# APPLICATION OF LOCAL ANN CONTROLLERS FOR POWER SYSTEM SECONDARY VOLTAGE CONTROL

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**Abstract**

The paper presents a new and efficient concept of local secondary voltage control (LSC) of a power system that is based on artificial neural networks (ANN). For its operation it requires only local information on power system operation that it collects by measuring the controlled variables in the controlled node and reactive power flows on the connecting lines with the neighboring nodes. All generators in the system participate in the secondary voltage control, each of them equipped with its own secondary controller. The correct response of the controller to the input data is calculated using ANN. Each ANN is trained separately using the same set of power system operating states. The set has to be large enough to encompass many different operating scenarios, with the optimal power flow (OPF) results used as the training reference. The local ANN controllers operate independently without coordination and free of the unwanted controller interaction. Although their adaptive local control action results in system-wide effect on voltage profile, they require no supervisory reference signal from the power system control center for their operation.

The performance of the control concept was tested on a Slovenian power system model with 22 generators and eight tap changing transformers. Test results show that the new local secondary voltage control successfully supplies reference voltages for generators and tap changing transformers based only on local measurements. Using the local ANN secondary voltage control we achieved local control of power system voltage profile and a notable reduction of power system losses.

**Keywords:** Power System, Local Secondary Voltage Control, Artificial Neural Network, Optimal Voltage Profile.

## Presenting Author's biography

**Andrej F. Gubina** received his Diploma Engineer degree, M.Sc. and Dr. Sc. in 1993, 1998 and 2002, respectively, from the University of Ljubljana, Faculty of Electrical Engineering. In 2000, he spent a year as a Fulbright Visiting Researcher at the Massachusetts Institute of Technology. From 2002 - 2005 he headed the Risk Management Dept. at HSE d.o.o., Ljubljana. Since May 2006 he is an Assistant Professor and since March 2007 the Head of the Laboratory for Energy Policy at the above Faculty. His main interests are in the field of power system analysis and control, renewable energy sources, power economics and risk management.

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# 1 Introduction

As learning non-linear approximators, the artificial neural networks (ANNs) are established as a promising tool in power system control and analysis. They excel especially in non-linear control and estimation problems where large-scale optimization requires unfeasible solution times, in tasks of statistical character or in identification and modeling of parts of the system [1],[2]. Most common applications of the ANN-s in power systems include load forecasting, alarm processing and power system fault detection, component fault diagnosis, static and dynamic security analysis and power system planning.

As a part of the ancillary services, voltage and reactive power control is gaining importance in a deregulated power system. It is dealing with complex, highly non-linear relations between voltage and reactive power, comprising reactive power production limits and unfavorable voltage behavior of the power system elements.

In a hierarchical voltage control concept of the power system, the primary voltage controller (PVC) controls the voltage of the power system node through automatic adjustment of the excitation level of the generator. Through the control of the reactive power generation level, the PVC controls the voltage of the generation node. Reacting to fast voltage variations, the PVC requires a supervisory reference voltage setting for its operation. That is supplied by secondary voltage control, which responds to large and slow voltage changes [3]. The overall power system voltage profile is then ensured by tertiary voltage control layer that provides for optimal power management and security, alleviating the problem of long distance reactive power transmission with system-wide actions. Tertiary level may be guided by optimal power flow (OPF) voltage results.

The traditional secondary voltage control has been implemented as static manual setting of the reference voltages for the PVCs [3]. It may also be centralized, effectively merged with the tertiary control layer, with references supplied from the control center. In some power systems, automatic secondary voltage control has been implemented using control "zones" to manage reactive power production. The "pilot node" concept has been introduced to control the zone voltage [4].

In the paper, we present an implementation of a local concept of the secondary voltage control, taking advantage of the local character of the voltage control. The reference voltage for each PVC would be supplied independently by a local secondary voltage controller (LSC). It would contain knowledge on the power system behavior and react to locally measured quantities, thus reducing the need for centralized decision and the information exchange. An early implementation of the idea used fuzzy reasoning, based on the concept of the equivalent load bus voltage [5]. A drawback of this implementation was its continuous dependence on a tertiary control reference voltage and its usage of non-optimal voltage profiles, [6].

The improved local approach uses ANNs to overcome the mentioned shortages. Due to their ability to identify and model an unknown non-linear process based on known inputs and desired outputs, they were ideal for use in the presented approach.

