FALLBACK SOLUTION FOR A LOW-VOLTAGE REGULATOR CONTROL USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

With the increase of renewable generation, violations of voltages or thermal limits are more likely to happen in particular in rural distribution networks. Instead of cost intensive grid expansions, other measures can be applied, such as transformers with on-load tap changers, voltage regulators or a novel regulator for power flow control in meshed grids. Depending on their control targets, these devices use remote measurement data, which are transferred by a communication network. However, in case of communication faults, the control processes are affected. A fallback solution using artificial neural networks is presented in this paper for estimating regulator tap positions and missing measurements. Simulation results show that the proposed solution is reliable and accurate.

INTRODUCTION

The increase of renewable generation, in particular photovoltaic (PV) systems in rural areas, and the growing number of electric vehicles lead to a sharp increase of load flows in low-voltage (LV) networks. This can result in voltage violations and thermal overloads of lines. For applications in meshed grids, a novel "Flexible Voltage and Active Power Regulator" (FLOW-R) was designed to control power flows and voltage magnitudes [1-3].
Due to the very low number of measurement points (MP) and the unknown customer-dependent load flows in rural LV grids, the mathematical model of such a network is under-determined. To fulfil different control targets, the regulator needs to calculate the related tap positions based on current and voltage values from various MPs located at specific grid nodes. Therefore, the regulator communicates with these MPs to receive the voltage and current values. However, in case of a communication interruption, the regulator will not receive these measurements resulting in a stop of the control process. Hence, a fallback solution is needed. In this paper, an artificial neural network (ANN) is used for this purpose.
An ANN is a mathematical model similar to but much simpler as human neural networks. Unlike the conventional predefinition of functions, an ANN can learn the relationships between data from observations [4]. ANNs are already used in network control [5-6]. Paper [5] uses an ANN to control the power flow with a unified power flow controller. Paper [6] builds a relationship between measured smart meter values and the voltages at selected buses.

In this paper, the FLOW-R regulator is taken as an example to test an ANN-based fallback solution. The control concepts of the FLOW-R regulator are briefly discussed first. Then, the fallback control strategies are presented. Finally, the simulation set-up is introduced and the results are analysed.

BASICS OF THE FLOW-R REGULATOR

Previous works show the validity of the FLOW-R regulator [1-3]. The power flow in the conductor of a meshed grid can be controlled by injecting a pre-calculated complex control voltage with magnitude U_{CV} and angle δ. δ refers to the line-to-ground voltage angle at the regulator position. The analytical relationship between U_{CV} and its influence on the regulator current I_R is discussed in [1]. Based on this relationship, characteristic curves can be determined. They represent the dependency between the regulator steps and the controlled currents and voltages at MPs, see Fig. 1.

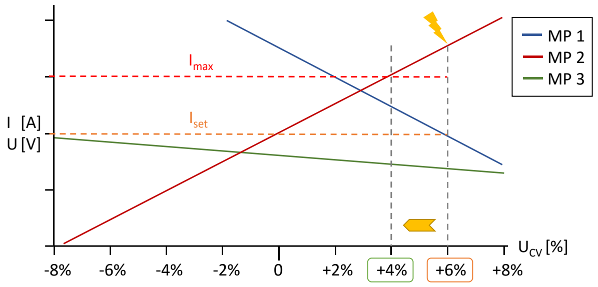

Fig. 1: Characteristic curves for setpoint/limit control

In case of setpoint control at MP1, the optimum U_{CV} is selected for the related setpoint I_{set} using the characteristic curve at MP1. For the resulting U_{CV} the related transformer tap position is calculated.

FALLBACK CONTROL STRATEGIES

Fig. 2 shows an actual meshed grid with 113 loads and 38 PV systems. The FLOW-R regulator is represented by a transformer with adjustable voltage magnitudes and angles at one side. Voltages and currents at various MPs are selected and controlled one by one using the characteristic curve method.
The application of the ANN-based fallback solution follows a three-step process. In the first step, data for all 10 measurements (8 measurements from MPs and 2 from local measurements at the regulator) and the regulator's tap positions are collected during normal operation.

