Coordination Control of ULTC Transformer and STATCOM Based on an Artificial Neural Network

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***Abstract*—This paper presents an artificial neural network (ANN)-based coordination control scheme for under load tap changing (ULTC) transformer and STATCOM. The objective of the coordination controller is to minimize both the amount of tap changes of the transformer and STATCOM output while maintaining an acceptable voltage magnitude at the substation bus. The coordination controller is designed to substitute for a classical ULTC mechanism by utilizing active and reactive powers, tap position, and STATCOM output. A competitive ANN is used as a classifier for tap positions and trained by a proposed iterative condensed nearest neighbor (ICNN) rule.**

***Index Terms*—Artificial neural network (ANN), condensed nearest neighbor rule, coordination control, STATCOM, ULTC transformer, voltage regulation.**

I. Introduction

IN general, voltage magnitude of a substation is controlled by an under load tap changing (ULTC) transformer and several capacitor banks; the transformer changes its tap position to control the lower side voltage magnitude directly, whereas the capacitor banks affect the higher side voltage magnitude indirectly by changing the amount of reactive power demand at the bus. These devices have two major problems; one is the discontinuity caused by their stepwise controls and the other is the limitation to the amount of switchings, which is the reason why dead-band and time-delay are needed in their control [1].

Recently, with the development of power electronics technologies, several flexible ac transmission system (FACTS) devices make it possible to control power flows as well as bus voltages rapidly and accurately [2]–[5]. Among the FACTS devices, static compensator (STATCOM)—an excellent reactive power source and load as well—is an adequate device to control the voltage magnitude in a specific bus.

A STATCOM has an internal action called Q-runback. Its objective is to prepare sufficient amount of capability margin against emergencies. If there are other voltage control devices, the Q-runback may pass the burden of the STATCOM to those devices slowly. Although an already installed ULTC transformer is one of the probable candidates for that coordination, there needs to be an additional coordination controller which substitutes for the role of the present ULTC controller because the present controller assumes that it is the only available controller. Paserba and others [6] proposed the first coordination controller for a ULTC transformer and a STATCOM, where the tap position is controlled based on the STATCOM output and its switching is restricted by the dead-band of the STATCOM. Son and others [7] added some more control parameters to the Paserba's control concept to enhance the control performance.

In this paper, an artificial neural network (ANN) is introduced to the coordination controller, which substitutes for the classical tap changing mechanism. The proposed controller decides its action according to four local variables such as active and reactive powers of the voltage controlled bus, tap position, and STATCOM output. In addition, by considering recent load trends, the coordination controller enhances its ability to balance the number of tap changes with the large capability margin of the STATCOM. In this paper, an ANN is utilized as a classifier with an integer value as the output, which is a tap position. As for this kind of classifier, a competitive ANN is sufficiently effective while it is very easy to train. Therefore, a nearest neighbor based competitive ANN is chosen for the ANN structure in this paper and its codebook vectors are decided by the iterative condensed nearest neighbor (ICNN) rule, which determines the codebook vectors of the ANN so accurately that the ANN classifies all training data correctly [8].

II. Coordination Controller

A STATCOM controls voltage magnitude of a specified bus very rapidly to match the measured voltage to its reference value. On the other hand, a ULTC transformer controls in a stepwise manner after some time delay, which is indispensable to limit the number of tap changes. Therefore, if a bus voltage is controlled by both a STATCOM and a ULTC transformer without coordination, there is no chance for the transformer to participate in controlling the bus voltage, except when the STATCOM is in its limit. This makes the coordination control between the two devices complicated. The purpose of this paper is to determine the proper tap position, which harmonizes the use of transformer with the STATCOM.

The coordination concept of this paper is as follows: The bus voltage is controlled by the STATCOM first, and then tap changing action follows to lessen the STATCOM output. Having the capability margin of the STATCOM is very important in case of emergencies. Therefore, the transformer becomes a main controller though its action is slower. The STATCOM makes the control continuous and consistent even in emergencies. The optimal tap position for this coordination depends on the power system topology and its operating point, which are not in an explicit form to be useful. However, it is easy to obtain four regional feature variables: active and reactive powers of the con-

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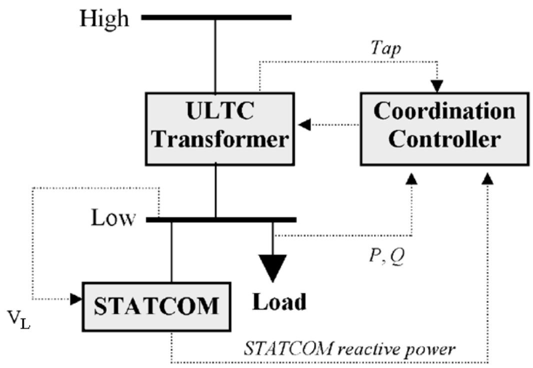


Fig. 1. Signal flow diagram of the coordination controller.

trolled bus, present STATCOM output, and present tap position. Among the four variables, the first two represent the operating point. The topology information is reflected in the last two variables. Fig. 1 shows the scheme of the coordination controller.

