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Optimal Voltage Regulation Method for Distribution Systems with Distributed Generation Systems Using the Artificial Neural Networks

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Abstract – With the development of industry and the improvement of living standards, better quality in power electric service is required more than ever before. This paper deals with the optimal algorithms for voltage regulation in the case where Distributed Storage and Generation (DSG) systems are operated in distribution systems. It is very difficult to handle the interconnection issues for proper voltage managements, because the randomness of the load variations and the irregular operation of DSG should be considered. This paper proposes the optimal on-line real time voltage regulation methods in power distribution systems interconnected with the DSG systems. In order to deliver suitable voltage to as many customers as possible, the optimal sending voltage should be decided by the effective voltage regulation method by using artificial neural networks to consider the rapid load variation and random operation characteristics of DSG systems. The simulation results from a case study show that the proposed method can be a practical tool for the voltage regulation in distribution systems including many DSG systems.

Keywords: Distribution system, Distributed Storage and Generation (DSG), Voltage regulation, Artificial neural network, On line real time method, Line Drop Compensation(LDC) method

1. Introduction

As one of the countermeasures against daily load factors worsening and global environmental issues, DSG systems such as photovoltaic cells, fuel cells and secondary battery storage, are being interconnected with power distribution systems. Under these circumstances, to deliver reasonable voltage to as many customers as possible, optimal voltage regulation methods in distribution systems need to be developed [1-2]. The Bank Line Drop Compensation (LDC) method is currently used at many utilities to maintain customer voltages within the allowable limits (220±6%). The method is based on the concept of an imaginary standard feeder to represent total feeder characteristics [3-4]. However, the determination of LDC setting values with the imaginary standard feeder configurations is difficult. Furthermore, DSG systems interconnected with distribution systems make voltage regulation very complicated. In this paper, a real time voltage regulation method using neural networks trained by error back propagation algorithm is presented to consider the rapid load variations and the random operation characteristics of DSG systems. Numerical examples are shown in order to verify the efficiency of the proposed method.

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2. Modeling of Distribution Systems with DSG

2.1 Load modeling for primary feeder

At first, one section is defined to represent a load modeling of the primary feeder [5-6]. It is determined by properly dividing a primary feeder according to certain rules such as changing point of wire size, branch point, location of voltage regulators, etc. Then, the total load amount in a feeder is estimated by summing both load amount of low voltage customers (kwh) and high voltage customers (kw) as shown in Fig. 1.

Real current value of a section can be calculated as:

$$I_{(n)} = i_{(n)} \times \frac{I_{SS}}{i_{SUM}} \tag{1}$$

where, $I_{(n)}$ and $i_{(n)}$ are the real and estimated currents of n

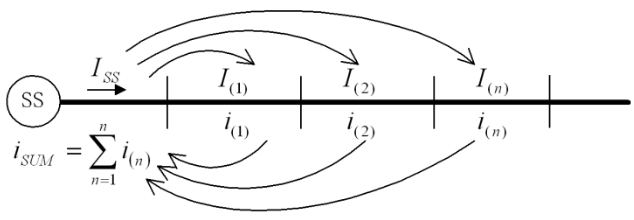


Fig. 1. Load modeling of primary feeders

section, I_{SS} is the measured (real) total current of the primary feeder, and i_{SUM} is the estimated total current.

Eq. (1) represents that the real value of each section can be obtained from the relationship between estimation value and measured value.

2.2 Algorithm for voltage profile calculation

The typical algorithms could deal with the voltage drop of a section by considering the power flow from distribution substations(sources) only as one direction [7-8]. However, the voltage rise can be also considered in the case where the reverse power flow of DSG is occurred. For doing this, this paper proposes an idea that the load current (I) is divided into 2 separate parts of real part (I_p) and imaginary part (I_q), in order to properly consider the load flow direction and power factor (imaginary power, Q) of DSG. As shown in Fig. 2, the forward power flow from sources to loads and the lead power factor do not exist in the 3rd quadrant, and then the reverse power flow and lag power factor must be considered at the voltage profile calculation. Thus, the voltage rise according to the reverse power flow occurs in the quadrant. In the same way, the voltage profile equations in 1st, 2nd and 4th quadrants can be obtained.

