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Validation of neural network-based fault diagnosis for multi-stack fuel cell systems: stack voltage deviation detection

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Abstract

This paper presents (i) an algorithm for the detection of unexpected stack voltage deviations in an Solid Oxide Fuel Cells (SOFC)-based power system with multiple stacks and (ii) its validation in a simulated online environment. The algorithm is based on recurrent neural networks (RNNs) and is validated by using operating data from the Wärtsilä WFC20 multi-stack SOFC system. The voltage deviation detection is based on statistical testing. Instead of a hardware implementation in the actual power plant, the algorithm is validated in a simulated online environment that provides data I/O communication based on the OPC (i.e. Object Linking and Embedding (OLE) for Process Control) protocol, which is also the technology utilized in the real hardware environment. The validation tests show that the RNN-based algorithm effectively detects unwanted stack voltage deviations and also that it is online-viable.

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Keywords: Solid Oxide Fuel Cell; Multi-Stack System; Voltage Fault Diagnosis; Online Validation ; Neural Networks

1. INTRODUCTION

The solid oxide fuel cell technology provides an efficient means of producing electric power from a variety of fuels. With the current material and manufacturing limitations, a large-scale SOFC power plant (>50kW) cannot rely only on a single stack of SOFCs, but several – tens or even hundreds – of SOFC stacks must be used in parallel to

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produce the necessary high-power output. In some designs, the stacks in such a multi-stack system are thermally connected (i.e. not separately insulted) but have separate fuel and air feeds and possibly have independent load control. The thermal connection of the stacks, among other things, makes it desirable to aim for operating the stacks in a controlled and uniform manner, so that the degradation rate and thus the heat production of all stacks is similar throughout their lifetime.

The stack voltage is a typical measure of stack performance and/or stack condition. If the voltage of one (or more) stack(s) in a multi-stack system starts to behave differently than before – than what is considered normal – this should be detected as early as possible as it signals that the stacks are changing differently, possibly indicating an incipient stack failure. The early detection of such stack voltage deviations then enables counteracting the changes via controlling the stacks' current values appropriately.

This paper presents a simple algorithm for automatic detection of stack voltage deviations and the simulated online validation of that algorithm with real system data. Section 2 focuses on the development of recurrent neural networks suitable to perform real-time one-step ahead prediction of SOFC voltage. Then, the stack voltage deviation detection principles are presented in Section 3. Afterwards, the simulation testing environment is described in section 4, particularly highlighting the successful integration of RNN estimators with the voltage detection algorithm within a unique software environment. The results and conclusions are finally discussed in Sections 4 and 5, respectively.

2. RECURRENT NEURAL NETWORK DEVELOPMENT

RNN predictors were often proven effective for real-time applications concerning energy systems, as described in [1][2]. Specifically in this work, the RNN model topology developed for SOFC stack and systems and presented in [2] was here deployed, to perform one-step ahead prediction of single-stack voltage within the above-mentioned Wärtsilä WFC20 multi-stack SOFC system. It is worth clarifying here that RNN structure, whose optimal selection positively impacts against overfitting issues, was firstly determined by running a trial and error analysis on the validation error made by an RNN simulator of the average multi-stack voltage. Fig. 1 resumes the results of such an analysis, particularly highlighting how a relatively low number of hidden neurons (i.e. 5) is sufficient to guarantee adequate accuracy and generalization, whereas past memory of input variables (past input data) should correspond to 8. However, since the error does not increase that significantly going from 8 to 10, it was decided to select the structure consisting of 5 hidden neurons and 10 past inputs, as it was proven more accurate, on average, on both the training and test sets. Regarding the output feedbacks number, it was assumed equal to 2, in accordance with past experience gained by the authors in previous experimentally tested applications [3].