The decision on the tap position that minimizes the STATCOM output based on the four feature variables needs exhaustive search to find its optimal value. It is necessary to repeat power flow calculations for every tap positions to obtain the optimal solution. Since this is not realistic in an online problem, an ANN is chosen in the form of a coordination controller for which training data can be gathered by offline power flow calculations. The output of the ANN is a tap position, which must be a positive integer. Therefore the ANN can be considered as a classifier in the four-dimensional space of the feature variables; the number of classes corresponds to the number of taps. In this paper, a competitive ANN such as a Kohonen neural network is selected as the classifier because it is much easier to train than other types of ANN classifiers.

The ANN output is expected to be a tap position that minimizes STATCOM output, and this may cause a very large number of tap changes. To alleviate this problem, the following composite rules are included in the coordination controller with the positive integers α and β ($\beta \geq \alpha$) defined in Fig. 2.

CR1: Change the tap by one step in the direction of ΔTap if the absolute value of ΔTap is greater than β, where $\Delta Tap = Tap_{\text{optimal}} - Tap_{\text{current}}$, Tap_{optimal} is the ANN output, and Tap_{current} is the current tap position.

CR2: Follow the next sub-rules if the absolute value of ΔTap is less than β but greater than α:
CR2-1: Increase the tap by one step if ΔTap is positive and bus power is in an increasing trend.
CR2-2: Decrease the tap by one step if ΔTap is negative and bus power is in a decreasing trend.

Though one-step tap changing may be slow, that is very helpful to avoid tap position oscillation. Therefore, following Calovic's ULTC transformer controller model [1], only one step tap change is made from each signal. Kasztenny and others [9] also designed a ULTC controller that gives one pulse at a time, if necessary, to the step motor which changes transformer tap position.

Bus power trend is obtained by analyzing chronological reactive bus power data, which is one of the input variables of the ANN. A trend is determined by comparing the average reactive

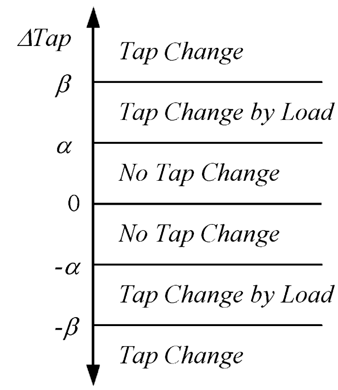


Fig. 2. Composite control rules for tap changing.

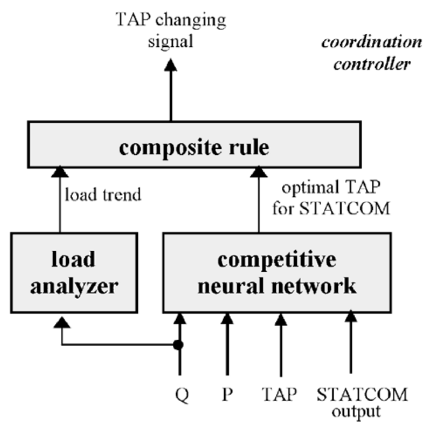


Fig. 3. Detailed scheme of the coordination controller.

powers during an interval between the past 1-hr and 2-hr time periods. The global load trend, not temporary variation, needs to be considered to avoid transformer tap oscillations. Therefore, load data during 2 hr are utilized in the paper to identify the global load trend. The 5 min would be a sufficiently short load acquisition period in identifying the global load trend in most power systems.

While the traditional control parameters for the ULTC transformer are time-delay and dead-band, the proposed coordination controller uses α and β as the control parameters. Large α and β mean the less chance of tap changes and also, at the same time, the smaller capability margin of the STATCOM. Small α and β are preferable to minimize the STATCOM output, but it may cause frequent tap changes. Fig. 3 shows the detailed components of the proposed controller and their relationships.

III. ICNN Rule

The condensed nearest neighbor (CNN) rule is a kind of codebook vector decision method for nearest neighbor based competitive ANNs. While the well-known learning vector quantizations (LVQs) decide codebook vectors statistically, the CNN rule simply selects codebook vectors from training data. The advantage of the CNN rule is the fact that it makes the classifier guarantee perfect classification of the training data. The following *Step 1* is the first CNN proposed by Hart [10], where the elements of *STORE* will be codebook vectors of an ANN classifier after learning.

Step 1:

P1-1: Store the first training data to *STORE*.

P1-2: Classify the next training data with the current *STORE*. Store the training data to *GRABBAG* if it is classified correctly, otherwise store it to *STORE*.

P1-3: Repeat P1-2 for all training data.

P1-4: Classify the element of *GRABBAG* with the current *STORE*. Move the classified element to *STORE* if it is mis-classified.

P1-5: Repeat P1-4 for all the element of *GRABBAG*.

P1-6: Go to P1-4 if any element is moved to *STORE* in P1-4 and P1-5; otherwise stop *Step 1*.