Although the computational intelligence tools, such as expert systems and ANNs have been used in voltage and reactive power control in power systems before, the approaches always treated the power system as a whole, with one large ANN controlling the generators in the entire power system in a centralized fashion [7],[8]. This approach faces conceptual as well as practical problems regarding training data, as the number of training samples becomes too large. In addition, it should lead to slow and inefficient operation in large power systems and has only been demonstrated on small-scale systems.

In the proposed control concept, we present the local secondary voltage and reactive power control, an autonomous closed-loop control that sets the voltage reference for the PVCs. Each controlled reactive power source is then equipped with its own LSC, based on the ANN. The LSCs are autonomous, independent from each other and do not require mutual coordination for their satisfactory operation. The LSC-ANNs operate simultaneously to attain a desired voltage profile in the power system, [9]. In the paper, the steps for forming such a nonlinear controller are described and its features are discussed. The control concept could be used for any reactive power source, but for the sake of clarity, we present results for generator control only.

# 2 Problem description

During the course of a day, the loading in a power system rises and falls within a relative wide margin. The secondary voltage control has to adapt the voltage profile – the voltages of all nodes in the power system – to the changing conditions, covering local reactive power demand with local sources.

Interdependency of reactive power sources, loads and voltages defines the matrix power flow equation, (1).

$$\mathbf{f}(\mathbf{x},\mathbf{u}) = \mathbf{0}\,, \tag{1}$$

The vector **x** consists of dependent variables and fixed parameters, while the vector **u** consists of control variables, Eq. (2).

$$\mathbf{x}^{\mathrm{T}} = \left[\mathbf{U}_{\mathrm{g}}^{\mathrm{T}}, \boldsymbol{\delta}^{\mathrm{T}}\right], \quad \mathbf{u}^{\mathrm{T}} = \left[\mathbf{P}_{\mathrm{g}}^{\mathrm{T}}, \mathbf{Q}_{\mathrm{g}}^{\mathrm{T}}\right]. \tag{2}$$

 

Assuming the standard active/reactive power decoupling, the dependency of voltage $U_{gi}$ for the i-th generator in a power system with n generator buses and m load buses bus may be expressed as in Eq. (3).

$$U_{gi} = U_{gi}(\mathbf{U}_b, \mathbf{Q}_b, \mathbf{Q}_g, \mathbf{P}_b, \mathbf{P}_g),\ i = 1,...,n \quad (3)$$

Here $\mathbf{U}_g$ and $\mathbf{U}_b$ represent matrices of generator and load bus voltages, and δ is a vector of phase angles. The $\mathbf{Q}_g$, $\mathbf{Q}_b$, $\mathbf{P}_g$ and $\mathbf{P}_b$ are the respective vectors of active and reactive power generation and load. The reactive power production of the i-th generator and thus its voltage profile is determined by the PVC reference voltage setting $U_{giref}$, supplied by the secondary voltage controller. The PVC automatically brings the generator voltage $U_{gi}$ to this reference setting by controlling the generator's excitation system.

A secondary voltage control law that is uniformly successful for any combination of generator voltages and reactive loads is difficult to derive due to high nonlinearity in (3). In an entirely local approach, each this law should be custom-tailored and embedded in the LSC. The ANN as a nonlinear tool was ideal for this task, determining the correct $U_{giref}$ while taking into account the influence of all the variables in (3).

To make the local control efficient, we had to select the minimum number of inputs that would supply adequate information for ANN voltage control. We relied on the inherently local character of reactive power, which can't be transported over a long distance without significantly increasing active power losses, while distant generators have a relatively weak voltage influence compared to those located near-by. Local reactive power flows could therefore carry sufficient information for local voltage control. They reflect local, generator-specific information on the operating state of the entire power system. According to this premise, the LSC-ANN at the i-th generator bus would require only the locally measured information for operation. After testing, we have selected the amplitude of the controlled node voltage $U_{gi}$ and the vector of reactive power flows $\mathbf{Q}_{fi} = [Q_{fij}]$, j=1…M, on the lines that connect the controlled node with the neighboring nodes, [12]. Regardless of the overall power system topology, the structure of a particular ANN would depend only on the number of lines connected to the controlled generator node.

