prediction-based Methods for Voltage Stabilization

Prediction-based methods for voltage stabilization are mainly aimed at predicting overvoltage conditions, electrical loads, and reactive power. Various machine learning and deep learning algorithms were used for prediction.

Bulac et al. [4] proposed a method to perform real-time voltage stabilization monitoring using a multi-layer perceptron (MLP). The target class is divided into stable, unstable, and dangerous. The proposed MLP model predicts the risk level of overvoltage in a given situation by receiving voltage-related features as input.

Zhu et al. [37] proposed a method of identifying a class imbalance problem [30] in which a situation corresponding to 'unstable' in a voltage stabilization system is very rare when predicting an overvoltage situation and improving performance using an imbalance learning. The class imbalance problem was solved by amplifying the unstable situation class data through the synthetic minority oversampling technique (SMOTE) [7], and the weighted cost was set to make the model learn more focused on a small number of unstable classes. In addition, they tried to improve the model's generalization performance and increase its applicability by allowing the model to learn with new data through incremental learning continuously. Similarly, since deep learning-based methods cause a high dependence on data and annotations for high performance, Li et al. [21] proposed combining data augmentation methods to lower this dependence.

Gomez et al. [11] tried to predict the overvoltage condition early using one of the powerful classification models, the support vector machine (SVM) [25], based on the idea that it is important to quickly predict how much the voltage will be affected immediately after the situation causing the overvoltage. The significant errors that can cause overvoltage include features such as generator voltage, speed, or rotation angle, and these variables

are used as inputs for the proposed SVM model. Also, a support vector regressor (SVR), which applied SVM to a regression problem, was used to predict the electrical load, and a chaotic genetic algorithm (CGA) [34] was used in the hyperparameter determination process of SVR [13].

Cao et al. [5] proposed a method combining convolutional neural networks (CNN) [1] and deep reinforcement learning (DRL) [15] to predict overvoltage stability in the energy internet. The proposed method predicts overvoltage stability by performing a convolution operation on time-series information composed of a two-dimensional matrix and determines whether the voltage can be stabilized within a given time in the current state through DRL.

Jiapeng et al. [31] proposed a method for identifying overvoltage types of high-voltage electrical systems of multiple units based on lightweight ShuffleNet [35]. The six overvoltage types are mapped to grayscale images by the B2G algorithm, and ShuffleNet takes them as input and classifies the overvoltage types.

Ko et al. [19] proposed a hybrid model that combines a radial basis function neural network (RBFNN) [3] and a dual extended Kalman filter (DEKF) [7] with SVR for electrical load prediction. SVR and DEKF are used in the initial value setting and learning process of RBFNN, respectively.

Zheng et al. [36] used a time-series deep learning model, recurrent neural networks (RNN) [23], and an improved version, long-short term memory (LSTM) [12], for electrical load prediction. The proposed model proposes a model that predicts the electrical load of the next 12 steps with the electrical load data of the past 12 steps through the RNN architecture using the LSTM cell. The LSTM architecture was also used in the reactive power prediction study and showed better performance as the length of the input sequence length increased [14].

Like our objective, Yin et al. [32] proposed an automatic voltage stabilization method using an emotional deep neural network (EDNN) structure and an artificial emotional Q-learning algorithm. Jiajun et al. [9] proposed GridMind using deep reinforcement for autonomous voltage control in the power grid. Hanchen et al. [29] proposed the use of computationally efficient Batch Reinforcement Learning (BRL), along with a formulation strategy using the Markov Decision Process (MDP) for voltage regulation in power distribution systems.

Our study is similar to that of Yin et al. [32], Jiajun et al. [9] and Hanchen et al. [29] in that it considers automatic voltage stabilization. However, since these studies are mainly aimed at minimizing the voltage deviation across the system, they differ from ours, focusing on solving the overvoltage situation. We also paid attention to practical aspects, including the user interface. Additionally, our study is similar to that of Hossain et al. [14] and Zheng et al. [36] in that it uses RNN and LSTM architectures. However, there is a difference in that the prediction target of our proposed method is input capacity. We predict the input capacity using RNN and LSTM architectures, given that voltage and input capacity have time-series characteristics. The following subsection provides a brief introduction to RNN and LSTM.

