Final Report

Please note that the contents of the Final Report can be found in the attachment.

4.1 Final publishable summary report

Executive Summary

GENIUS is a collaborative European project aiming at developing a GEneric diagNosis InstrUment for SOFC Systems. It was funded by the Fuel Cell and Hydrogen Joint Undertaking (FCH-JU) within the scope of STATIONARY POWER GENERATION & CHP application area and its topic "Operation diagnostics and control for stationary applications" (SP1-JTI-FCH.3). The project gathered 12 partners from 7 countries: 6 industrial partners, 5 academic institutions and one partner responsible for administrative project management. (Cf. Figure 1). The project total budget was 3.928 M€ for an EU funding of 2.068 M€.
Two different diagnostic approaches were considered and compared (Cf. Figure 2):
• Residual based approaches. In this approach, the system is modelled either through a behavioural model directly obtained from experimental results and the residuals between experimental and predicted values is calculated. This residual value is further compared with previously defined threshold and, depending on whether the residual goes over the threshold or not, a fault is detected.
• Pattern recognition based approaches. Indicators are extracted from the signal and directly classified according to their mathematical behaviour.
Algorithms developed from these both approaches were tested and validated, either off-line (on sets of pre-acquired experimental results and on-line (on real systems under operation, including a commercial one). At least two algorithms were successfully validated on least two systems). For validation purpose, system hardware had to be modified in order to mimic faults.
Besides this algorithm validation, the project also succeeded in performing Electrochemical Impedance Spectroscopy (EIS) on real commercial system. These measurements were of a great help for the development of the diagnostic algorithms.

Figure 1: Genius consortium mapping Figure 2: Principle of diagnostic

Summary description of project context and objectives

The project was initiated by the necessity to improve SOFC systems reliability so as to favour their commercial deployment. At project start-up, it appeared that system fault/failure prevention was only based on the regulation by the control system of some pre-defined operating parameters (temperature, pressures, gas composition) within closed range of variation. As soon as one of these parameters goes out the "normal" range of variation, the system is automatically shut-down or put in stand-by mode. But, for that purpose, different sensors have to be implemented in the system in order to detect any deviation from these "nominal" conditions. However, such approach is problematic for stack and system designers since any increase in system complexity increases costs and lowers reliability. Additionally, in real systems, there are practical limitations on the number and sophistication of sensors that can be incorporated.
It therefore appeared that the handling of faults/failures with an appropriate counter measures was hindered by the difficulty of evaluating systems' state of health. Moreover, stack internal actual operating conditions vary significantly during life-time (e.g. due to components ageing) and, in large-scale systems including several stacks, there might be heterogeneities in operating conditions between the different stacks. The behaviour of a fuel cell system is also rarely predictable, since a certain degree of variability is often present in: operating conditions, system inputs, physical and/or chemical internal processes...
For all these reasons, in order to optimise the control actions and degradation prevention capabilities and in order to reduce system complexity, specific diagnostic methods are needed to determine the actual state of the stacks in real-time. Since process values are already measured from the system, the development of a state estimate that uses such values and is based on a validated model was envisaged for the project in order to define an optimal operating point.

This project's objectives was to develop a generic diagnostic tool that could be implemented by each manufacturer on its specific own system, according to its own specification. But, the specific operating modes, architecture and applications constraints shifted this objective from the development of generic diagnostic “tool” to a generic “approach” that could, after customization, further be validated on several real systems.

Description of main S & T results/foregrounds

Introduction: Project’s structure:
In order to achieve the previously mentioned objectives, the project was structured in five main tasks:

Definition of diagnostic tool technical specifications by stack/systems manufacturers.

On the basis of the algorithm developers’ needs and the actual possibilities of experimental facilities and practical “limitation” of real stacks/systems, test plans were defined in order to provide algorithm developers with the data they need. For that purpose, stacks and systems from 4 different manufacturers (CFCL, TopSoE, Hexis, HTc) were characterized, partly using the Design of Experiment methodology, so as to isolate the main parameters and interactions that impact faults and failures. For that purpose, specific modifications have been carried out on some systems.

Data treatment for the analysis in order to provide algorithm developers with given types of information (e.g. EIS spectra) or for the analysis by design of experiments methodology.

Development of three different types of diagnostic algorithm: signal based (developed by FC Lab) and both grey box (developed by UniGE) and black box (developed by UniSA) model based.