The typical equation for voltage drop is expressed by △V = Z (impedance) × I (current). The new equation can be expanded by considering the concepts of 4 quadratics and real and reactive currents as : where, k is wire connection type(single phase k=1, 3 phase 3wire k=√3, 3 phase 4wire k=1). $I_{sp(n)}$ and $I_{sq(n)}$ are real and reactive inflow current in nth section as shown in Fig. 3, $I_{Rp(n)}$ and $I_{Rq(n)}$ are real and reactive outflow current in nth section, $r_{(n)}$ and $x_{(n)}$ are resister and reactance in nth section, $\triangle V_{(n)}$ is voltage profile in nth section.

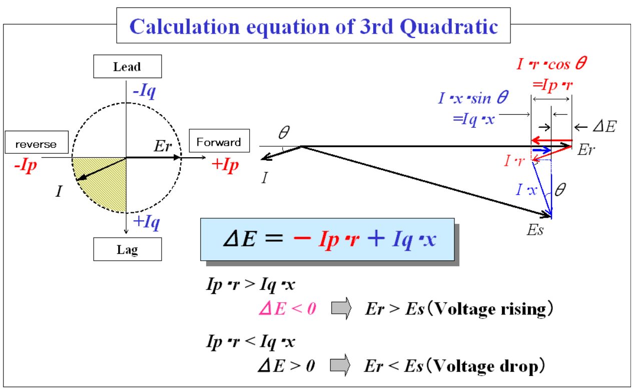


Fig. 2. Voltage profile calculation of 3rd Quadratic

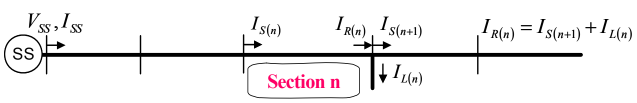


Fig. 3. Inflow and outflow current in n section

$$\Delta V_{(n)} = k \cdot \left\{ \frac{I_{Sp(n)} + I_{Rp(n)}}{2} \cdot r_{(n)} + \frac{I_{Sq(n)} + I_{Rq(n)}}{2} \cdot x_{(n)} \right\} \tag{2}$$

where, k is wire connection type(single phase k=1, 3 phase 3wire k=√3, 3 phase 4wire k=1). $I_{sp(n)}$ and $I_{sq(n)}$ are real and reactive inflow current in nth section as shown in Fig. 3, $I_{Rp(n)}$ and $I_{Rq(n)}$ are real and reactive outflow current in nth section, $r_{(n)}$ and $x_{(n)}$ are resister and reactance in nth section, $\triangle V_{(n)}$ is voltage profile in nth section.

3. Algorithm for On-line Real Time Voltage Regulation Method

3.1 Existing LDC methods

The decision problem of optimal sending voltages at voltage regulator of Load-Ratio control Transformer (LRT) by the LDC method as shown in Fig. 4 is to find the optimal LDC setting values to deliver suitable voltages to as many customers as possible. The existing LDC method firstly determines ideal optimal sending voltages, and then obtains optimal setting values by the statistical analysis according to the relationship between idea optimal sending voltages and total load currents [9-12]. The method presents the idea that for the worst conditioned case having the biggest voltage drop and a severe voltage fluctuation, if all customers throughout this feeder are to be maintained within the allowable voltage limits and also have reasonable voltage distributions.