The above procedure always puts sample data into *STORE* if they are proved to be necessary to guarantee perfect classification of training data. However, some element already existing in *STORE* may become unnecessary after inserting new element. This is why Gate [11] proposed the next *Step 2*, which follows *Step 1* to eliminate noncrucial element out of *STORE*.

Step 2 of CNN:

P2-1: Move one element of *STORE* to *GRABBAG*. Restore the moved element back to *STORE* if any training data is misclassified with the current *STORE*.

P2-2: Repeat P2-1 for all the element of *STORE*.

P2-3: End of CNN.

The above *Step 2* needs $n \times m$ classifications if there are m elements in *STORE* along with n training data. For example, if $n = 10\,000$ and $m = 1,000$, classifications should be performed as much as 10^7 times. The number may increase in proportion to the square of the number of training data. To overcome this difficulty, an iterative CNN (ICNN) rule was proposed by Cho, *et al.* [8], which replaces *Step 2* of CNN with the following:

Step2 of ICNN:

P2-1: Move one element of *STORE* to *GRABBAG*. Restore the moved element to *STORE* if it is misclassified with the current *STORE*.

P2-2: Repeat P2-1 for all the element of *STORE*.

P2-3: Go to P2-1 if any element is moved to *GRABBAG* in P2-1 and P2-2, otherwise go to P1-4 of *Step 1*.

While the CNN rule achieves the final codebook vectors through single *Step 1* and *Step 2*, the ICNN repeats *Step 1* and *Step 2* until the resultant *STORE* converges to a sufficiently satisfactory solution. Since the proposed ICNN is an iterative method, there needs to be an appropriate end condition like the following:

End Condition:

EC1: Stop ICNN rule if there is no addition to *STORE* in *Step 1* or no deletion from *STORE* in *Step 2*.

EC2: Stop ICNN rule if *Steps 1 and 2* are repeated $i_{\max}$ times.

The performance of the proposed ICNN is compared with the Gate's method using a frequently referred classification problem [10]–[13]. The test is performed 10 times with Pentium PC and their average values are listed in Table I; both methods guarantee perfect classification of training data.

Although the numbers of codebook vectors of the two methods are similar, Gate's method takes more training time than ICNN: about 7, 10, and 14 times when the numbers of training data are 2000, 4000, and 8000, respectively. As the number of training data increases, ICNN is more effective than the Gate's method.

TABLE I
COMPARISON OF ICNN AND GATE'S METHOD

# of Test Data	# of codebook vectors		elapsed time [set]	
	ICNN	Gate's	ICNN	Gate's
2000	75	77	2	15
4000	106	106	5	53
8000	141	141	16	231

Discussion:

In the following discussion, n, m, i_1, i_2, and $i_{\max}$ mean

- n number of training data;
- m number of elements of STORE in average;
- i_1 number of iterations of P1-6 in Step 1 in average (ICNN only);
- i_2 number of iterations of P2-3 in Step 2 in average (ICNN only);
- $i_{\max}$ number of iterations of Steps 1 and 2 (ICNN only).

In P2-1 of CNN rule, every training data need to be tested if it is classified correctly without a specific element in *STORE*, which should be performed for every element in *STORE* in P2-2. Therefore, there needs a total of $n \times m$ classifications in *Step 2* of CNN rule.

In P2-1 of ICNN rule, only a specific element in *STORE* needs to be tested if it is classified correctly without itself, which should be performed for every element in *STORE* in P2-2. Therefore, there needs a total of $i_2 \times m$ classifications in *Step 2* if P2-3 needs i_2 iterations. It is not difficult to verify that the number of needed classifications in *Step 1* is $i_1 \times (n - m)$. Since the ICNN rule iterates $i_{\max}$ times in *Steps 1* and *2*, a total of $i_{\max} \times \{i_1 \times (n - m) + i_2 \times m\}$ number of classifications are needed.

For example, if $n = 10\,000$, $m = 1,000$, $i_1 = i_2 = i_{\max} = 5$, the ICNN rule needs about 2.5×10^5 classifications, while the CNN rule needs 10^7 ones. Table I shows the time comparison between the ICNN and CNN rule. The ICNN rule is described in more detail in reference [8].

IV. Case Study

A. Building Coordination Controller

The proposed coordination controller was applied to the voltage control of the IEEE 14-bus system in Fig. 4. Although the specific bus and line data are not listed in this paper, they are available in other references, such as [14]. This paper assumes that a ULTC transformer and a STATCOM are installed in a substation, named Bus 14. In Fig. 4, Bus 15 corresponds to the lower voltage side bus of the substation. The control objective of the coordination controller is to maintain the voltage magnitude of Bus 15 at one per-unit.

This case study assumes the followings: First, load level varies from 50% to 250% of the standard value given for the IEEE 14 bus system. Second, ULTC transformer has 33 taps within a range of $\pm 10\%$. Third, the tap position can be changed as often as in 5 min.