On-line and off-line validation of developed algorithms on complete systems. Some of these validation activities were successfully done by mimicking faults on a full system. Table 1 below synthesizes the validation activities performed by the different partners:

Figure 3: Genius project structure.

Diagnostic approach technical specification:

The performance and the degradation of a SOFC system is influenced by a complex interplay of several parameters such as the operation parameters and mode, the system and cells' design, the materials and the processing. Consequently, a generic approach has to take all these parameters into account. The two key requirements for this generic approach are:

Monitor the critical parameters of the system and identify deviations in the performance

Identify and monitor the stack degradation.

Model boundaries: For a first modeling approach, the consortium decided to focus on the stack input parameters (e.g. gas input, gas quality, temperatures, current density …). With respect to the approach generality, the best overlapping of input parameters is expected, at stack level, for different stacks and systems. General input parameters of the system/stack are, for instance: gas and air flows, gas composition and stack temperature. The stack power or voltage are output parameters.
Feasible Parameters: In a first approach, Genius consortium agreed to study the generic approach on three different types of systems/stacks: an open micro-CHP system (Hexis), a closed mirco-CHP system/stack (Topsoe Fuel Cells, CFCL, HT Ceramix) and a large system (Wärtsilä). This had mainly two reasons:

Each industrial partner would get a specific solution for their system/stack.

The generality of the approach can be validated

To make a design of experiment, the controllable parameters of each system/stack and their variation range were collected. They were defined from the boundaries of the system/stack for safe operation. By comparing the three different SOFC-systems (open, closed and large) several input parameters were found in common such as: air and gas flow rates and both stack power and temperature. For all studied systems, these parameters are easy to measure/control continuously and could therefore be considered as the key input parameters of the generic approach. Furthermore, the gas composition is known from measurements or thermodynamic calculations and can therefore also be regarded as an input parameter. Gas in- and outlet pressures are not measured from all partners. However they are in general easy to access and less expensive. Therefore the gas pressures might be included as realistic input parameters in some cases.

Note: The number of controllable parameters is limited in SOFC systems. Furthermore the controllable input parameters have no scientific accuracy. Parameters such as the temperature and the gas composition show local deviations over the stack or cell. Therefore a generic approach validation would required additional measurements such as: impedance spectroscopy or gas flow, composition, pressures or temperature. However, these additional measurements are hardly feasible under real field operating conditions.

Test plan definition

DoE:
In this methodology, we define:

Variable: any physical measurable entity.

Parameter: any variable which value is studied, controlled and regulated during the experiments.

Response: any measurable variable which variation is a consequence of parameters variations.

The parameters are first transformed into “reduced cantered parameters”: their range of variation is reduced to [-1, +1]. Moreover, parameters are not changed as "one factor at a time" with several points within the range of variation, but on "2-3 level points with several factors at a time". This methodology is also based on:

A postulated model. For each considered response Y, and each reduced centred parameter X, we have, in case we limit our study to direct effects and interactions:

(Eq. 1)

Where: Y0 corresponds to the average value of Y measured for all the experiments, ai corresponds to the direct effect coefficient (a positive/negative value indicates that an increase of the considered parameter induces an increase/decrease of the considered response), aij corresponds to the interaction effect (a positive value indicates a synergistic effect while a negative value indicates a compensative effect).
In such case, where no optimum is considered, the parameters values are taken at only two values: their maximum and their minimum.
The set of equations Eq. 1 can be rewritten in a matricial form as follow:
Y=X.A+E (Eq. 2)

Some statistical hypothesis. Two of them are:

Gaussian error distribution.

Homoscedasticity: the standard deviation of a response is homogenous in the whole studied domain (i.e. all the values in vector E are equals to #0, the measurement's uncertainties measured at the centre of the domain).

Some mathematical constraints that can guarantee the test plan’s “well conditioning”. In such case, the variance covariance matrix (X^T.X)^(-1) Is diagonal. One of the option to fulfil this requirement is to use a “full” or “fractional factorial” test plan.

A randomisation of experimental sequence.

The necessity to perform at least 3 (better 5 or more) reproductions of the experiments in the centre of the domain (i.e.: the value of reduced centred parameters equals zero), in order to quantify measurements’ reproducibility (and determine the significance of coefficients ai and aij versus the errors) and detect potential ageing during the experimental sequence.