Afterwards, 6 different RNNs were trained on a simple training-set, which mainly consisted of a ramp variation in current density. The good level of generalization achieved by the RNN structure addressed by the above-described trial-and-error analysis (see Fig. 1) is confirmed by the good agreement between experimental and simulated trajectories over the test data-set shown on Fig. 2.

Finally, Fig. 3 shows how the six RNN predictors were assembled together into a unique Matlab/Simulink® block, which was subsequently interfaced to the detection algorithm, as described later on in the current paper. Further details on theoretical background of RNN models can be retrieved from [4].

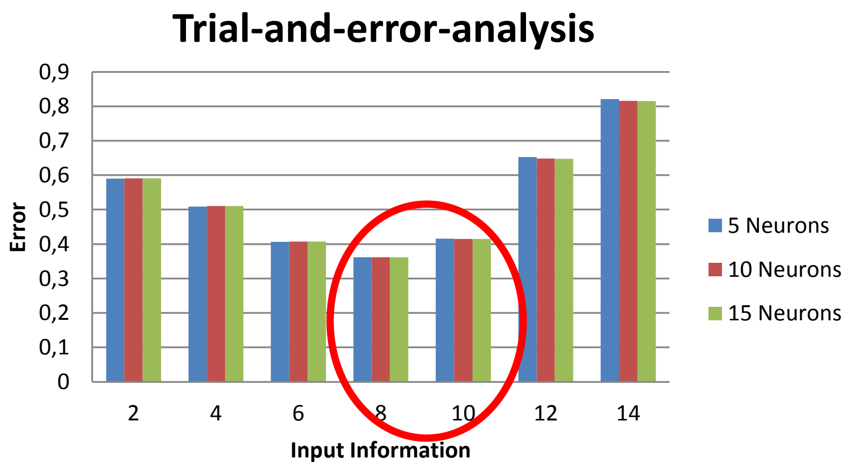

Fig. 1. Test error variation as a function of the RNN structure used to simulate average multi-stack voltage trajectory.

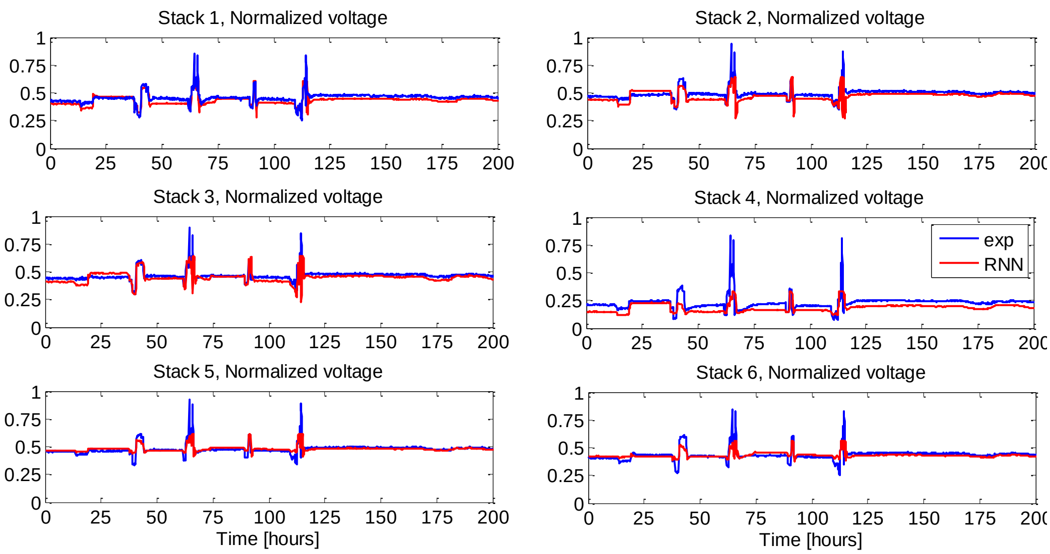

Fig. 2. Comparison between experimental and simulated voltage trajectories, here considered as test-sets for 6 stacks included in the Wärtsilä WFC20 multi-stack SOFC system.