2.2. Recurrent Neural Networks

LSTM has the architecture of a RNN. RNN is a deep learning architecture specialized for time series data processing [18,23,32]. The most straightforward architecture of RNN is

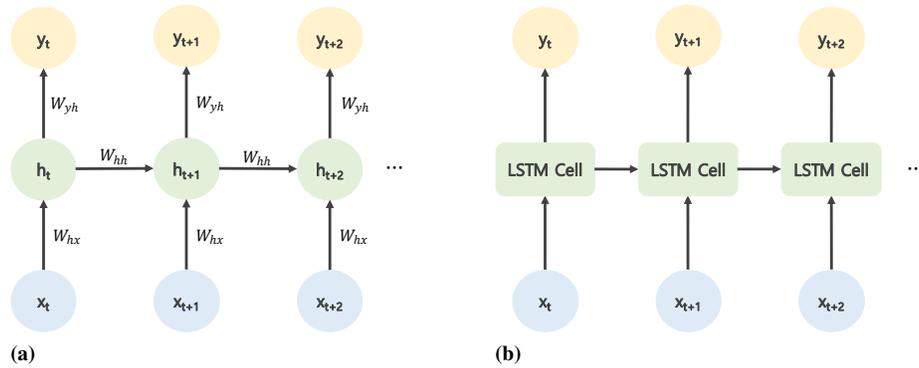


Fig. 1. A simple RNN and LSTM architecture. (a) RNN architecture. (b) LSTM architecture

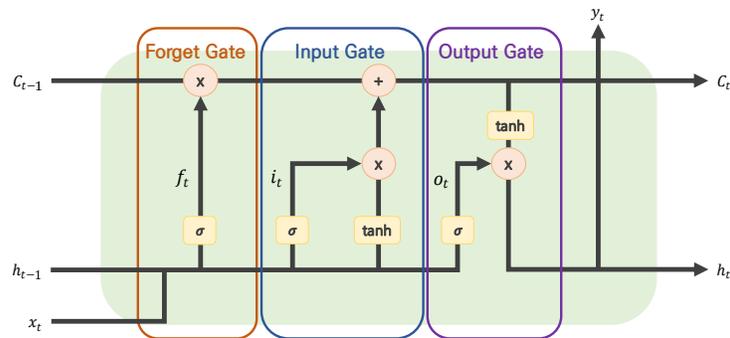


Fig. 2. The internal structure of the LSTM cell

shown in Fig. 1 (a). Like other deep learning models, the RNN goes through one or more hidden layers for a given input and returns the output. However, the unique feature of the RNN architecture is that the output of the hidden layer comes back into the input of the corresponding hidden layer. This structure considers the characteristic of sequence data that the data point of each time step is not independent of the data point of the previous time step. Information of each time step is accumulated, which is reflected in the next time step processing to process sequence data.

The LSTM refers to an architecture in which the part corresponding to the hidden layer in the RNN is replaced with an LSTM cell [12]. A simple LSTM architecture is shown in Fig. 1 (b). Although the purpose of processing sequence data is the same, LSTM operates slightly differently from general RNN processing due to this structural change. The internal structure of the LSTM cell is shown in Fig. 2. Unlike the previous RNN, the LSTM has a cell state indicated by C_{t-1} and C_t . The cell state is the path of information passing through the entire time step. By not only using the hidden state for information accumulation and reflection but by defining a separate cell state to flow information that can be utilized in the entire time step, LSTM can process longer sequences than general RNN structures and has superior performance [20]. In LSTM, the flow of information through the cell state is controlled by three gates. Forget gate determines how much information in the cell state to forget. The input gate decides how much to reflect the current input and hidden state in the cell state. The output gate determines how much of the cell state to send as the current output and hidden state. We used this LSTM architecture for input capacity prediction.

3. Proposed Method

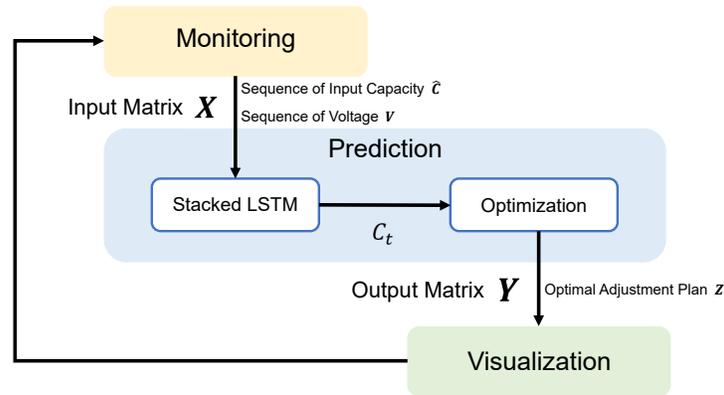


Fig. 3. The proposed automatic voltage stabilization system

In this paper, we implemented an automatic voltage stabilization system based on the input capacity prediction. The overall flow chart of the proposed system is presented in Fig. 3. First, the proposed system monitors the voltage of the applied substation. At the

same time, a time-series input matrix \mathbf{X} consisting of the monitored voltage and past input capacity is extracted for input capacity prediction. The stacked LSTM model predicts C_t , the required input capacity at the current time t , through the \mathbf{X} . Based on the predicted C_t , an optimal regulation plan for whether to operate each reactor is derived through the optimization process. This information constitutes the output matrix \mathbf{Y} . In addition, the monitored voltage and optimal regulation plan are visualized through the designed user interface. This process is repeated at fixed time intervals. The voltage regulation process can be automated through the proposed system, so the problems of existing manual operation can be solved.