To solve the system of equations Eq. 1, the following equation is applied:
A=(X^T.X)^(-1).X^T.(Y-E) (Eq. 3)

Test matrix for black box models:
The 1st test round was based on a test plan defined with the Design of Experiment (DoE) methodology. The varied parameters were: natural gas input power (W); Lambda CPO (#CPO) (ratio between oxygen and natural gas flow rates at reformer inlet); average cell voltage (Ucell); average temperature (T). However, the data analysed with the DoE treatment approach showed that the chosen parameters have no statistically significant interactions. Additionally, the most promising

diagnosis algorithms developed at that point were all black- and grey-box model-based and needed a high amount of tested operating conditions. Therefore, the test plan for the 2nd test round was an extension of the DoE test plan, including many more points that were suitable to assess and validate the model-based diagnosis algorithms developed within the project. It covered the parameter variation domain much more extensively than the one for the 1st test round. It was generated by randomizing the variation of the 4 parameters within their range of admissible values. An algorithm was developed to generate the operating conditions to be tested so that the variation domains were exhaustively covered. Specifically:

a test plan with 54 random and 16 DoE operating conditions was developed for TOFC. With respect to the 1st test plan, the considered parameters were the same, i.e. furnace temperature Tfurn, current density j, Fuel Utilisation FU and Air Utilisation AU, but the current density and AU variation ranges were reduced to avoid excessively harmful conditions that caused stack failures during the first test round.

a 90 random point plus 16 point DoE test plan was designed for VTT. In this case, more points were investigated since the stack to be tested was smaller and allowed faster measurements. The DoE test plan had to be carried out before and after the other test plan. In the 1st test plan, the 4 investigated parameters were furnace temperature Tfurn, current density j, Fuel Utilisation FU and oxygen-to-carbon ratio at the reformer inlet #CPO simulated with a mixture of hydrogen, oxygen and water as input fuel. However, the data analysis pointed out that the simulated #CPO has a negligible effect on all the monitored signals and responses. Consequently it was replaced with the Air Utilisation AU.

a 51 random operating condition test plan was developed for EIFER, considering new operating domain defined by Hexis for their Galileo 1000N.

Results of stack/system characterization for data generation:

Tests at EIFER:
A test bench was built in the EIFER's laboratories to test the Galileo N1000 system to guarantee long term tests and completely self-control features. All the sensors signals were monitored with LabVIEW on a dedicated PC, which also controlled all the actuators installed on the EIFER test bench. A picture of the EIFER test bench used to test the Galileo 1000N is provided in Figure 4 with the Natural Gas (NG) supply line and a ventilation system to manage the gas inlet and outlet flows. Additionally, the generated thermal power, carried by a liquid flow, is dissipated with a thermal load (which plays the role of the final user) by means of a liquid-liquid heat exchanger. The generated electrical power is fed directly into the electrical grid since the Galileo 1000N has an integrated DC/AC inverter. A power monitoring system allows measuring the net AC output power. A customised switch has also been built and installed between the stack and the inverter to allow performing Electrochemical Impedance Spectroscopy (EIS) measurements directly on the stack. In particular, by using the switch, it is possible to disconnect the stack from the inverter and connect it to the electronic load part of the EIS spectrometer.

Figure 4 - Picture of the EIFER test bench to test the Galileo N1000 system

An example of the results obtained at EIFER during phase 1 is shown in Figure 5, where the effect of the four control parameters and their interactions on the response AC current is analysed. It is possible to conclude that the current is proportional to the natural gas input power (coefficient a1) and the product of all the inputs (a1234), but inversely proportional to the single cell voltage (a4) and the interactions P_NG*U_Cell (a14) and P_NG*#_CPO*T (a123).

Figure 5 - Full Factorial Design regression coefficients for the AC current phase 1 for the Hexis Galileo 1000N

Another important result was the measurement of EIS on the stack integrated into the Galileo 1000N. Such measuremlents were particularly challenging because of the inaccessibility to the stack and the fact that the Galileo is a pre-commercial system and thus strongly coupled with all the BoP and power management components. During normal operation, the fuel cell stack is indeed connected to an inverter and the system delivers power to the electrical grid. When EIS spectra are to be recorded, the stack was brought to Open Circuit Voltage (OCV) and the inverter was disconnected. By means of an electrical switch the stack was then connected to the electronic load used to perform EIS measurements and the voltage was driven to its minimum value (this was also an I-U curve). Thereafter, the voltage was ramped again up to the OCV (this was again an I-U curve) and the stack was then switched to the inverter again. EIS spectra were recorded either when the voltage was ramped down to the minimum value or up to OCV. Figure 6 shows the case for a spectrum recorded at an average voltage of 56.7 V during the ramp up while examples of EIS spectra recorded over time are provided in Figure 7.