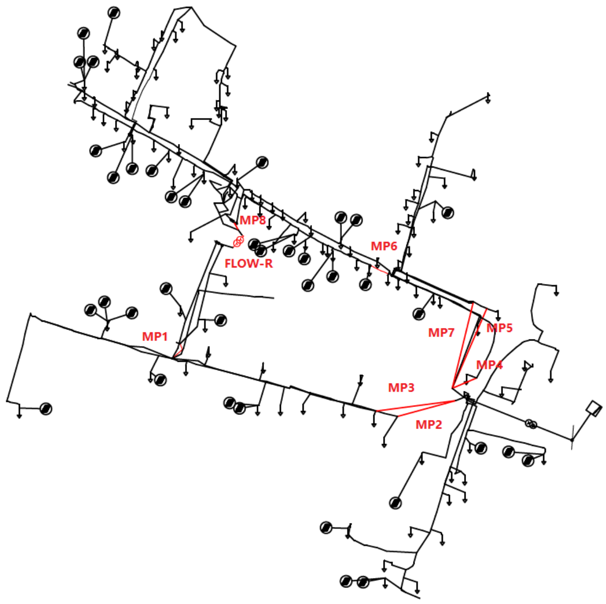

Fig. 2: Actual LV network with a FLOW-R regulator

In the second step, the ANN is trained with the collected data. In this paper the back propagation (BP) method is used for training. The BP method has less computational effort and fits well to the tasks of this paper. In the third step, the weights gained from the training are tested.

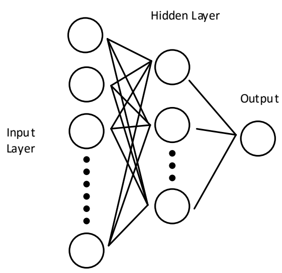

Fig. 3: ANN structure

Fig. 3 shows the three-layer ANN structure used for this project. The input layer contains 9 neuros, which result from the 10 measurement values in step 1 and stand for 'known' values. The hidden layer contains 8 neuros. The number of neuros for hidden layer is an empirical value, higher numbers increase the accuracy but may lead to overfitting and slow training and vice versa. Depending on the control set-up, the output layer contains either the 'missing' values of the MP to be controlled or the tap positions for the regulator.

SIMULATION AND ANALYSIS

Simulation Set-ups

The no-fault situation is simulated first with set control targets of a selected line (e.g. limit/setpoint control). Load and PV values are generated by a time series tool in 15-minute time steps. The regulator's tap positions and all the measurement values from Fig. 2 are collected.
Since the sigmoid function with an output range between 0 and 1 is applied in the ANN, the input and output values are scaled accordingly to get more accurate results. For current values, the thermal limit current of lines is defined as the maximum and 0 A as the minimum. For voltage values, ±10% of the nominal voltage is defined as the maximum and minimum, respectively. For tap positions, the maximum and minimum values correspond to the max and min tap positions.
The simulation results of the ANN-fallback solution are presented separately for offline training and online training. For offline training, the ANN is trained and applied offline and the taps/missing measurements are estimated. For online training, the ANN sends the estimated missing measurement values to the FLOW-R regulator which is controlled with the characteristic curve method.

Offline training

Selection of ANN Outputs

During real operation, communication to any MP may fail. As an example, the communication with MP1 is assumed to be missing in the following. Fig. 4 shows the tap position estimation using ANN for this case. The regulator setpoint for MP1 is I_{set} = 40 A. The ANN is trained during normal operation for three weeks using the currents at other MPs as input and the related regulator tap positions as output. In Fig. 4, the communication loss for one week is assumed, the upper part shows the estimated tap positions and the true values while the lower part shows their differences. The small differences between estimated and real tap positions demonstrate the good performance of the ANN.

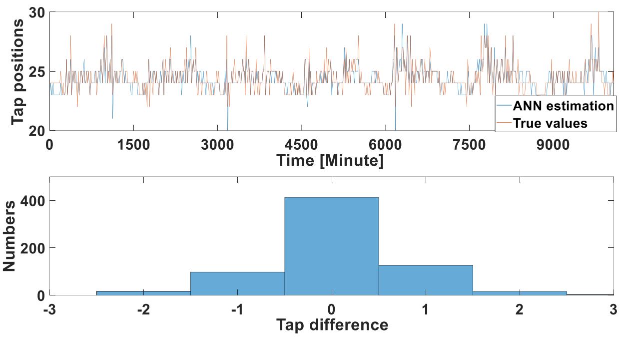

Fig. 4: Error in tap position estimates from ANN

In case of a FLOW-R, its tap positions are the most important information as they are the actuating variable. Hence, the ANN output is directly used to set the FLOW-R while the normal control algorithm is inactive. However, a more generally applicable approach is to estimate the missing measurement values and use them as input for the controller. Fig. 5 presents the ANN estimates of the measurement values at MP1 for regulated operation. Again, the ANN is trained with regulated values for three-weeks. Fig. 5 shows the test values at MP1 for one-week. The upper part shows the true and the estimated currents from the ANN in case of the communication failure of MP1. The lower parts present the differences between the true values and the ANN estimation in absolute values and in percent. Two conclusions are obtained from Fig. 5: first, the FLOW-R is able to regulate the current values of lines, and ANN is capable to estimate the missing measurement values with a maximum deviation of ±10 %.