The proposed system is largely divided into two parts: optimal regulation plan prediction (Section 3.1) and visualization (Section 3.2). First, a trained stacked LSTM model predicts the required input capacity from a given input. Next, a final optimal regulation plan is derived through the optimization process. Finally, information such as the derived optimal adjustment plan and voltage is visualized through the user interface.

3.1. Deriving the Optimal Regulation Plan

Input Capacity Prediction

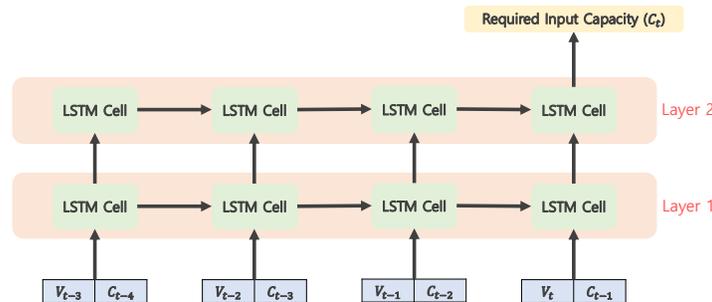


Fig. 4. Proposed input capacity prediction model architecture

The corresponding voltage and input capacity also have a time-series feature because electricity demand has a time-series characteristic. Therefore, a statistical time series model using time as a variable can be used to predict the input capacity [6]. However, given that electricity demand is a non-linear time series, a more robust prediction model than a statistical model is needed [19]. Additionally, it is also necessary to consider additional variables such as past voltages rather than using time as the only variable. Therefore, in this paper, we use the stacked LSTM, a deep learning model specialized in the sequence data processing. Through this, it is possible to consider the time series characteristics of input capacity, further improve performance by considering non-linearity, and consider additional variables other than time.

The proposed input capacity prediction model is shown in Fig. 4. The model has an LSTM architecture. In addition, by stacking two hidden layers composed of LSTM cells, more non-linearities can be considered. The stacked LSTM architecture has the advantage of learning various characteristics of time series data at each time step over the basic

LSTM architecture [33]. The input is composed of the past voltage and the input capacity along with the current voltage. In addition, the length of sequence data coming in as input is 4 (The details of the hyperparameter setting are described in Section 4.2). Therefore, the input matrix \mathbf{X} described in Fig. 3 is composed as follows:

$$\mathbf{X} = \begin{bmatrix} V_t & C_{t-1} \\ V_{t-1} & C_{t-2} \\ V_{t-2} & C_{t-3} \\ V_{t-3} & C_{t-4} \end{bmatrix} \in \mathbb{R}^{4 \times 2} \quad (1)$$

In (1), V_t means the voltage at each time point, and C_t means the input capacity at each time point. Since the purpose of prediction is C_t , which is the required input capacity at the current time t , note that C is composed of 4 starting at $t - 1$ instead of at t like V . The model predicts the currently required input capacity C_t by sequentially processing the input matrix \mathbf{X} .

Optimization

After predicting the required input capacity through the model, it is necessary to decide how to regulate the power facilities (i.e., reactors). In this paper, the optimal regulation plan is derived through the optimization formula. The optimization formula was designed considering economic feasibility and efficiency. As mentioned in Section 1, the probability of failure increases as the number of operations of the power facility increases [16]. Therefore, it is necessary to distribute the number of operations for each power facility, which can be a basis for deriving an optimal regulation plan.