Figure 6 – Example of switching procedure from inverter to EIS device for the Hexis Galileo 1000N stack

Figure 7 – Example of EIS data recorded over time on the Hexis Galileo 1000N

Tests at VTT:

VTT performed three test rounds on different 6 cells HTc stacks with 48 cm² active area:
a test plan defined according to a DoE methodology (full factorial 2 levels test plan for 4 parameters = 16 experiments + 5 reproductions in the domain centre) with an operation under pure hydrogen.
a test plan defined according to DoE methodology (full factorial 2 levels test plan for 4 parameters = 16 experiments + 5 reproductions in the domain centre) with an operation under reformate.
A sequence of 85 experimental points aiming at gathering extensive empirical data of the stack operation for static and dynamic, grey-box and black-box model parameterization.
The stacks (shown in Figure 8) were tested on a test bench which scheme is presented on Figure 9. All cell voltages were measured and all flows were controlled. Temperature and pressure of gas flows were measured in both the stack inlets and outlets. The furnace temperature was controlled and the stack temperature was measured with a thermoelement. Additionally, the humidity and O2-content of the cathode outlet were measured (along with humidity measurement in the cathode inlet). All data were recorded with a 1s sampling time. In addition, IV-curves, EI spectra and high-frequency (10 Hz) measurements were carried out in selected cases.

Figure 8: HTc short stack in the open furnace at VTT. Figure 9: Test rig set-up for the HTc short stack at the VTT test laboratory.

IV-curves measured in the domain centre were used to follow the stack degradation during "ageing". If the overall stack degradation is negligible (Cf. Figure 10 for 1st test round), some slight individual cell degradation can however be clearly observed (Cf. Figure 11 for 1st test round).

Figure 10 – Stack IV-curves measured at the repeated points of the 1st round 21-point DoE test.

Figure 11 - Individual IV-curves measured for the different reproductions in the domain centre.

As an example of DoE analysis, Figure 12 shows the influence of the different studied parameters and interactions on stack voltage. It appears that stack voltage is submitted to three really significant effect, which are in a decreasing magnitude: a negative direct effect of current, a direct positive effect of furnace temperature and a synergistic effect of temperature and applied current density.

Figure 12: Influence on stack voltage of the different studied parameters and interactions.

In the early part of the second tests round, one of the six cells, (cell nr 3), broke. Nevertheless, the test was continued as the five other cells produced useful data. Figure 13 displays the stack current and the cell voltages. Unfortunately, the broken cell deteriorated the stack EIS measurements.

Figure 13 - Stack current and cell voltages evolutionsduring the 2nd test round.

The 2nd round testing was continued for 660 h in order to collect extensive data for model parameterization: 85 random experimental points were studied. White noise input excitation was employed and repetitions in the test domain centre were carried out every 10 operating conditions. The result was generally considered well sufficient. Figure 14 gives an overview of the test conditions, with stack current and the voltages of the stack's "healthy" cells (i.e. cell nr 3 excluded) plotted in the sub-figures. The gradual but continuous degradation of cell nr 6 is visible.

Figure 14 - Overview of the 2nd round 85-point test run at VTT.

Tests at TopSoE:

In this project, TOFC tested its own stacks but no full system was tested. Instead a stack test station (Figure 15) is used for evaluating the response to planned "faults"/changes of: outlet temperature/pressure and fuel/air flow values at the stack's inlet boundaries. Tested stacks are a full size 50 cells stack with a cell active area of approximately 100 cm2. Cells are anode supported with an optimal operation temperature of 700-750°C. A new stack (of similar design) was used for each test round. All stacks have voltage probes mounted on several interconnects, which allows voltage data collection for several cell groups. This has been exploited to detect differences in stack response related to cell position in the stack.

Figure 15: Sketch of TopSoE's test station.