The ANN would need to be trained to incorporate the information on the power system properties. For this purpose, a set of power system operating states is needed, which would encompass all possible loading conditions within the load diagram, combined with various voltage profiles encountered during normal operation. By training the ANN to these data and to the desired optimal power system states, each trained LSC-ANN would independently assume its task, thus eliminating the need for the coordination of the controllers.

The required set of operating states can be obtained by simulation, using the calculation of the standard power flow (PF), [10]. For the ANN training, two sets of values of the variables in (3) are required:

- the values resulting from the security constrained power flow (CPF), used as input samples, and
- the optimal values from the OPF solution, used as target values in training.

In CPF, the power flow calculation is performed as to respect all the operational generation and voltage limits of the power system.

The power flow calculations should be carried out for power system loadings, ranging from the minimum- to the peak load as encountered in the load diagram. Every power system loading has to be combined with a set of possible generator voltages for all generators to create a large set of power system states. Since unreasonable combinations of voltages and loads may result in instability of the CPF or OPF calculation, the load flow results stemming from these combinations must not be used in the ANN training.

It is uncertain which initial combinations of loads and voltages for power flow calculation are valid for various normal operation states, so a statistical search method has been designed to investigate the problem space, [11]. For all load buses, a uniform probability density function of loading has been used. Similarly, the generator voltages could take any value within the standard voltage interval defined by the physical limitations, for instance (0.9, 1.1) p.u. The statistical search method takes into account the entire set of power system states. For each loading, a random initial generator voltage setting of $U_{gi}$, i=1,..,n, with uniform probability density functions is selected for all generators. The power flow calculation is carried out for CPF and OPF.

In the paper, only the operating states describing the normal operation and complete topology of the power system were considered, during the course of a typical daily load diagram. The performance of the ANN controllers under contingencies was investigated in [12].

## 3 The design of the LSC-ANN

### 3.1 The ANN control scheme

The control scheme of the proposed LSC-ANN is shown in Fig. 1. During its operation, the LSC-ANN receives the information on the power system operating state by measuring the relevant quantities in the controlled node, $U_{gi}$ and $\mathbf{Q}_{fi}$. The primary voltage controller is assumed to set the system voltage according to the secondary reference $U_{ANNi}$ instantaneously. Since the control actions of the LSC-

ANN are much slower, typically in the range of 5 minutes, they can be treated as a time-discrete control with a time interval $T_U$ between the control intervals. The measured quantities in the k-th control step are denoted by a superscript (k). Due to the primary controller action, the measured node voltage in the (k+1)-th step is equal to the LSC-ANN-supplied reference in the k-the step, $U_{gi}^{(k+1)} = U_{ANNi}^{(k)}$. The measured quantities between the control actions are delayed for a time interval $T_U$, and this delay is denoted with a symbol $z^{-1}$.

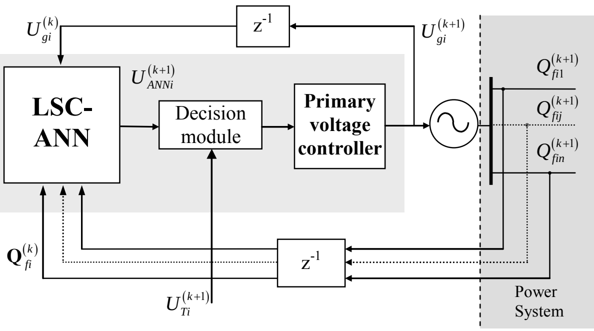


Fig. 1 LSC-ANN control scheme for generator i

Using the Decision module, the secondary voltage-control reference could periodically be superseded by the voltage control signal $U_{Ti}$, either to optimize the system-wide voltage profile via tertiary voltage control or to set the required voltage profile manually. If the input measurements failed, the LSC-ANN would switch off and set the reference voltage to a predetermined value, [6].

### 3.2 The ANN architecture

The most suitable ANN architecture proved to be the feed-forward perceptron ANN, using the Levenberg-Marquardt (LM) training rule based on error back propagation with a very fast convergence, [13]. The difference between the actual and the desired ANN output is minimized through the mean square error. The selected perceptron is relatively simple and suitable for the non-linear identification task.