The defined optimization formula is as follows:

$$\begin{aligned} & \text{minimize}_{z_1, \dots, z_n} \quad \sum_{i=1}^n \gamma_i z_i \\ \text{subject to} \quad & \sum_{i=1}^n C_i z_i \geq C_t \\ \text{subject to} \quad & \sum_{i=1}^n C_i z_i - C_t \geq C_{min} \end{aligned}$$

(3.1) is the objective function of the optimization formula. In (3.1), z_i means the operating state of each power facility of the applied system and has a value of 0 or 1. γ_i means the cumulative number of uses of the corresponding power facility. The optimization process treats the sum of the cumulative use times of each power facility as a cost, and aims to determine whether to operate each power facility in which the cost can be minimized. (3.1) is the first constraint. In (3.1), C_i means the input capacity of the corresponding power facility, and C_t means the predicted required input capacity. If there is no constraint, the optimization process will minimize the cost to zero by disabling all power facilities. Therefore, (3.1) solves this problem by forcing the optimization process to input the power equipment as much as the predicted required input capacity. (3.1) is the second constraint. In (3.1), C_{min} means the input capacity of the power facility with the smallest input capacity among all power facilities. If there is no constraint, the optimization process will try to keep the previous state when the previous input capacity is greater than the currently needed input capacity. Therefore, (3.1) solves this problem by forcing the optimization process to change the state within the expressible input capacity range. In summary, the optimization process means considering economic feasibility and

efficiency by lowering the power facility management cost and the chance of damage by forcing the power facility to operate first with the lowest cumulative use frequency.

Through the optimization, an optimal regulation plan is derived. The derived optimal regulation plan becomes the output matrix \mathbf{Y} of Fig. 3, and its composition is as follows:

$$\mathbf{Y} = \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix} \in \mathbb{R}^n \quad (z_i \in \{0, 1\}) \quad (5)$$

In (5), \mathbf{Y} means the optimal regulation plan and contains information on whether each optimized power facility operates.

3.2. Visualization

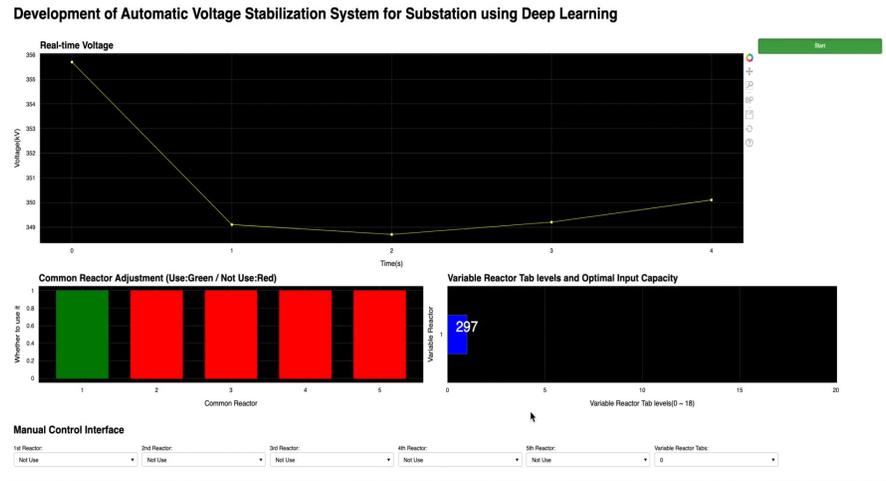


Fig. 5. Designed user interface

The derived optimal regulation plan is visualized through a designed user interface and information on the recorded voltage sequence. The user interface makes it easy to see how the system works and its results. The designed user interface is shown in Fig. 5.

In Fig. 5, when the start button at the top right is pressed, the user interface is operated. The user interface consists of three elements. First, the voltage graph appears at the top. The voltage at the latest 20-time points is expressed, and the overall flow of the voltage can be checked. Second, the optimal regulation plan is visualized in the center. Whether each of the derived power facilities operates and the predicted input capacity value are simultaneously expressed. The green bar means active, and the red bar means inactive. Finally, at the bottom is a manual operation button. In addition to the results automatically predicted by the system, it can be applied when a manual operation is required. As mentioned earlier, the user interface is updated according to a predefined time interval, and prediction and visualization are executed sequentially.

4. Experimental Results

In this section, the performance of the proposed system is evaluated. It is divided into the evaluating input capacity prediction model and the actual operation analysis.