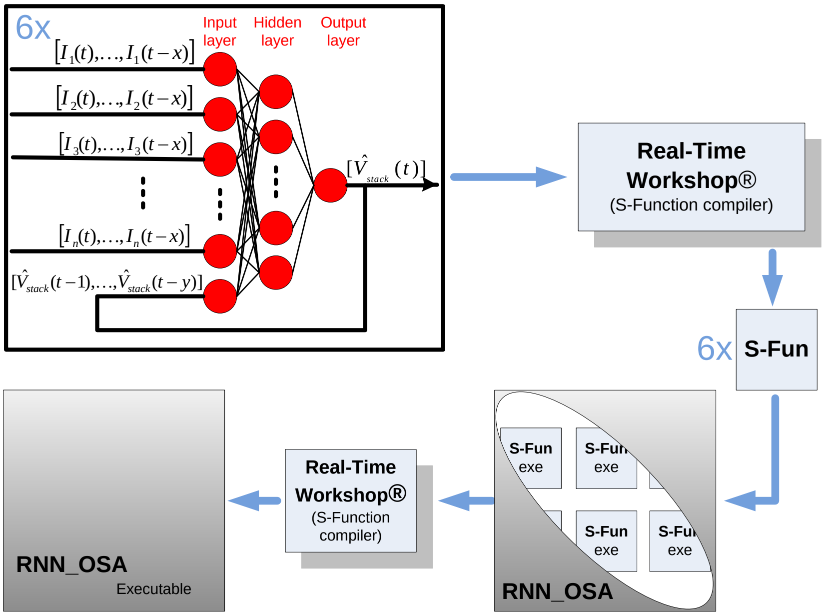

Fig. 3. Schematic description of the multi-RNN executable, which was specifically developed for testing the model-based diagnostic tool in a simulated online environment (see sections 4 and 5).

3. DETECTION OF STACK VOLTAGE DEVIATION

The scheme of the stack voltage detection algorithm is given in Fig. 4. As in any model-based diagnosis algorithm, also the basis of this one is the RNN model, which gives an estimate of what the stack voltages should be assuming normal operating conditions and normal stack condition. The stack voltage estimate then enables computing a difference between the observed current voltage value U [V] and the estimated voltage value U_{est} [V], the residual, which is used as information of what the stack's condition is with respect to its normal condition. Ultimately, the problem boils down to (a) determining the limits within what the stack voltage, and thus its condition, is considered normal and (b) finding a good mechanism for detecting when these limits are crossed, i.e. filtering the residual.

3.1. Normal limits (a)

In the example case, the normal condition of the stack was set by a pre-determined range, within which the stack voltage should be at every operating condition. This range was then used to calculate how large a stack voltage residual (i.e. deviation amplitude) is allowed, assuming a certain error for the model and the measurement. Defining the numerical values for these properties was mainly based on engineering experience.
In the example case, the deviation amplitude threshold U_{th} was set to 100 mV per stack (Table 1), which is ca. 0.2 % of the full stack voltage. The average residual error was estimated by logging the standard deviation (STD) of stack voltage U_{std} for each stack always after activation of the detection algorithm and using this STD value in the limit-crossing test. The stack voltage measurement STD was on average ca. 110mV, varying slightly per stack. The STD for the stack voltage estimate and the calculated residual were notably smaller, which is why the stack voltage measurement STD value was used in the algorithm.

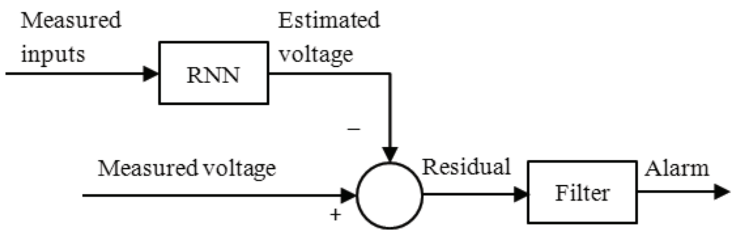

Fig. 4. Illustration of the model-based stack voltage deviation detection scheme.