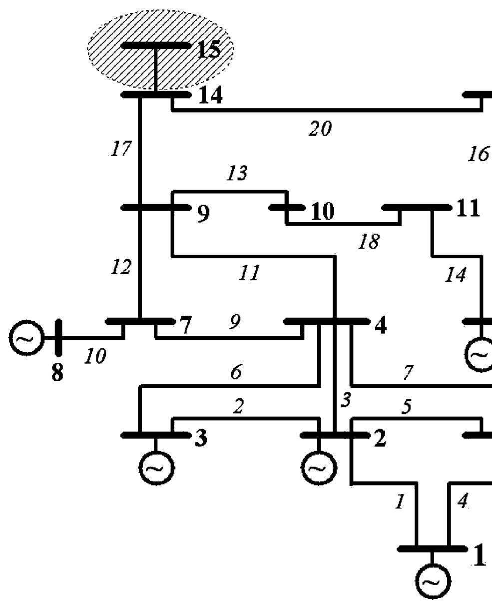


Fig. 4. One-line diagram of the IEEE 14-bus system.

In this case study, inputs to the coordination controller are the active and reactive powers of Bus 15, tap position, and STATCOM output. Since there are 33 possible tap positions, the following 33 quadruples would be formed from the power flow calculation results for each load level:

$$\left(P_{bus}^{current}, Q_{bus}^{current}, Q_{STATCOM}^{i}, TAP^{i}\right), \quad 1 \leq i \leq 33.$$

The voltage magnitude of Bus 15 should be fixed at 1 p.u. during the power flow calculation.

Among the above 33 quadruples, the tap position TAP^{i} for the minimum $Q_{STATCOM}^{i}$ is the optimum tap position in view of STATCOM output minimization, and it is selected as $TAP^{optimum}$ at the load level.

The inputs to the proposed ANN classifier in Fig. 3 are the current bus power (P and Q), STATCOM output, and TAP position. Since the objective of the ANN is the minimization of the STATCOM output, the form of training data from the above 33 power flows are

$$\left(P_{bus}^{current}, Q_{bus}^{current}, Q_{STATCOM}^{i}, TAP^{i}\right) \rightarrow \left(TAP^{optimum}\right), \quad 1 \leq i \leq 33.$$

As mentioned in the coordination controller, Fig. 1, the first two inputs (P_{bus} and Q_{bus}) of the training data reflect the load level and the third and fourth inputs ($Q_{STATCOM}$ and TAP) reflect the system topology such as system reconfiguration.

Since the ANN trained through the above data can inform the tap position which minimizes the STATCOM output, there needs additional rule to reduce the number of tap changes. The *load analyzer* and *composite rule* in Fig. 3 are introduced for this purpose.

The following is the procedure for getting training data.

TR1: Assume a load level.

TR2: Perform power flow calculation per every tap position, 33 cases, with the assumed load level.

TR3: Select the optimal solution among the results of TR2.

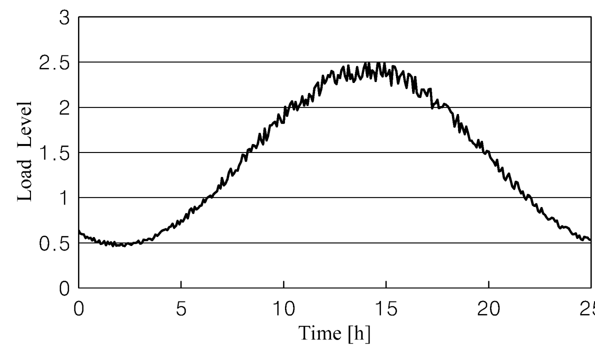


Fig. 5. Daily load curve. (Load level is the ratio between instantaneous bus load and original load data of the IEEE14 bus system).

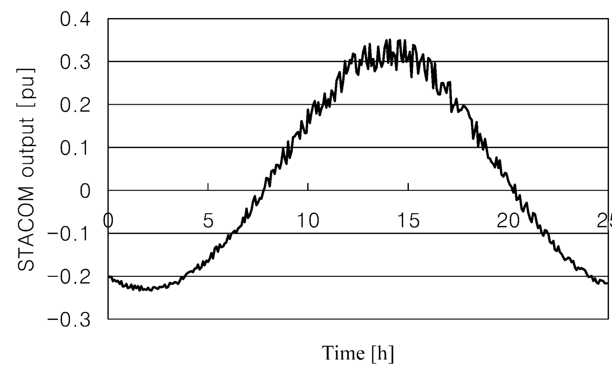


Fig. 6. STATCOM output when tap is fixed to 16.

Since the target of the ANN is to generate tap position which minimizes STATCOM output, the optimal solution in TR3 is the tap position with minimum STACOM output among the 33 cases.