4.1. Experimental Environment and Dataset

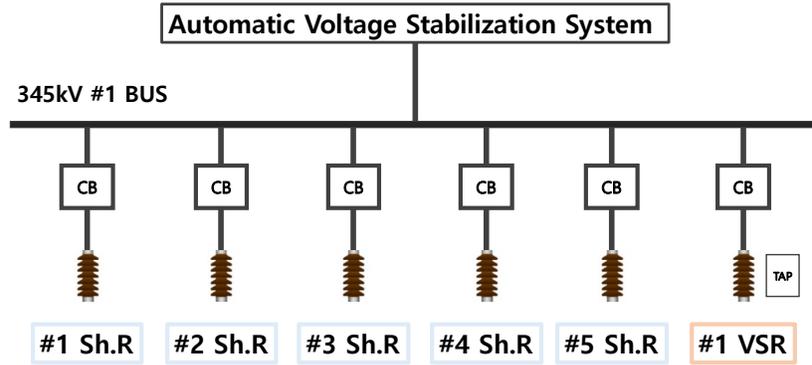


Fig. 6. Assumed substation environment

Before evaluation, it is necessary to assume the environment of the substation to which the system is applied. The considered substation environment is shown in Fig. 6. We assume that the applied substation consists of one 345 kV bus. Additionally, it consists of five Sh.R and one variable shunt reactor (VSR), each with an input capacity of 200 Mvar. VSR is a reactor that can control power more delicately through a tap device. The tap of the VSR consists of a total of 18 stages [16]. Unlike the existing Sh.R, VSR operates on a tap basis, so the output matrix in (2) should be changed as follows:

$$\mathbf{Y} = \begin{bmatrix} z_1 \\ \vdots \\ z_5 \\ \hat{z}_1 \end{bmatrix} \in \mathbb{R}^6 \quad (z_i \in \{0, 1\}, \quad \hat{z}_1 \in \{0, \dots, 18\}) \quad (6)$$

In (6), \hat{z}_1 means the operating state of the VSR and has a value between 0 and 18.

The experimental data were collected in the real substation environment defined above. The substation automatically saves various information, including voltage, according to defined intervals (*i.e.*, one minute). The data contains operation information for each power facility constituting the substation system between 2019 and 2021. Data features include uptime, generation load, transmission load, input capacity, and ancillary information such as temperature, wind speed, and precipitation. We extracted only information about voltage and input capacity required for prediction. The total data size is about 450,000 data points; we used 25% as test data and the rest as training data.

4.2. Input Capacity Prediction Performance

Table 1. Input capacity prediction model performance (RMSE)

Model	Input Combination					
	\mathbf{X}_1	\mathbf{X}_2	\mathbf{X}_3	\mathbf{X}_4	\mathbf{X}_5	\mathbf{X}_6
XGBoost	183.13	79.07	182.22	20.57	20.41	14.32
LightGBM	183.12	124.93	179.04	21.13	19.59	14.01
RandomForest	183.13	78.55	182.15	20.60	20.00	14.14
GradientBoost	183.15	148.68	182.08	20.44	19.66	19.72
ElasticNet	184.12	180.35	184.10	67.93	32.63	32.54
DNN	184.90	138.97	183.09	20.53	19.54	13.97
LSTM	183.69	143.28	183.39	20.54	19.25	13.31
Stacked LSTM	183.69	185.30	182.85	20.56	19.30	12.86

First, we evaluated the performance of the input capacity prediction model. The purpose of the model is to predict the required input capacity given the appropriate inputs. Several models were trained and evaluated to find the optimal model and input combinations. Root mean squared error (RMSE) was used as the evaluation metric.

The overall result is shown in Table 1. A total of eight machine learning and deep learning models were trained and evaluated. XGBoost [8], LightGBM [17], and Gradient-Boost [22] are machine learning algorithms that show strong performance as tree boosting ensemble methods. RandomForest [10] is an ensemble model using the bagging method, and it is a model that reinforces the randomness of data and features. ElasticNet [38] is a regulated regression model that combines L1 and L2 regulation into linear regression. DNN is a structure in which several hidden layers are stacked in general artificial neural networks (ANN) [28], and we constructed a model with four hidden layers. As input combinations, six combinations were evaluated. \mathbf{X}_1 means only the current voltage at t is used as an input. \mathbf{X}_2 means using input time information such as a month, day, hour, etc., considering seasonal characteristics along with the current voltage at t . \mathbf{X}_3 means using the voltage sequence of the past time as an input together with the current voltage of time t . \mathbf{X}_4 means that only the input capacity at $t - 1$ is used as input. \mathbf{X}_5 means that the past input capacity of the same length as \mathbf{X}_3 is used as input. \mathbf{X}_6 means to use a sequence composed of the input capacity of the past time as an input together with the voltage sequence of \mathbf{X}_3 .

All models achieved the best performance when \mathbf{X}_6 was used as the input combination. As can be seen when \mathbf{X}_4 and \mathbf{X}_5 are used as inputs, the model's performance is significantly improved when it can explore the past input capacity or input capacity sequence rather than when voltage alone is used. However, the performance is further enhanced when the past voltage and the current voltage are used together with the past input capacity sequence (\mathbf{X}_6). Additionally, the model performance of the RNN architecture specialized for sequence data processing was the best among all models, and the performance of the stacked LSTM model was the best with RMSE 12.86. Therefore, stacked LSTM was selected as the final model, and it was decided to use current voltage, past voltage, and past input capacity together as the input combination.