3.2. Limit crossing detection (b)

Because neither the stack voltage measurement nor the model output is noise-free, a fixed threshold value for detecting residual limit crossing would lead to many (very short) false alarms. Therefore, a combination of (i) residual sampling over a moving time window with statistical testing of this sample against the residual limit value and (ii) a temporal threshold for the statistical test result was utilized to obtain reliable yet crisp and timely alarms. Furthermore, this combination is also simple enough so that the number and meaning of free parameters remains conceivable to the operator.

In practice, the statistical z-test is applied on the residual sample $U_{res} = [U(t) - U_{est}(t), \ldots, U(t - N_{res}) - U_{est}(t - N_{res})]$ to check if the sample mean deviates from zero towards the negative more than the chosen threshold value U_{th} allows, with the chosen probability of 95%. The z-test is performed by calculating the z-score assuming a mean population value μ_0 equal to U_{th} and a standard deviation σ computed based on the data collected right after a steady-state condition has been detected. Subsequently, if according to the z-test, the sample U_{res} is such that the corresponding z-score falls out of the 95 % confidence region (meaning that there is a less than 5% chance that the sample U_{res} belongs to a distribution that satisfies the null hypothesis, being that the residual mean is within the threshold), then the value of a counter, named t_{alarm}, is increased by the value Δt. If, however, the z-test is positive (i.e. residual sample mean is within given limits), the counter t_{alarm} is reset to zero. Finally, if the counter t_{alarm} reaches the value of t_{th} (the residual having deviated continuously for so long), an alarm is raised.

In the example case, the z-test was carried out on a sample of N_{res} = 24 residual data points (corresponding to a sample time window of 2 hours) and the z-test would have to give a positive indication of significant residual deviation continuously for over t_{th} = 5 h of time before raising the alarm.

3.3. Algorithm operation

Although the RNN model enables estimating the stack voltage also during transient operation, the diagnosis algorithm was implemented only for steady state operation. To this end, a simple detection rule was used to enable or disable the diagnosis algorithm when a steady state or a transient, respectively, is detected. The detection of a steady operating state is achieved by simply comparing the moving average $x_{MA}(t) = \alpha x(t) + (1 - \alpha)x_{MA}(t - \Delta t)$ (with $0 < \alpha < 1$) of the system inputs x to their current (measured) value. If these two are (close to) equal – i.e. if $|x_{MA}(t) - x(t)| < \beta$, where β is small – the system was considered to be in a steady state, otherwise not. (The approach is identical to monitoring the change of the moving average of the inputs). The observed variables could of course be other process measurements than just the inputs.

In the example case, the load current is the only input that changes and is monitored. The parameter values $\alpha = 1/4$ and β = 0.1 A were used (see Table 1).

When a steady state of operation is detected and the diagnosis algorithm is enabled, the statistical properties (in the example case only the standard deviation U_{std}) of the measurements are logged for later use in the *z*-testing phase. An illustration of the algorithm operation is given in Fig. 5.

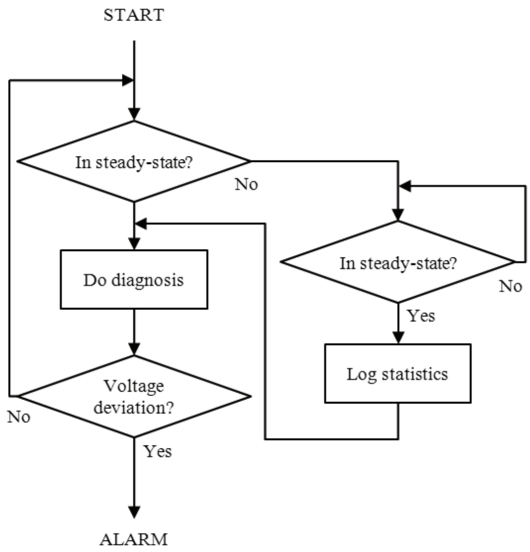

Fig. 5. Flow of stack voltage deviation detection algorithm.