Among the investigated multilayered ANN-s, a two-layered perceptron has been selected. The number of input neurons, $S^{(0)}$, ranged between 3 and 10, comprising one neuron for the generator voltage $U_{gi}$ and one neuron for each local line on which reactive power flow was measured. The number of neurons in the hidden layer, $S^{(1)}$, was determined according to the empirical rule, [14], Eq. (4).

$$S^{(1)} = 4 \cdot S^{(0)} + 2 \tag{4}$$

In these two layers, all neurons had sigmoidal transfer functions. Adding more hidden neurons only slowed down the training without significant performance gain. The output layer had a single neuron with a linear transfer function. Each LSC-ANN supplied one PVC with reference voltage, so one output neuron was sufficient. The output of the ANN $U_{gANN}$ could assume any value within the interval (0.9, 1.15).

In the LM training rule, setting of its learning rate $\alpha$ can control the speed of training and its sensitivity to local minima [13]. In some adaptive approaches, the learning parameters can be set dynamically, however no systematic methods exist to find initial settings that would guarantee a global optimal solution [2]. The learning rate has been empirically set to $\alpha$=0.7. The inputs have been normalized to the interval (0,1), and the initial synaptic weights have been randomized using Nguyen-Widrow method to avoid entrapment in the local minima, [15]. To prevent overtraining, we have implemented the early stopping procedure during the training by comparing the out-of-sample performance of the ANN; once the out-of-sample mean square error started to rise, the training was terminated.

To train the ANNs, a large set of training samples **P** had to be prepared. In addition to the $U_{gi}$ and $\mathbf{Q}_{fi}$, each training sample also contained the optimal generator voltage, $U_{OPFi}$, as supplied by the OPF, which served as a reference during ANN training. The training vector of training samples **p**, K = 7440, can be written as in Eq. (5).

$$\mathbf{p} = \left[\mathbf{p}^{(k)}\right] = \left(\mathbf{U}_{i}^{(k)}, \mathbf{Q}_{f}^{(k)}, \mathbf{U}_{OPM}^{(k)}\right), \quad k = 1, \ldots, K \tag{5}$$

To obtain this set of power system operating states, the standard voltage interval for power system buses has been set to (0.9, 1.15) p.u. Using the procedure described in [11], a set of 240 initial generator voltage profiles has been combined with 31 load profiles of the power system, resulting in K = 7440 power system states.

The training samples were divided into three sets:

- The training set with 5952 samples (80 %),
- The training-test set with 597 samples (8 %) for detection of ANN ovetraining, and
- The test set with 891 (12 % of all samples) for subsequent testing of the trained ANN.

A single ANN training was limited to 200 epochs, although due to fast convergence it typically took around 50-70 epochs. The time required for the training of a single ANN grew with the square of the number of the input neurons. It took between several minutes to several hours on a Pentium III, 870 MHz using a Matlab 6, Neural Network Toolbox. Since the operation of a trained ANN is in the range of a second, the performance of the LSC-ANN should be quick enough for the secondary voltage control with five- to ten-minute response time.

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After training, the LSC-ANN performance has been evaluated using the test set. The ANN-s have been individually trained and tested, and the test results can be found in [12]. In the paper, more relevant results of the voltage control simulation are shown, with all the ANN-s performing simultaneously in a discrete simulation loop.

## 4 Discrete simulation loop

To evaluate the performance of the trained LSC-ANNs during their simultaneous operation, a discrete simulation loop has been set up, Fig. 2. The power system operation with the embedded ANN-LSCs was simulated with unconstrained power flow (PF). Contrary to the OPF, the PF did not take into account any operational limits of the power system, so the resulting generator voltages were indeed only result of the LSC-ANN control action. In the k-th simulation step, the LSC of the i-th generator receives the inputs $[U_{gi}^{(k)}, \mathbf{Q}_{fi}^{(k)}]$. The resulting ANN voltages $U_{ANNi}^{(k)}$ were used in the next cycle of the loop as a reference for the PVC. The power system state is changing under the influence of the changing reactive load, $\mathbf{Q}_b$.