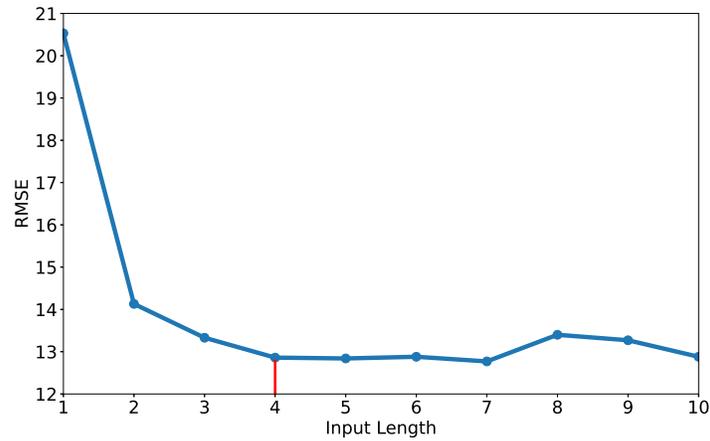


Fig. 7. Performance of the stacked LSTM model by the length of the input sequence

When using a sequence of voltage and input capacity as input, additional evaluation was performed to select the optimal length of the sequence, that is, to what point in the past voltage and input capacity information will be used. The results are shown in Fig. 7. In Fig. 7, the model showed significant performance improvement until the sequence length reached 4. After this, there was no significant performance improvement thereafter, so we set the optimal sequence length to 4.

4.3. Operation Analysis

Table 2. Operational Analysis Results

Item	Time Point				
	t	$t + 1$	$t + 2$	$t + 3$	$t + 4$
Voltage (kV)	353.8	349.8	354.5	349.7	345.5
Predicted Input Capacity (Mvar)	735	697	897	697	497
#1 Sh.R	1	1	1	1	1
#2 Sh.R	0	0	0	0	0
#3 Sh.R	0	0	1	1	1
#4 Sh.R	1	1	1	1	0
#5 Sh.R	1	1	1	0	0
#1 VSR (Tap Position)	9	1	1	1	1

Second, we conducted an operational analysis to see if the system actually works well. The results are shown in Table 2. In addition, Table 3 shows the assumed cumulative numbers of uses for each reactor in the optimization process.

Table 3. Assumed Cumulative Use Count

	#1 Sh.R	#2 Sh.R	#3 Sh.R	#4 Sh.R	#5 Sh.R	#1 VSR
Cum. Num. of Uses	200	150	100	80	50	20

In Table 2, system operation results for five consecutive time points from t to $t + 4$ are presented. Additionally, information on items such as voltage, input capacity, and reactor operation status at each time point is presented together. In more detail, at time t , the voltage was observed to be 353.8 kV, and the model predicted that an input capacity of 735 Mvar was required. For the predicted input capacity, the operating state of each Sh.R and the tap position of the VSR were determined through an optimization process. After that, the observed voltage at time $t + 1$ is 349.8 kV, which is lower than before. This is because reactors consumes reactive power equal to previously input capacity to lower the voltage. Additionally, for the lower voltage, the model predicted that an input capacity of 697 Mvar lower than the time t was required. This shows that the input capacity prediction model predicts the appropriate input capacity considering the level of voltage. When checking the operation state of each reactor at time $t + 1$, it can be seen that the tap position of the VSR has changed from 9 to 1. This means that voltage adjustment was performed by changing the tap of the least frequent VSR through the optimization process in consideration of the number of uses for each reactor assumed in Table 3. In other words, it can be seen that the optimization process is properly distributing the operation for each reactor with the number of uses as a cost as intended. These results are also the same at all time points thereafter, including time $t + 2$. According to the experimental results, it can be seen that an automatic voltage regulation system can be effectively implemented through the designed system, and it can be confirmed that the goal of the study and the required performance requirements can be met.

5. Conclusion

This paper covered the development of an automatic voltage stabilization system for voltage regulation automation. First, a trained stacked LSTM model was designed to predict the input capacity required for a given situation using actual voltage and input capacity data. In addition, it was possible to derive the optimal regulation plan considering the economic feasibility of power facility operation by using the optimization method. Finally, the user interface shows how the model works as intended.

In this paper, only two variables of time-series voltage data and input capacity were used as inputs when training the model to predict the optimal input capacity. However, in addition to these two variables, there are other variables that could affect voltage changes, such as weather, season, temperature, and humidity. It is expected that future studies can use these variables to improve model performance considering complex voltage environments.