The 33 sets of training data are gathered through the above procedure at every load level. For this case study, 13 233 sets of training data are generated at 401 different load levels. And, in the same way, another 26 466 sets of training data are generated assuming permanent removal of Line 17 and Line 20, which are connected directly to Bus 14. Although there is no training data for other types of faults, favorable results are expected due to the robustness and interpolation ability of the ANN. From the 39 699 sets of training data, the ICNN rule selects 6008 codebook vectors for the ANN. Its misclassification rate among 3300 new test samples is only 2.5%. Moreover, the correct tap positions are within the ± 1 taps from the results, even when considering the misclassified cases. Meanwhile, the reactive power of Bus 15 at 5-min interval is used in the load analyzer to estimate the load trend. Therefore, 24 previous reactive power data during the last 2 hr are necessary for the calculation.

Fig. 5 shows a daily load curve used in this study, which can be obtained by adding $\pm 5\%$ random disturbances to the sinusoidal pattern within a range of 0.5 to 2.5, where the load level means the ratio between instantaneous bus load and original load data of the IEEE 14-bus system.Fig. 6 shows the STATCOM output when the transformer tap is fixed at its center position (the 16th step) and where its base MVA is 100. In Fig. 6, the unit of STATCOM output is p.u. as noted in the figure. For example, the total reactive load is 1.84 p.u. in the case of load level 2.5, which is supplied by the combination

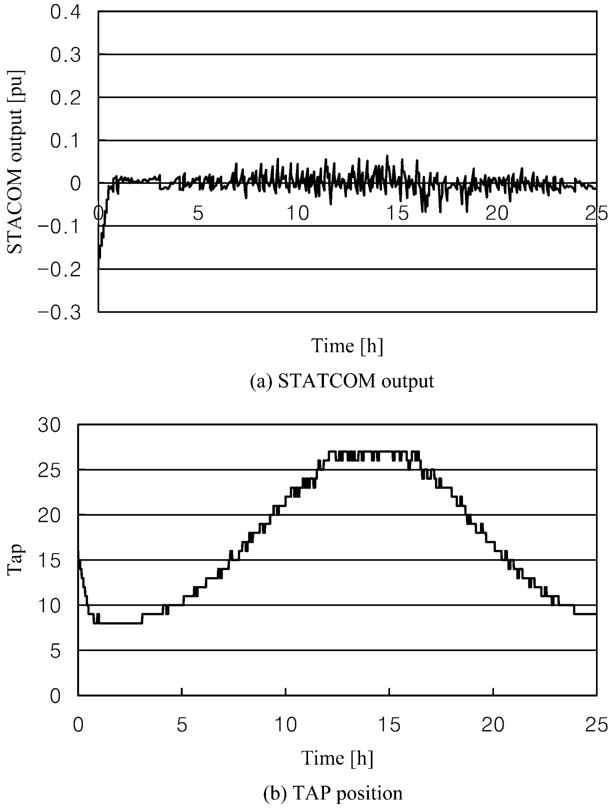


Fig. 7. STATCOM output and TAP position for normal state ($\alpha = \beta = 1$).

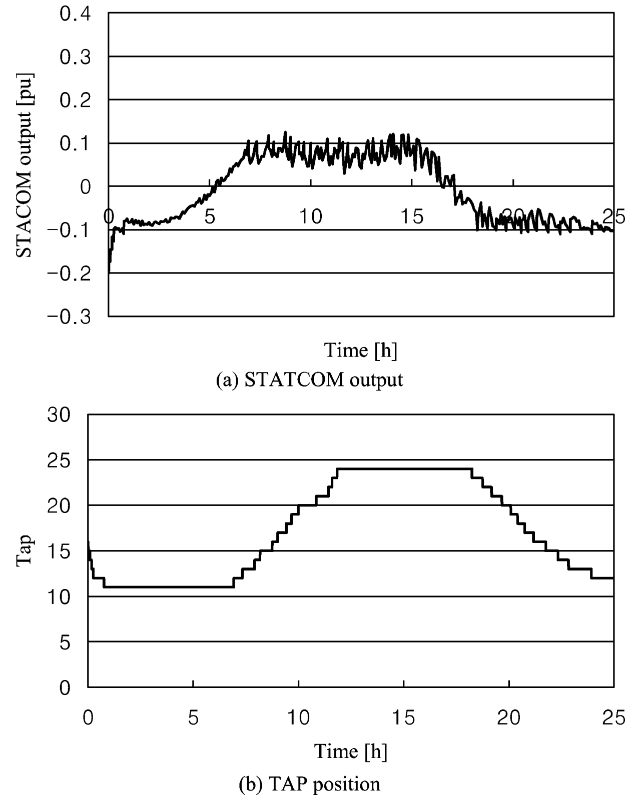


Fig. 8. STATCOM output and TAP position for normal state ($\alpha = \beta = 4$).