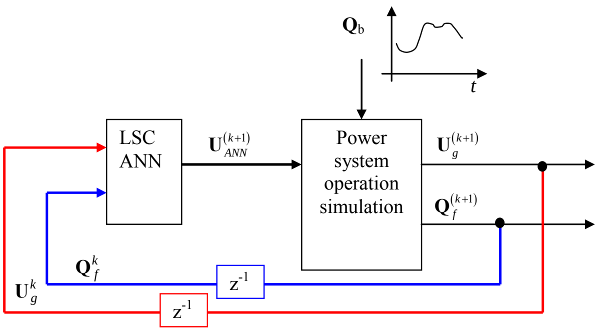


Fig. 2. Discrete simulation loop

The dynamic response of the power system was simulated using the discrete simulation loop for a standard 24-hour load diagram, Fig. 3. The discrete simulation loop was run continuously for 24 steps, mimicking a period of 24 hours in hourly cycles. During a single step, the $\mathbf{Q}_b$ of the system remained constant. In the results, the bus voltage vector $\mathbf{U}_g$ is shown as the system voltage profile.

## 5 The results

The LSC-ANN control was tested on a model of Slovenian high voltage power system with 192 nodes, 273 lines, 23 generators and 55 transformers. The system included also 15 nodes of the neighboring power systems, including the slack bus that was not equipped with a LSC-ANN. Each of the 22 generators had its own LSC-ANN, which has been separately trained on the results of the same CPF- and OPF calculations. The details on the test system and the load simulation conditions are described in [12].

First, the static response of the power system, equipped with LSC-ANNs has been evaluated for all operating states in the test set. A voltage profile for one of them, a day in November at 13.00 hours is shown in Fig. 5. The first 22 nodes are generator nodes, and the rest are load nodes. We can observe that except in some load buses in reactive power deficient areas, the ANN voltage profile coincides well with the OPF-supplied one. In the nodes where OPF-based centralized control increases the voltage, the ANN control performs similarly. When we compare the generator voltage profiles for the same operating state, Fig. 4, we can again see that the ANN control mimics the OPF reference successfully.

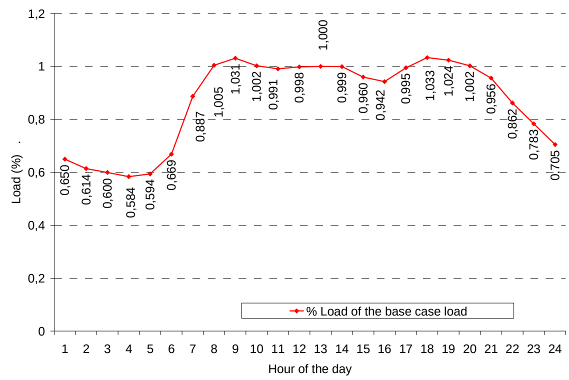


Fig. 3 Standard load diagram

Following the system operation through the 24 hours of the day, the LSC-ANN-controlled generator voltages remain within the prescribed limits, guiding the reactive power generation throughout the day despite of the changing reactive power load, Fig. 6.

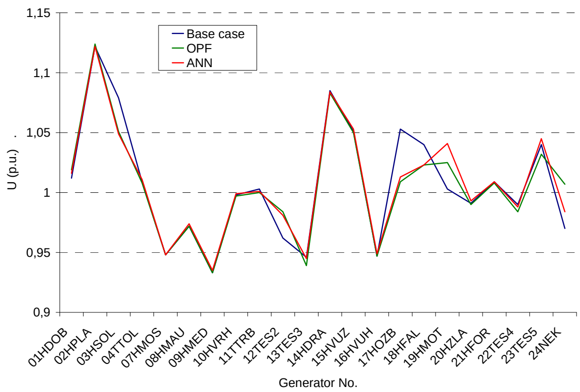


Fig. 4 Generator voltage profile comparison

At the same time, we can observe that at the end of the 24-hour period that some of the voltages exhibit a big change from the morning levels, although ideally they should end up at the same voltage levels. One of the reasons for that may also be the fact that the ANNs were trained to simulated operating states, not the actual ones. If we trained the ANNs to the actual power system states, we could possibly improve their operation. We should also bear in mind that the ANN control in this case does not comprise any measures for LSC-ANN coordination or enhancement of their operation, e.g. conditional controller output limiters, gradual reference setting or inclusion of additional measurements into input samples. All these measures could significantly improve the results of the proposed LSC-ANN control.

## 6 Conclusion

A new completely decentralized secondary voltage control framework based on ANNs is presented. It includes all the generators in the system and only requires local information for its operation. The proposed local ANN local secondary voltage control can successfully handle a wide range of power system states. The new ANN secondary voltage control scheme also yields suboptimal control and robust operation even in a dynamic control of a realistic power system model. The simulation results of the voltage control using a discrete simulation loop are presented for Slovenian power system model with 22 controlled generator nodes.