However, the existing LDC method are not suitable for consideration of the rapid load pattern variations and radon operation characteristics of DSG systems because these methods are basically operated with the same LDC setting values for a long real time period once they are fixed. An on-line real time voltage regulation method whose LDC setting values are appropriately decided by the load variations is desirable for solving those problems. But, it requires computational burden and a large quantity of on-line measurement data. This paper proposes an on-line real time voltage regulation method using artificial neural

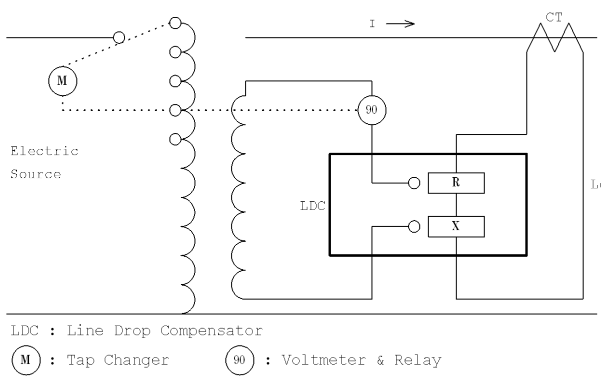


Fig. 4. Concepts for LDC methods

networks (ANN), since the voltage regulation method is considered as the pattern recognition problem. This proposed method can be expected to reduce the computational burden and telemetering devices by using only the measurement data of active power at each feeder. Generally, ANN shows the error robustness and provides satisfactory solutions based on the trained knowledge. Also, ANN has the capability of fast data processing by parallel processing. ANN is designed to improve the voltage compensation capability of LRT. It dynamically determines the most appropriate LDC setting values by recognizing the load pattern and operation pattern of DSG systems for each time period.

3.2 Concepts of artificial neural networks

This study adopts the multi-layer feed-forward machine of Rumelhart et [12-14] The model is trained by error back propagation algorithm and adjustment process of interconnecting weights(Wi) and thresholds(θ) is repeated until the recognition capability is obtained. The input and output relationship of multi-layer perceptron is represented as Eq. (3).

$$u = f\left(\sum_{i=0}^{N-1} W_i \cdot X_i(t) - \theta\right) \tag{3}$$

where, y : output value, Xi : input value, Wi : weighting factor, θ : threshold value, N : layer number, f : nonlinear function

And, the improvement algorithm for weighting factor based on the generalized delta rule is as follows :

$$\Delta_p W_{ji} = n(t_{pj} - o_{pj})i_{pi} = n\delta_{pj}i_{pi} \tag{4}$$

where, n: learning rate, tpj : j component of pth target output pattern, Opj : j component of pth real(computed) output pattern, ipi : i component of pth input pattern, δpj : error of target and real output.

3.3 Design of ANN structure

A separate-type neural network model for the determination of the LDC setting values is designed as shown in Fig. 5, to consider the load variation as well as the operation characteristics of DSG systems. A total of n neural networks are built to consider the operation patterns of DSG systems, which are divided into n levels such as 0%, 25%, 50%, 75% and 100% based on the rated output of DSGS systems. The individual neural network, ANNs, has input units. 25 hidden units and 7 output units through learning experience, and determines the equivalent impedance Zs for s=1,2,.....,n with the input Itotal, Pt for t=1,2,......g. Itotal, Pt and g are the total current of the LRT, active power and total feeder number, respectively. If the impedance is divided into k levels, the total number of output units in ANNs is k. Thus, the individual neural