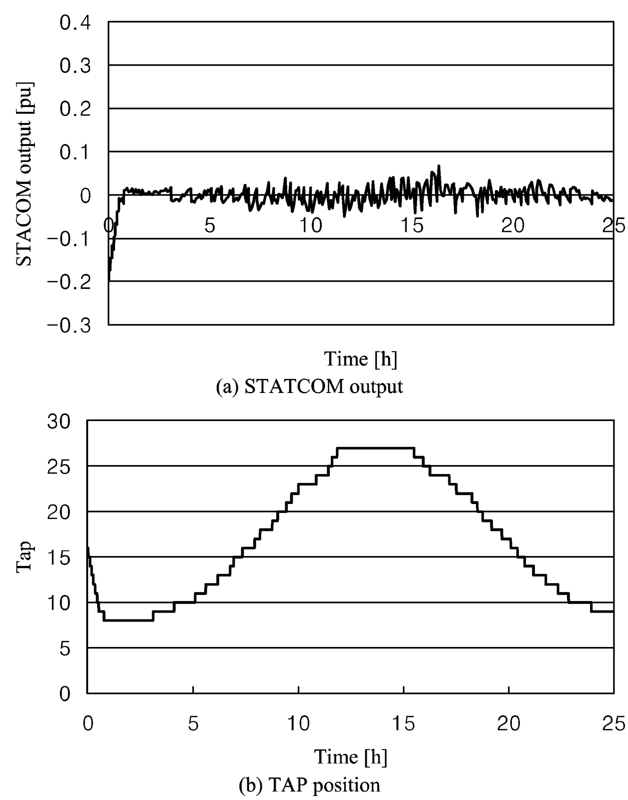


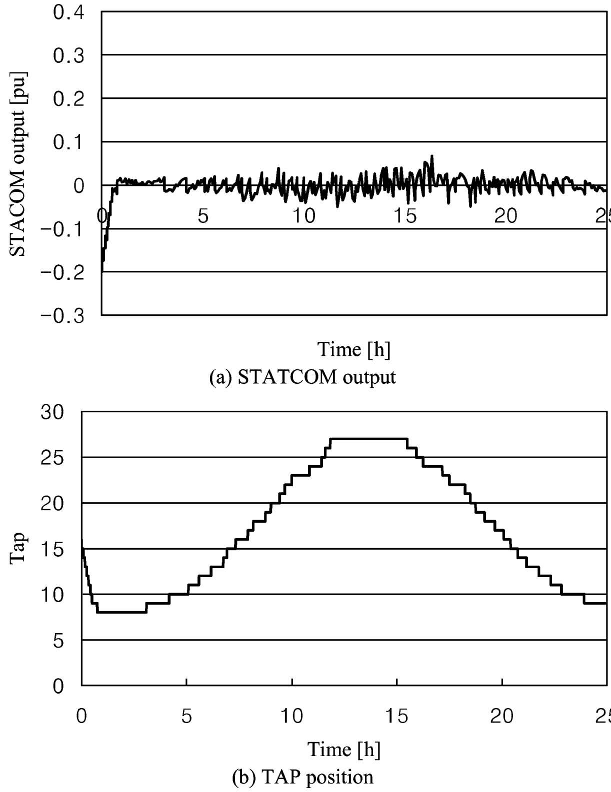
Fig. 9. STATCOM output and TAP position for normal state ($\alpha = 1, \beta = 4$).

of generators, a shunt capacitor at Bus 9, and STATCOM (0.3 p.u.). Since the STATCOM output reaches over 30 MVar at its peak to maintain the voltage magnitude of Bus 15 at unity, it is vulnerable in the case of a system failure at that time. Load variation of 2.0 in a day is not usual. If the range of load variation is narrower than the study case, the ANN may be trained more easily. The paper shows the validity of the proposed coordinated control despite of severe conditions. Since total system load may vary between 0.5 and 2.5 in a whole year, the ANN in the paper can be utilized during a whole year without retraining.

B. Coordination Control Results

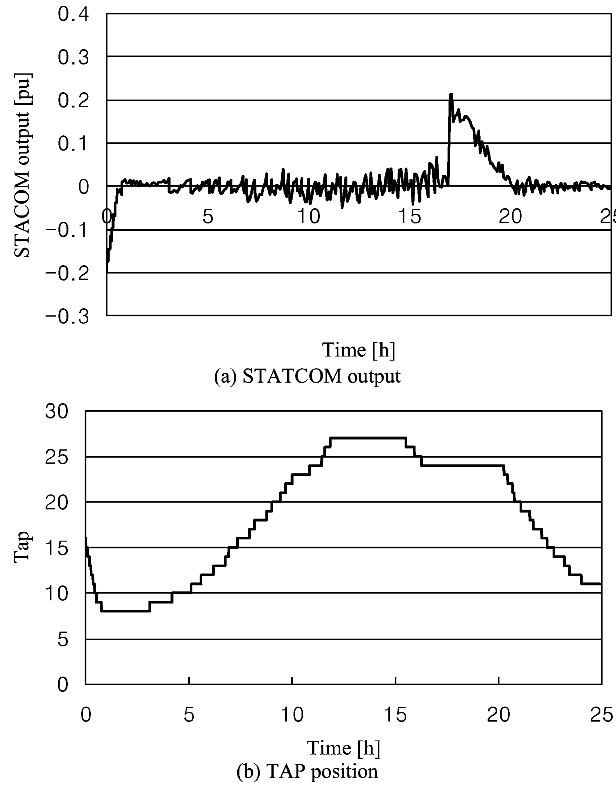
Figs. 7 and 8 show control results when the control parameters α and β are both one and four, respectively. In the case of $\alpha = \beta = 1$, the tap position is always changed whenever it can reduce the STATCOM output; therefore, large amount of tap changes are inevitable in minimizing the STATCOM output. On the other hand, in the case of $\alpha = \beta = 4$, the controller changes tap position only if the difference between the current tap position and the ANN output is at least four. In this case, the amount of tap changes decreases drastically while the STATCOM output becomes worse. In Figs. 7 and 8, the hour 25 is the hour 1 of the next day. If load pattern of Fig. 5 is repeated as a daily load cycle, the tap positions and STATCOM output will also be repeated with 24-hour period. However, the control results near hour 0 of the first day are not same as those of other days because the initial tap position is not optimal in the first day.