This automatic voltage stabilization system is more effective and economic than the conventional voltage control system. This not only enables a stable power supply but also increases the lifespan of power facilities and reduces the cost burden on the company for facility failure. Additionally, this paper can also contribute to the goals of informatization and securing big data in the substation field.

Acknowledgments. This research was supported by the MSIT (Ministry of Science, ICT), Korea, under the High-Potential Individuals Global Training Program) (2021-0-01549) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation).

References

1. Albawi, S., Mohammed, T.A., Al-Zawi, S.: Understanding of a convolutional neural network. In: 2017 International Conference on Engineering and Technology (ICET). pp. 1–6 (2017)
2. Almeshaei, E., Soltan, H.: A methodology for electric power load forecasting. *Alexandria Engineering Journal* 50(2), 137–144 (2011), <https://www.sciencedirect.com/science/article/pii/S1110016811000330>
3. Broomhead, D.S., Lowe, D.: Radial basis functions, multi-variable functional interpolation and adaptive networks. Tech. rep., Royal Signals and Radar Establishment Malvern (United Kingdom) (1988)
4. Bulac, C., Triştiu, I., Mandiş, A., Toma, L.: On-line power systems voltage stability monitoring using artificial neural networks. In: 2015 9th International Symposium on Advanced Topics in Electrical Engineering (ATEE). pp. 622–625 (2015)
5. Cao, J., Zhang, W., Xiao, Z., Hua, H.: Reactive power optimization for transient voltage stability in energy internet via deep reinforcement learning approach. *Energies* 12(8) (2019), <https://www.mdpi.com/1996-1073/12/8/1556>
6. Chakhchoukh, Y., Panciatici, P., Mili, L.: Electric load forecasting based on statistical robust methods. *IEEE Transactions on Power Systems* 26(3), 982–991 (2011)
7. Chawla, N.V., Bowyer, K.W., Hall, L.O., Kegelmeyer, W.P.: Smote: synthetic minority over-sampling technique. *Journal of artificial intelligence research* 16, 321–357 (2002)
8. Chen, T., Guestrin, C.: Xgboost: A scalable tree boosting system. In: Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining. pp. 785–794 (2016)
9. Duan, J., Shi, D., Diao, R., Li, H., Wang, Z., Zhang, B., Bian, D., Yi, Z.: Deep-reinforcement-learning-based autonomous voltage control for power grid operations. *IEEE Transactions on Power Systems* 35(1), 814–817 (2020)
10. Friedman, J.H.: Greedy function approximation: a gradient boosting machine. *Annals of statistics* pp. 1189–1232 (2001)
11. Gomez, F.R., Rajapakse, A.D., Annakkage, U.D., Fernando, I.T.: Support vector machine-based algorithm for post-fault transient stability status prediction using synchronized measurements. *IEEE Transactions on Power Systems* 26(3), 1474–1483 (2011)
12. Hochreiter, S., Schmidhuber, J.: Long short-term memory. *Neural Computation* 9(8), 1735–1780 (1997)
13. Hong, W.C.: Hybrid evolutionary algorithms in a svr-based electric load forecasting model. *International Journal of Electrical Power & Energy Systems* 31(7), 409–417 (2009), <https://www.sciencedirect.com/science/article/pii/S0142061509000507>
14. Hossain, N., Hossain, S.R., Azad, F.S.: Univariate time series prediction of reactive power using deep learning techniques. In: 2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST). pp. 186–191 (2019)
15. Hua, H., Qin, Y., Hao, C., Cao, J.: Optimal energy management strategies for energy internet via deep reinforcement learning approach. *Applied Energy* 239, 598–609 (2019), <https://www.sciencedirect.com/science/article/pii/S0306261919301746>
16. Kang, Y.W., Seo, C.S., Han, B.J., Jang, Y.H., Song, B.C., Kim, D.H.: The development of voltage stability system(vss) device for variable shunt reactor(vsr). Proceedings of the Korean Electrical Society Conference pp. 881–882 (2021)

17. Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., Liu, T.Y.: Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems* 30 (2017)
18. Kim, K., Lee, J.H., Lim, H.K., Oh, S.W., Han, Y.H.: Deep rnn-based network traffic classification scheme in edge computing system. *Computer Science and Information Systems* 19(1), 165–184 (2022)
19. Ko, C.N., Lee, C.M.: Short-term load forecasting using svr (support vector regression)-based radial basis function neural network with dual extended kalman filter. *Energy* 49, 413–422 (2013), <https://www.sciencedirect.com/science/article/pii/S0360544212008766>
20. Lee, M.C., Chang, J.W., Hung, J.C., Chen, B.L.: Exploring the effectiveness of deep neural networks with technical analysis applied to stock market prediction. *Computer Science and Information Systems* 18(2), 401–418 (2021)
21. Li, Y., Zhang, M., Chen, C.: A deep-learning intelligent system incorporating data augmentation for short-term voltage stability assessment of power systems. *Applied Energy* 308, 118347 (2022), <https://www.sciencedirect.com/science/article/pii/S0306261921015944>
22. Liaw, A., Wiener, M., et al.: Classification and regression by randomforest. *R news* 2(3), 18–22 (2002)
23. Medsker, L.R., Jain, L.: Recurrent neural networks. *Design and Applications* 5, 64–67 (2001)
24. Park, J.H.: Voltage regulating device (Sh. C) automatic operation system expansion and construction. *Journal of Electrical World Monthly Magazine* , 28–34 (2013), <http://www.dbpia.co.kr/journal/articleDetail?nodeId=NODE02084990>
25. Sain, S.R.: *The nature of statistical learning theory* (1996)
26. Viawan, F.A., Karlsson, D.: Combined local and remote voltage and reactive power control in the presence of induction machine distributed generation. *IEEE Transactions on Power Systems* 22(4), 2003–2012 (2007)
27. Viawan, F.A., Karlsson, D.: Voltage and reactive power control in systems with synchronous machine-based distributed generation. *IEEE Transactions on Power Delivery* 23(2), 1079–1087 (2008)
28. Wang, S.C.: *Artificial Neural Network*, pp. 81–100. Springer US, Boston, MA (2003), https://doi.org/10.1007/978-1-4615-0377-4_5
29. Xu, H., Dominguez-Garcia, A.D., Sauer, P.W.: Optimal tap setting of voltage regulation transformers using batch reinforcement learning. *IEEE Transactions on Power Systems* 35(3), 1990–2001 (2020)
30. Xu, Y., Dong, Z.Y., Zhao, J.H., Zhang, P., Wong, K.P.: A reliable intelligent system for real-time dynamic security assessment of power systems. *IEEE Transactions on Power Systems* 27(3), 1253–1263 (2012)
31. Yang, J., Yang, S., Song, K., Liu, Z.: Research on overvoltage identification method of emus high voltage electrical system based on deep learning. In: *2021 IEEE 4th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)*. vol. 4, pp. 1985–1990. IEEE (2021)
32. Yin, L., Zhang, C., Wang, Y., Gao, F., Yu, J., Cheng, L.: Emotional deep learning programming controller for automatic voltage control of power systems. *IEEE Access* 9, 31880–31891 (2021)
33. Yu, L., Qu, J., Gao, F., Tian, Y.: A novel hierarchical algorithm for bearing fault diagnosis based on stacked lstm. *Shock and Vibration* 2019 (2019)
34. Yuan, X., Yuan, Y., Zhang, Y.: A hybrid chaotic genetic algorithm for short-term hydro system scheduling. *Mathematics and Computers in Simulation* 59(4), 319–327 (2002), <https://www.sciencedirect.com/science/article/pii/S0378475401003639>
35. Zhang, X., Zhou, X., Lin, M., Sun, J.: Shufflenet: An extremely efficient convolutional neural network for mobile devices. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. pp. 6848–6856 (2018)

36. Zheng, J., Xu, C., Zhang, Z., Li, X.: Electric load forecasting in smart grids using long-short-term-memory based recurrent neural network. In: 2017 51st Annual Conference on Information Sciences and Systems (CISS), pp. 1–6 (2017)
37. Zhu, L., Lu, C., Dong, Z.Y., Hong, C.: Imbalance learning machine-based power system short-term voltage stability assessment. *IEEE Transactions on Industrial Informatics* 13(5), 2533–2543 (2017)
38. Zou, H., Hastie, T.: Regularization and variable selection via the elastic net. *Journal of the royal statistical society: series B (statistical methodology)* 67(2), 301–320 (2005)

Jiyong Moon, Department of Business Administration, Dongguk University, Seoul, Korea.

Minyeong Son, Department of Medical Biotechnology, Dongguk University, Seoul, Korea.

Byeongchan Oh, Department of Statistics, Dongguk University, Seoul, Korea.

Jeongpil Jin, Department of Industrial System Engineering, Dongguk University, Seoul, Korea.

Younsoon Shin, Department of Computer Science, Dongguk University, Seoul, Korea.

Received: May 09, 2022; Accepted: October 26, 2023.