The hardware required for the proposed controller is easily attachable to the existing primary voltage regulator, making its cost/benefit ratio favorable. The ANNs could easily be retrained in case of topology changes in the power system. Since it can be implemented gradually in stages, the concept is suitable for the independent power producers as well as the system generators to market their potential and offer adequate voltage control service to the transmission grid companies.

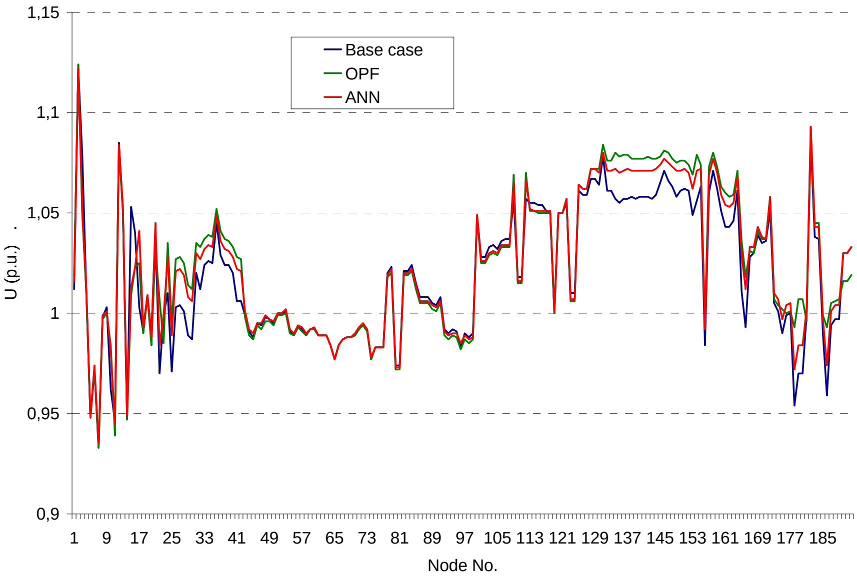


Fig. 5 Power system voltage profile comparison

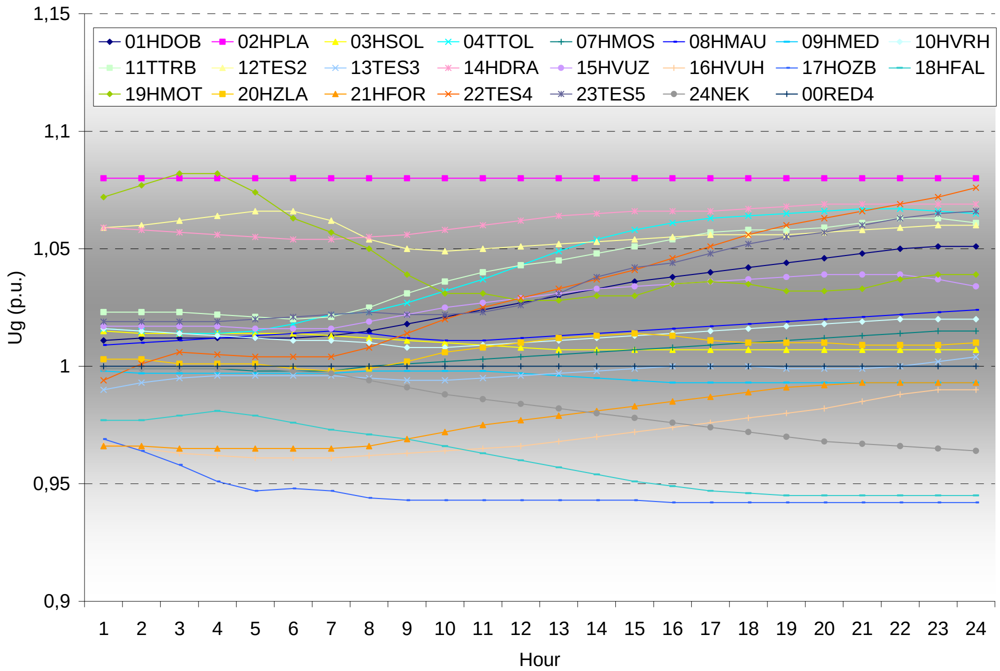


Fig. 6 Generator voltage profile for 24-hour period, ANN control

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