4. ALGORITHM TESTING

The algorithm was tested with recorded real operating data from the case system, the Wärtsilä WFC20 system, located in Vaasa, Finland [5][6]. The system was operated with landfill gas and has a nominal electric power output of 20kW. The system contains a total of 24 SOFC stacks and the stack voltage of all stacks is measured. For the sake of clarity, however, the signals of only six stacks with identical current are presented in this paper.

The test case consists of ca. 200 hours of operation, during which the stacks' load current changes from 12 to 15 amperes (at ca. 40 hours of operation). The stacks' current and voltage trajectories (both simulated and experimental) in the test case are shown in Fig. 6. The voltage of stack 3 shows slight abnormal degradation at ca. 120 hours of operation and a clear drop in the stack performance is seen at ca. 160 hours.

The voltage deviation detection algorithm was tested by using a simulated online environment. In practice, the previously recorded real operating data from the multi-stack SOFC system was accessed through an identical data I/O interface as the one that is used in the actual hardware environment, in this case the OPC protocol [7]. The simulated online testing environment was implemented by using the Apros [8] and Matlab™ [9] software tools and a regular PC. Apros provided an access to the data through an OPC server and Matlab was used to run both the RNN stack voltage model (see Fig. 3) as well as the voltage deviation detection algorithm. The system was then operated in real world time or faster, with the data being read, the estimates and alarms being continuously computed. Typically, the test environment operated at an average speed of ca. 120 times the real world clock, thus illustrating online feasibility of the algorithm.

The input data utilized by the RNN model for the stack voltage estimate computation includes the load current per stack (A), fuel flow ([V]/[t]) and composition (-), air flow ([V]/[t]) as well as the pressure [p] and temperature [T] measurements from the flow inlets [2]. As the aim of this work was to evaluate the RNN-based diagnosis algorithm and its online feasibility, ca. 100 hours from the beginning of the test case data set (considered healthy data) were used for the RNN training process to assure an appropriate RNN estimation accuracy.

The values of all simulation and algorithm parameters in the test case are collected in Table 1.

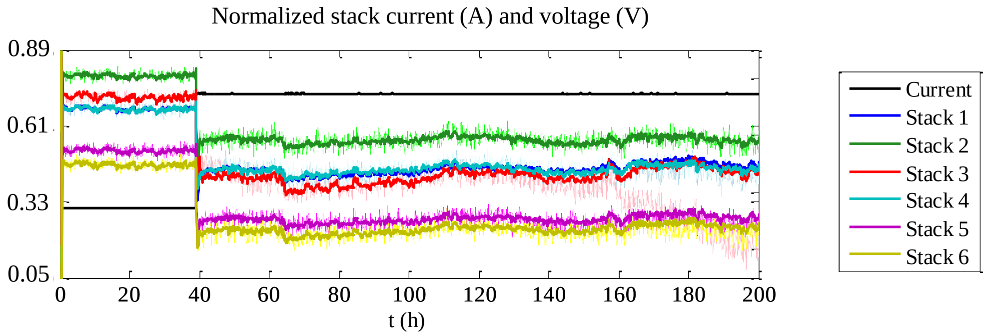

Fig. 6. The current (black) and voltages (colors) of six stacks (see Fig. 2 and Fig. 3) in the test case. Bold lines indicate stack voltage estimates, the light lines are measurement data.