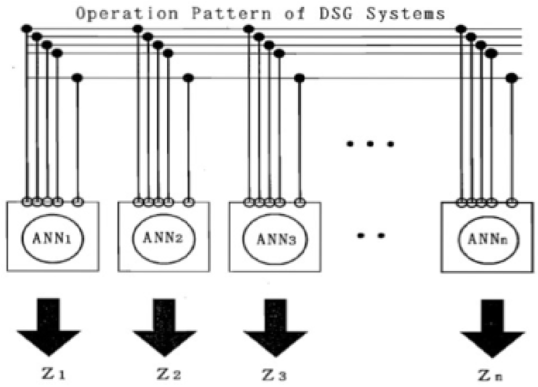


Fig. 5. Design of separate-type ANN model

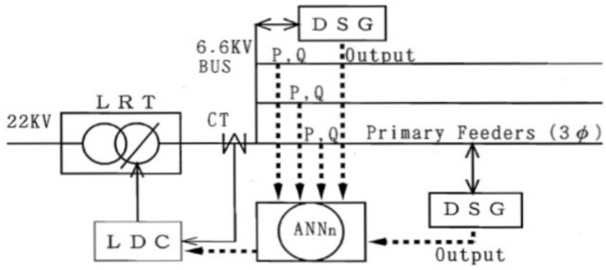


Fig. 6. On-line real time method using neural networks

network determines the appropriate impedance by outputting 1 for the unit with the most similar load pattern to that given, and 0 for the other units. Then, the neural network output corresponding to the operation patterns of DSG systems is decided, which is the impedance of the LDC setting values. Therefore, an outline of the on-line real time voltage regulation using the neural networks can be shown as given in Fig. 6. The dotted lines are the information flow of on-line real time control.

3.4 Training set build-up

The pattern recognition capability of neural networks is dependent upon the quantity and quality of the training set within the possible learning boundary, the type and magnitude of the section load in a distribution system should be appropriately divided. For the levels W, P of the load type and magnitude, respectively, the number of ANNs training patterns becomes Pw. The load types are classified into three groups such as the residential (R), the commercial (C) and the industrial (I). The load magnitudes are also divided into 4 levels, 100%, 80%, 60% and 40% on the basis of peak load. We now describe the building procedure of the ANNs training set in the following:

[step1] For n-Pw load level combinations, execute the voltage profile calculation of chapter 2. Also, calculate the total load current of LRT, the feeder active and reactive powers, the customer voltages of all nodes, and the optimal sending voltage for each time period.

[step2] For n-Pw load patterns, calculate the equivalent impedance (Zeq) corresponding to the load center voltage (Vo) which is provided by experience.
[step3] Divide the impedance of [step2] into k levels between the minimum and the maximum.
[step4] Obtain the knowledge patterns with the values of [step1] as the input pattern and the values of [step3] as the output pattern. Then, divide the knowledge patterns into n operation patterns of DSG systems, and build n training sets for ANNs, s=1,2, ..., n.

The flowchart of building the training set as mentioned above is as shown in Fig. 7.

3.5 Neural network modeling

In this paper, 2 types of neural network models are presented to evaluate the pattern recognition capability. One is a separate-type neural network model as shown in Fig. 5 and the other is a single-type model. The latter has one neural network and considers the operation pattern of DSG systems as a unit of input patterns. Table 1 shows the experimental conditions of the models. ANNs training of the separate-type model requires approximately 2,000 presentations as shown in Fig. 8 and the values of the learning rate and the momentum factor are determined as 0.1 and 0.2 through learning experience, respectively.

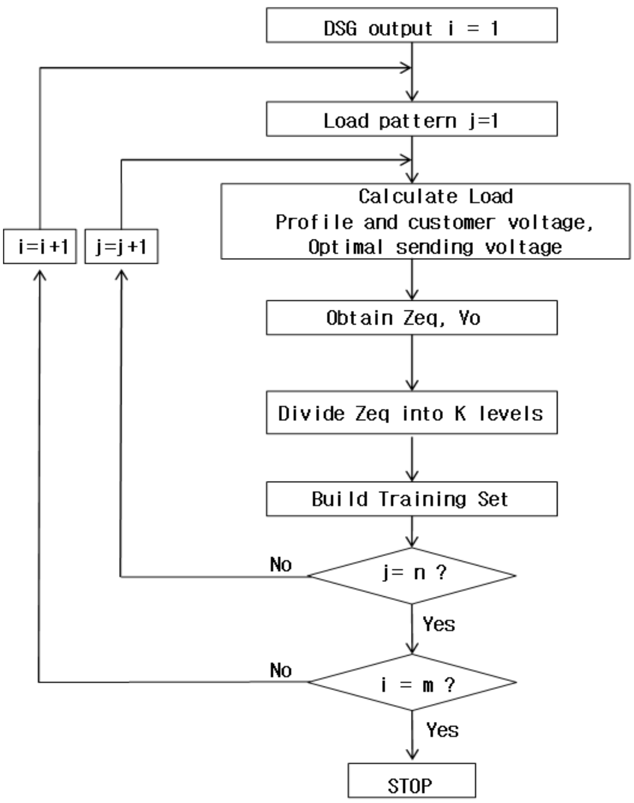


Fig. 7. Flowchart for training set building of ANNs

Table 1. Experimental Conditions of ANN models

ANN Model	Input Pattern	Output Pattern	Training Pattern	ANN No.
Single Model	- DSG output - Total Current - Active Power of each feeder	Impedance	320	1
Separate Model	-Total Current -Active Power of each Feeder	Impedance	64	5