Figs. 9 and 10 show control results when the control parameter α is fixed at one but β is changed to four and infinity, respectively. In both cases, load trends play an important role because the tap is changed only if the changing direction of the ANN



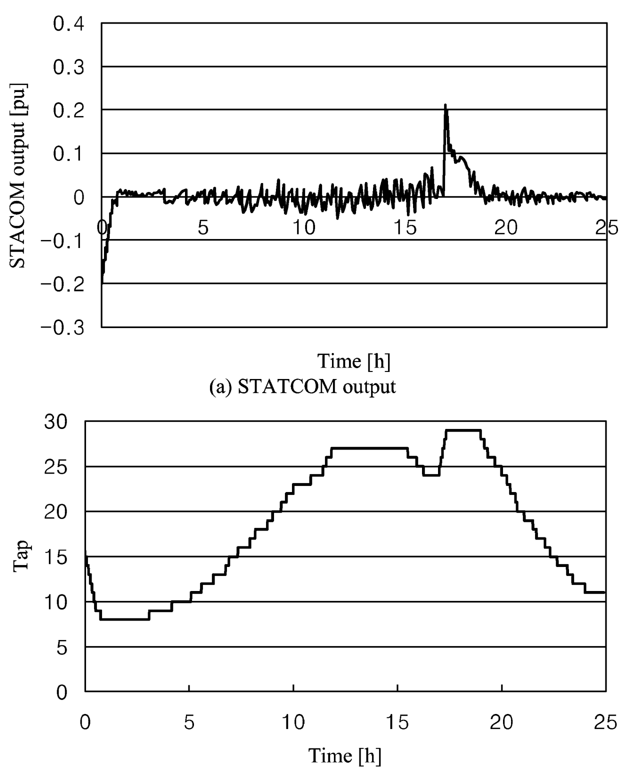
(a) STATCOM output
(b) TAP position

Fig. 10. STATCOM output and TAP position for normal state ($\alpha = 1, \beta = \infty$).



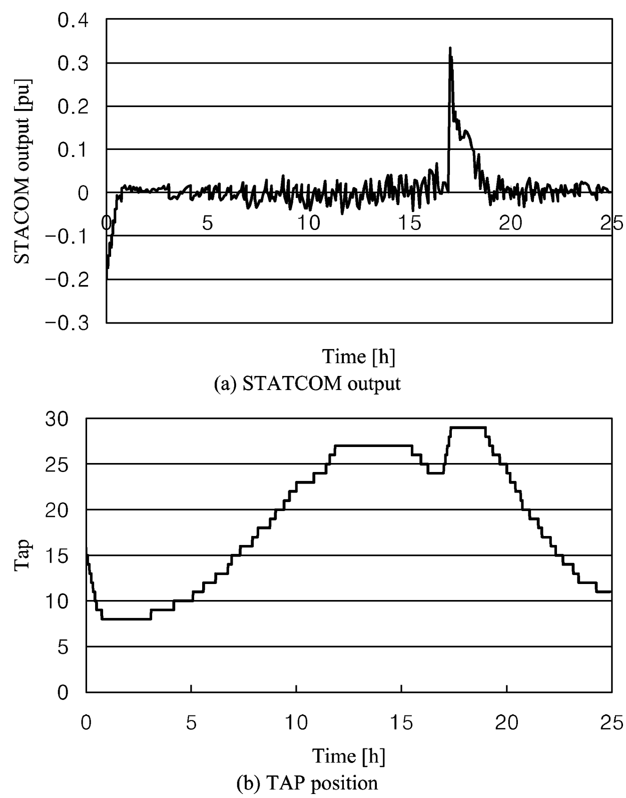
(a) STATCOM output
(b) TAP position

Fig. 12. STATCOM output and TAP position for line 20 fault ($\alpha = 1, \beta = \infty$).



(a) STATCOM output
(b) TAP position

Fig. 11. STATCOM output and TAP position for line 20 fault ($\alpha = 1, \beta = 4$).