5. RESULTS AND DISCUSSION

The stack voltage estimation residual signals and the alarm signals (per stack) are shown in Fig. 7 (a) and Fig. 7 (b), respectively. In the examined case, the algorithm gives a crisp notification at ca. 150 hours of operation that the voltage of stack number 3 is deviating from the normal values in a manner that is considered significant by the operator. Looking at the residual of stack 3 in Fig. 7 (a), it is clear that the stack indicates abnormal behaviour already at the input step change at 40 hours. Based on the residual plot, it can be also said that the continuous deviation of the residual begins at ca. 120 hours. However, when looking only at the measured stack voltage in Fig. 6, a significant deterioration of the stack voltage is only observed by the human eye at ca. 160 hours. Therefore it is reasonable to say that the alarm is sounded on time.

The parameters – Given a fixed deviation amplitude threshold (U_{th}), the time instant at which an alarm is raised can be adjusted with the parameters N_{res} and t_{th}. Increasing them both basically improves the detection reliability, but increases the lag-time between failure initiation and its "detection" and vice-versa. However, it is clear that N_{res} should not at least be larger than the number of samples measured during t_{th} (i.e. $\sim t_{th}/\Delta t$). Such a configuration could cause the algorithm to miss, where an alarm should be raised. Furthermore, with the said limit for N_{res}, the parameter t_{th} can be considered the parameter which dominates the frequency of raising false alarms, and in the contrary, N_{res} affects the most when an alarm is reset (since an alarm is always reset after one non-alarming residual sample being found).

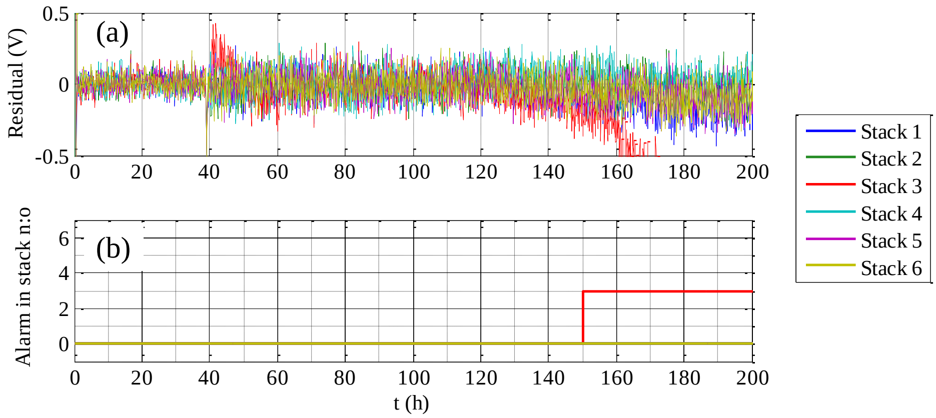

Fig. 7. Stack voltage estimation residuals (a) and the voltage deviation detection output, i.e. the alarm (b).

Table 1. Stack voltage deviation detection algorithm parameters.

Parameter description	**Symbol**	**Value**	**Unit**
Sampling time	Δt	300	S
Residual sample size in limit-crossing *z*-test	N_{res}	24	-
Amplitude threshold for stack voltage deviation	U_{th}	0.1	V
Signal deviation threshold for limit-crossing *z*-test (varies by stack)	U_{std}	ca. 0.1	V
Temporal threshold for deviation before alarm	t_{th}	18000	s
Moving average weight for steady state detection	α	1/4	-
Steady state threshold for current	β	0.1	A

6. CONCLUSIONS

A simple algorithm for automatic detection of stack voltage deviations in a multi-stack fuel cell system was created and tested in a simulated online environment. The algorithm is a typical model-based FDI algorithm and is based on a recurrent neural network model, which is used to estimate the stack voltages in normal operating state. Operational data-sets from a real multi-stack SOFC system were used in the RNN network training and test, as well as in the detection-algorithm testing. The test results show that the algorithm is capable of detecting and identifying a deviation in a stack voltage, and that it is applicable for online use.

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