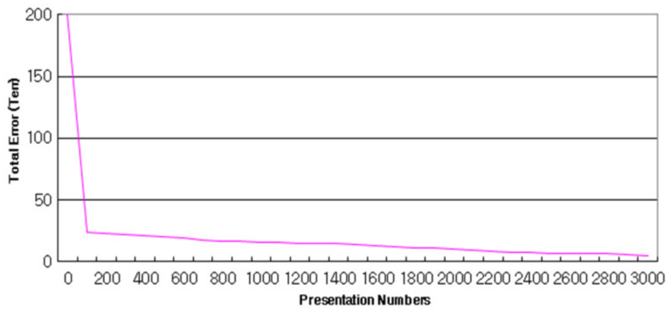


Fig. 8. Iteration number of ANNs

4. Numerical Examples

4.1 Performance index

The criteria of the customer voltage distributions according to the operation of DSG systems can be evaluated by the degree of how close customer voltages are maintained to the nominal voltage. Therefore, a performance index can be defined as a form of the squared differences between the nominal voltage and customer voltages of all nodes as follows:

$$PI(t) = \sum_{K=1}^{K}[V1(t,k) - Vstd]^2 + [Vstd - V2(t,k)]^2 \tag{5}$$

where, PI(t) is a performance index of time interval t, K is the total number of nodes, V1(t,k) and V2(t,k) are the first and last customer voltages of each node and is the nominal voltage (220V). It is clear that the customer voltage distributions become better with the smaller value of PI(t).

4.2 Modeling parameters

① Fig. 8 and Table 1 show a model 22.9kV distribution system and a section data for primary feeders, respectively.
② The load patterns of 100~20% load rates based on the 45MVA are assumed as shown in Fig. 9, which represent a ratio of the hourly load to the peak load.
③ The voltage drops of the pole transformer, secondary feeder and lead wire at the peak load are 4.0V, 8.0V and 4.0V, respectively.