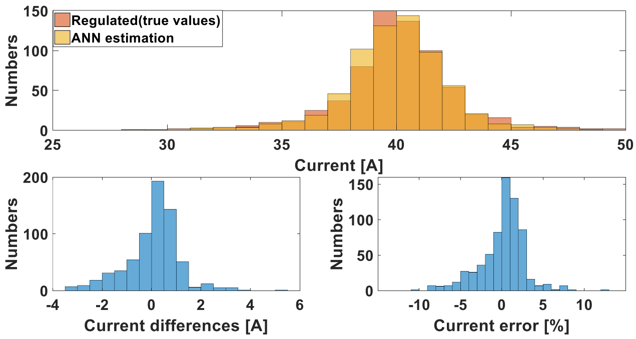

Fig. 5: ANN offline test of missing MP1

Besides MP1, other missing MP can also be estimated as shown in Fig. 6.

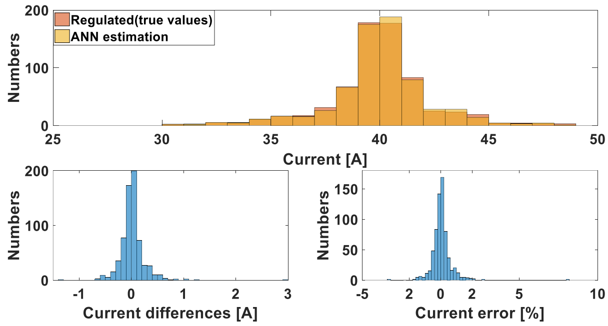

Fig. 6: ANN offline test of missing MP7

Fig. 6 presents the estimation of MP7 with I_{set} = 40 A. The layout is the same as in Fig. 5. In this case the ANN estimation is more accurate compared to MP1, because there are other MPs close to MP7. This can be explained by a Pearson correlation coefficient (PCC) as shown in Table 1. The PCC is a way to measure the linear correlation between two variables [7]. When the PCC is closer to 1, the two variables are more linearly correlated, which is easier for ANN to learn.

Table 1: PCCs of MP1 and MP7

Control MP	PCC									
	MP1	MP2	MP3	MP4	MP5	MP6	MP7	MP8	MP9	MP10
1	1	0.558	0.520	0.145	0.152	0.239	0.152	0.383	0.910	0.910
7	0.377	0.306	0.312	0.990	1.00	0.670	1	0.631	0.392	0.388

The PCCs between regulated values in Fig. 5 and Fig. 6 are presented in Table 1. For MP7, the correlation to MP4 and MP5 are very high. This explains the higher accuracy in Fig. 6 compared to Fig. 5.

Loss of more than one measurement

The previous simulations are based on the assumption that only the values from one MP are missing. However, in real operation more than one communication link can get lost. The regulator only needs the measurement values from the MP where the setpoint is defined, e.g. MP1. But during the estimation process, additional communication links may get lost, possibly even all of them except from the local measurements at the regulator. In principle, the ANN could be trained separately for all the 128 possible combinations of the test system, but that would result in a too high computational effort. Instead, random zeros indicating missing MPs are introduced to the training process.

Table 2: Test set-up and results for MP1

	Set-up 1	Set-up 2	Set-up 3	Set-up 4
Training with random zero	No	No	Yes	Yes
In-/outputs for training	9/1	9/1	9/1	9/1
In-/outputs for test	9/1	2/1	9/1	2/1
Mean of differences [A]	-0.063	319.98	-0.081	0.700
SD of differences [A]	1.08	2.53	1.13	1.22

Table 2 presents the test set-ups and the mean values and standard deviations (SD) of the true and estimated current differences at MP1:

- Set-up 1: train with 9 inputs/1 output, with no random zeros replaced; test with 9 inputs;
- Set-up 2: train with 9 inputs/1 output, with no random zeros replaced, test with 2 inputs;
- Set-up 3: train with 9 inputs/1 output, with 15% inputs are replaced by zeros randomly replaced; test with 9 inputs;
- Set-up 4: train with 9 inputs/1 output, with 15% inputs are replaced by zeros randomly replaced; test with 2 inputs.

Comparing set-up 1 and 2, they use the same information for training, but set-up 2 uses two inputs instead of 9. This causes extreme current deviations from the setpoint. To deal with this, random zeros are introduced in the training i.e. input values are randomly replaced by zeros. During test (application), when additional communications are missing, the lost inputs are replaced by zeros, see set-up 3 and 4. Comparing set-up 3 and 1, the accuracy decreases. However, comparing set-up 4 and 2, it is significantly improved when more communications are lost.

Fig. 7 and Table 3 present the results of random zero in case of different MPs missing.