(a) STATCOM output
(b) TAP position

Fig. 13. STATCOM output and TAP position for line 12 fault ($\alpha = 1, \beta = 4$).

output is the same as that of the current load trend. Comparing with the case of $\alpha = \beta = 4$, they show better results because the STATCOM output is reduced significantly with few more tap changes. Figs. 9 and 10 are very similar because seldom the taps are changed more than three taps abruptly in normal condition.

Figs. 11 and 12 show the control results when $\beta = 4$ and infinity, respectively, and α is fixed at one, assuming Line 20 is removed at 5 pm. In the case of $\beta = 4$, with the small amount of additional tap changes, the STATCOM recovers its large capability margin earlier than the case when β is infinity. This means the parameter β plays a crucial role in emergencies since there may be a chance of abrupt tap change.

The next simulation assumes a fault at Line 12 followed by the permanent removal of the line. This case was not considered when preparing the training data, which means the case has never been considered during the controller design. However, Fig. 13 shows an acceptable control performance when $\alpha = 1$ and $\beta = 4$ owing to the robustness and interpolation ability of the ANN.

V. Conclusion

This paper proposes an ANN based controller for the coordination of a ULTC transformer and a STATCOM installed at the same bus. The proposed coordination controller controls only the transformer in minimizing the amount of tap changes and at the same time maximizing the capacity margin of the STATCOM. The role of the ANN is to make a decision on the optimal tap position, which minimizes the STATCOM output. Current load trend is also utilized in the proposed controller to produce a better solution together with the ANN classifier.

The proposed controller has two control parameters α and β that are used to resolve the conflict between the transformer and the STATCOM. According to the case study, only α is effective in normal condition while β needs to be set at an appropriate value for emergencies. There need to be prior analyzes to obtain the best α and β for each power system because they depend not only on the system topology but also on the operators' mind set.

References

[1] M. S. Calovic, "Modeling and analysis of under-load tap-changing transformer control systems," *IEEE Trans. Power App. Syst.*, vol. 103, no. 7, pp. 1909–1915, Jul. 1984.

[2] C. Schauder, M. Gernhardt, E. Stacey, T. W. Cease, and A. Edris, "Development of a ± 100 MVAR static condenser for voltage control of transmission systems," *IEEE Trans. Power Del.*, vol. 10, no. 3, pp. 1486–1495, Jul. 1995.

[3] C. Schauder, M. Gernhardt, E. Stacey, T. Lemak, L. Gyugyi, T. W. Cease, and A. Edris, "Operation of ± 100 MVAR TVA STACON," *IEEE Trans. Power Del.*, vol. 12, no. 4, pp. 1805–1811, Oct. 1997.

[4] S. W. Hong, J. T. Cha, and H. S. Lee, "Trends of FACTS device development for distribution system (2)—a study on the DSTATCOM installation," *Proc. KIEE*, vol. 47, pp. 37–42, Mar. 1998.

[5] B. H. Chang and Y. B. Yoon, "Development of the technique for FACTS device operation," *Proc. KIEE*, vol. 47, pp. 5–12, Mar. 1998.

[6] J. J. Paserba, D. J. Leonard, N. W. Miller, S. T. Naumann, M. G. Lauby, and F. P. Sener, "Coordination of a distribution level continuously controlled compensation device with existing substation equipment for long term VAR management," *IEEE Trans. Power Del.*, vol. 9, no. 2, pp. 1034–1040, Apr. 1994.

[7] K. M. Son, K. S. Moon, S. K. Lee, and J. K. Park, "Coordination of an SVC with a ULTC reserving compensation margin for emergency control," *IEEE Trans. Power Del.*, vol. 15, no. 4, pp. 1193–1198, Oct. 2000.

[8] H. S. Cho, J. K. Park, and G. W. Kim, "Power system transient stability analysis using Kohonen neural networks," *Int. J. Eng. Intell. Syst.*, vol. 7, pp. 209–214, Dec. 1999.

[9] B. Kasztenny, E. Rosolowski, J. Izykowski, M. M. Saha, and B. Hillstrom, "Fuzzy logic controller for on-load transformer tap changer," *IEEE Trans. Power Syst.*, vol. 13, no. 1, pp. 164–170, Jan. 1998.

[10] P. E. Hart, "The condensed nearest neighbor rule," *IEEE Trans. Inf. Theory*, vol. 14, no. 3, pp. 515–512, May 1968.

[11] G. W. Gate, "The reduced nearest neighbor rule," *IEEE Trans. Inf. Theory*, vol. 18, no. 3, pp. 431–433, May 1972.

[12] I. Tomek, "Two modifications of CNN," *IEEE Trans. Syst., Man. Cybern.*, vol. 6, no. 11, pp. 769–772, Nov. 1976.

[13] K. C. Gowda and G. Krishna, "The condensed nearest neighbor rule using the concept of mutual nearest neighborhood," *IEEE Trans. Inf. Theory*, vol. 25, no. 4, pp. 488–490, Jul. 1979.

[14] M. A. Pai, *Computer Techniques in Power System Analysis*. New York: McGraw-Hill, 1979.

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