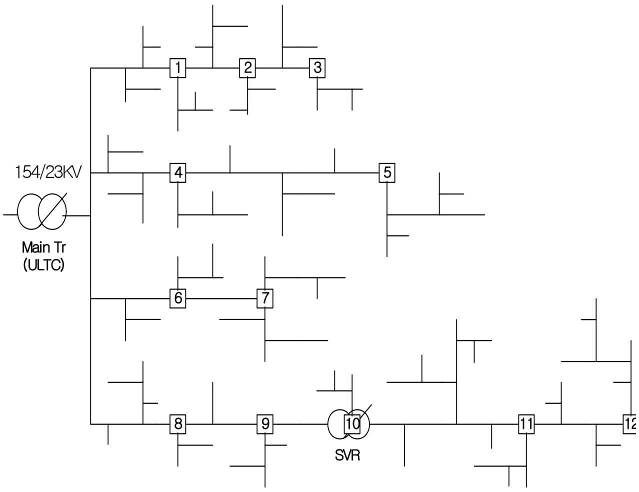


Fig. 8. Model distribution systems

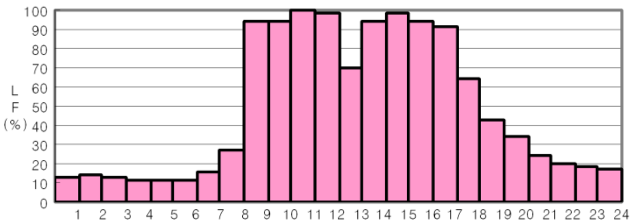


Fig. 9. Daily load curve of main transformer

Table 2. Section data for primary feeders

Fedder number	Section number	Node number		Impedance		Length (km)	Pole Tr. Tap	Load (%)
		From	To	R(Ω/km)	X(Ω/km)			
1	1	0	1	0.182	0.391	2.0	22900/230	5%
	2	1	2	0.182	0.391	2.0	22900/230	10%
	3	2	3	0.182	0.391	5.0	22900/230	10%
2	4	0	4	0.182	0.391	5.0	22900/230	10%
	5	4	5	0.304	0.440	10.0	21400/230	15%
3	6	0	6	0.182	0.391	4.0	22900/230	15%
	7	6	7	0.182	0.391	4.0	22900/230	10%
4	8	0	8	0.182	0.391	3.0	22900/230	5%
	9	8	9	0.182	0.391	5.0	22900/230	5%
	10	9	10	0.182	0.391	5.0	22900/230	5%
	11	10	11	0.304	0.440	10.0	21400/230	5%
	12	11	12	0.304	0.440	5.0	21400/230	5%

④ The voltage profiles of primary feeders can be calculated by the load flow of the Gauss-Seidel method. And the standard tap changing points of pole transformers are considered as 5% voltage drop at the peak load on the basis of 22.9kV.

4.3 Simulation results

For the control strategy evaluation of this study, we use the model system of Fig. 8 and Table 2 and perform the simulation under the assumption that three load types vary randomly between 40% and 100% of the peak load. The training data represents 64 load patterns (time intervals) of the case where DSG systems are not operated. The performance index of Table 3 indicates that the single-type ANN model cannot have proper pattern recognition capability, whereas the separate-type ANN model is more effective on the on-line real time voltage regulation. We will thus concentrate on the separate-type ANN model

Table 3. Evaluation results of ANN models

ANN Model	Performance Index (Training data)
Separate Model	4845.9
Single Model	9206.3
Existing LDC Method	5748.2

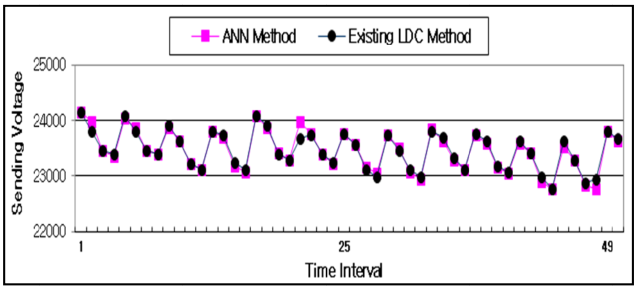
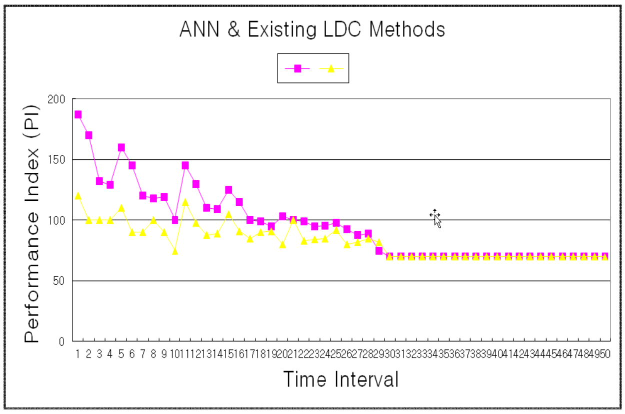
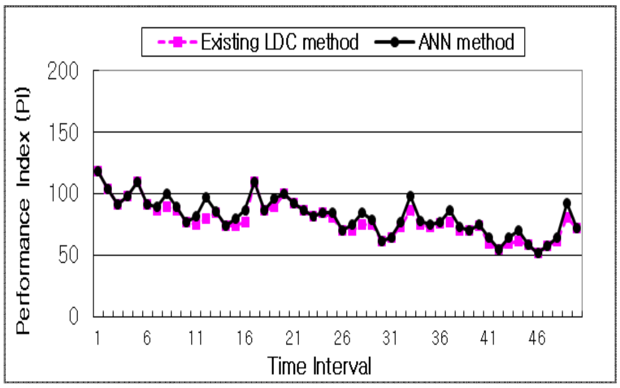