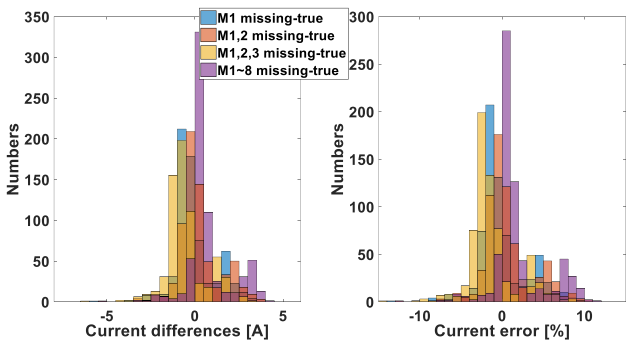

Fig. 7: ANN Test with random zero implementation, MP1

Table 3: Results of differences for random zero

Miss of MPs	1	1,2	1,2,3	1,2,3,4,5,6,7,8
In-/outputs for training	9/1	9/1	9/1	9/1
In-/outputs for test	9/1	8/1	7/1	2/1
Mean of differences	-0.081	0.224	-0.50	0.70
SD of differences [A]	1.13	1.15	1.15	1.22

The mean and SD of Fig. 7 are presented in Table 3.

Based on the above results, it can be concluded that training the ANN with random zeros decreases the accuracy but allows to continue control in cases where more measurements get lost.

Online training

Training length

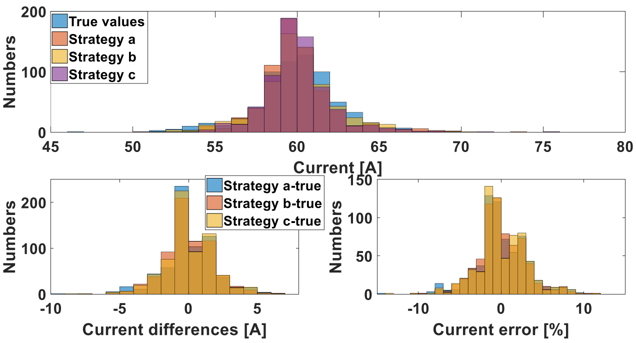

Fig. 8: Online training of different strategies, MP1

Fig. 8 presents the online training results of one week for different training strategies. The upper part shows the regulated currents for the true values and three different strategies:

- Strategy a: values of one single day are used for training, training is done once.
- Strategy b: values of seven days are used for training, training is done 7 times (day by day)
- Strategy c: values of seven days are used for training, training is done once for the seven days

The mean and SD of these three strategies compared to true values are summarized in Table 4.

Table 4: Current differences for different training lengths

Strategy	a	b	c
Batch size [day]	1	1	7
Training frequency	1	7	1
Mean of differences [A]	-0.026	-0.016	0.013
SD of differences [A]	1.88	1.71	1.78

Strategy a shows worst results, but all the strategies are comparable. Therefore, big storage sizes are not necessary for implementation.

Control of voltage limits

Unlike setpoint control where the 'regulated' values are used for training, limit control needs 'unregulated' values. As 'regulated' measurements cannot reach the limits, this will lead to wrong regulation. The 'unregulated' values are estimated using characteristic curves. In the test process, the 'unregulated' missing values are estimated using ANN, and the regulator will control based on the estimated 'unregulated' values together with the characteristic curves.

For strategy b, Fig. 9 presents the online results of MP6 voltage limit control. The ANN is trained with 7 days' 'unregulated' values and tested with other 7 days' values. The regulator is able to limit the voltage of MP6 to 420 V and the ANN is able to estimate the true value and keep the limit. The voltage differences are presented in the lower part of Fig. 9.

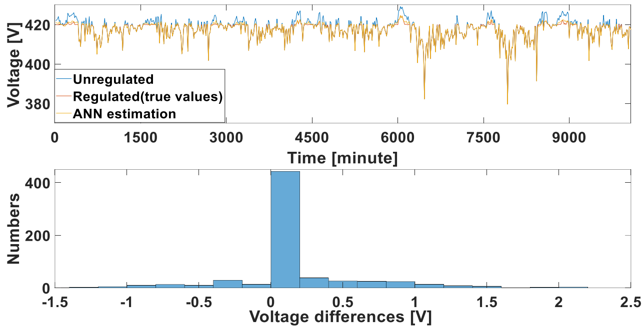

Fig. 9: ANN Test of limit control for MP6

CONCLUSION AND OUTLOOK

Based on the above simulations and discussions, it can be concluded that with using the ANN fallback solution the FLOW-R regulator can continue to act properly even in cases where one (or more) MPs are lost. The proposed ANN fallback solution can be used not only for the FLOW-R regulator but also for other applications since it estimates missing measurement values. The simulation results show that the usage of the ANN is a reasonable solution to communication interruptions.

At switching from normal operation to the ANN fallback some jumps in the control values might occur. Hence, further work will focus on avoiding such jumps. Also, the question of ANN training during fallback time and the response to topology changes will be considered.

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