Fig. 10. Sending voltage by ANN and existing LDC methods



(a) Several outputs of DSG systems



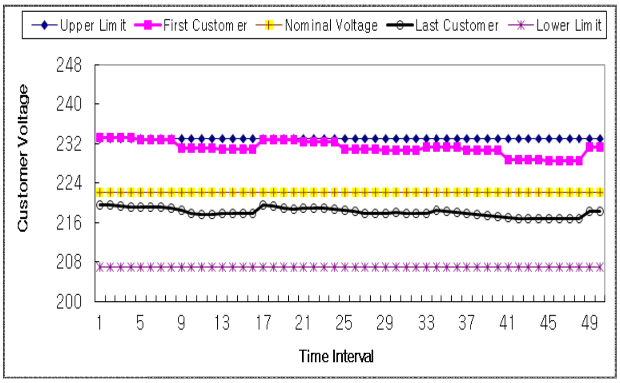
(b) 0% outputs of DSG systems

Fig. 11. Performance index of each method

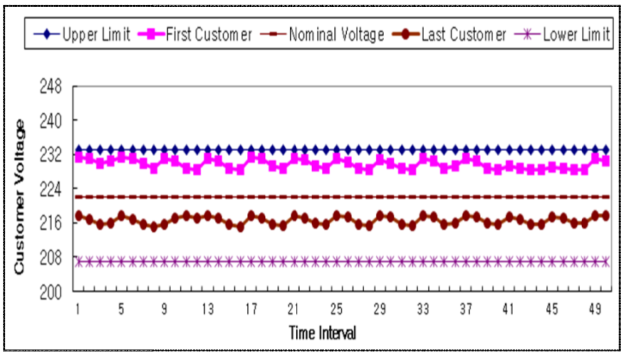
from now on. Fig. 10 shows the sending voltages by the existing LDC method and by the responses of the ANN method presented.

Fig. 11(a) shows the performance index of the ANN and the existing LDC method, and the time intervals of 1~10, 11~20 and 21~30 represent the case where DSG systems are operated as 0%, 50% and 100% of the rated output, respectively. Fig. 11(b) is the comparison results of ANN and existing LDC methods for the case where DSG systems are not operated. This figure shows that PI values of the ANN method have reasonable distributions through the entire time intervals, however, those of the existing LDC method have unreasonable characteristics in proportion to the increase of load (decrease of time interval) since the setting values are determined as the smaller ones according to the peak cut operation of DSG systems. Thus, it is verified that the on-line real time method using the neural networks can improve the voltage compensation capability.

In addition, Fig. 12 shows the customer voltage distributions of the ANN and existing LDC methods. From the simulation results, the customer voltage distribution by the ANN method presented is greatly improved and maintained with more suitable conditions in comparison to that of the existing LDC method. Thus, it is verified that the on-line real time method using the neural networks can improve the voltage compensation capability.



(a) Existing LDC method



(b) ANN method

Fig. 12. Customer voltage characteristics

5. Conclusions

In this paper, the authors have discussed the effectiveness of an on-line real time voltage regulation method using neural networks. By comparison between the proposed method and the existing LDC method, their effectiveness was illustrated and demonstrated.

The proposed ANN method using pattern recognition is expected to reduce the computation burden with no voltage profile calculation of each load patterns.

It is verified that the customer voltage distribution by the ANN method presented is greatly improved and maintained with more suitable conditions than the existing LDC method.

It is also noted that the proposed on-line real time voltage regulation method using the separate-type neural network model has an appropriate pattern recognition capability within the possible training boundary and improves the voltage compensation capability of LRT in distribution substations.

The ANN method presented has the capability to feedback customer voltage conditions to the voltage regulators of distribution systems. This method can be expected to perform one of the functions of the Distribution Automation. Further, it can be expected that the ANN method will be more effective in the future as the telemetering device and budget are resolved.

Acknowledgments

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