In cooperation with the other testing partners, 4 input parameters were identified in WP3 as relevant for simulating system faults: fuel utilisation, air utilisation, current density and furnace temperature. Based on the relevant ranges provided by TOFC, EIFER designed a test consisting of 17 operating conditions. An overview of the experiment is given in Figure 16.

Figure 16: Overview of 1st round of experiments.

This first test round revealed the difficulty of

Running close to stack limits (without damaging the stack).

Incorporating rapid changes of flow and especially temperature.

Avoiding test stand interruptions from software/alarm limits/supply failures etc.

From a data analysis point of view (WP4) it was concluded that the following changes were important prior to test round 2:

Number of operating conditions should be increased from 17 to 70 with several repetitions of domain centre to check for performance drifting throughout the experiment.

Temperature sensors should be placed very close to the inlet/outlet of the stack to avoid heat loss, which compromises the accuracy of models and therefore the effectiveness of a diagnosis algorithm.

Sampling rate should be increased to at least 1Hz instead of 1/60Hz for quicker diagnosis.

Input variables ranges (FU, AU, i, T) should be narrowed to avoid stack damage (performance drifting) during the experiment.

An overview of the 2nd test round is given in Figure 17. This test round was successful because:

Incorporated changes significantly increased the amount and quality of data for subsequent modelling in WP4.

Testing experience with software and hardware from test round 1 eliminated most of the interruptions and subsequent damage to the stack, which had compromised the quality of 1st test round's data. Generally, testing experience of the used setup is required, simply because of the amount of test conditions contained in such mapping of the stack/system needed for WP4 algorithm

development.
A third round, additional to those initially planned, was conducted for algorithm validation. Its primary focus was on immediate changes of operation conditions. On this background a simple test was conducted with several such immediate changes of operation conditions (primarily current density).

Figure 17: Overview of 2nd test round.

Algorithms development:

Overview:
Two different diagnostic approaches were considered

Residual based algorithms. Two different types of models were developed in order to determine the residuals: black box behavioural models and grey box models.

Pattern recognition based algorithms. Indicators are extracted from the signal and directly classified according to their mathematical behaviour.

Figure 18: Principle of diagnosis

Grey box model based algorithms:
Among the various approaches which were taken into account in the project, diagnosis algorithms based on grey box model were developed. A grey-box model is based on a combination of an a priori knowledge of the process (black-box) and some mathematical and physical relations which describe the system behaviour. Initially, different one-dimensional algorithms were available at UNIGE, UNISA and VTT; these models have been tested in the framework of a cooperative benchmark performed among the three partners. The reference point considered for the analysis has shown a good agreement among the results obtained by the partners. Both the development and the cross validation of the algorithms are deeply presented in D4.1-Grey Box and Black Box Fuel Cell Model Development.
In Genius, the developed model is one-dimensional: it was divided into uniform sections with incremental steps along air and fuel paths. The simulation characteristics were chosen as a good compromise between calculation time, model reliability and adaptability to different cell geometry. A detailed heat-transfer model is included because the overall voltage and associated losses are strongly temperature dependent and the temperatures in each section are calculated in order to obtain the most accurate results. Since model's accuracy represents a lower bound for the detection threshold in the monitoring phase, a big effort was put in enhancing its accuracy under both steady state and dynamic conditions. Indeed, inaccurate models lead to high values of the detection threshold and thus reduce the diagnosis sensitivity.
This information was used to generate residuals i.e. difference between values measured on the real system and values calculated by the model, r(t), according to the scheme represented in Figure 19. The process model was inserted in the control loop in order to compare the system output under the same input provided by both external input, u(t), and controlled parameter c(t). The residuals are the input for the subsequent “fault detection and identification” block which embedded the diagnosis strategy.

Figure 19: Residual Generation, process model in the control loop.

As monitoring phase, the fault detection and identification analysis block compares the values coming from the Residual Generator with thresholds that are set for each signal on the basis of model accuracy and measurement quality. If one of the residuals exceeds the allowed value, the obtained pattern is analyzed by a comparison with a diagnostic state table in order to identify the cause of the identified faulty condition. At fuel cell level the information about temperature, FC power and pressure losses cathode side, and the warning information about voltage distribution are combined to identify different faults.
This was developed taking into account both “on line” diagnostic and "off-line" diagnostic

requirements. The diagnosis would generate a set of indicators able to quantify either the drift or the difference of the actual status with respect to nominal or expected performance. A diagnostic strategy was developed and validated in two different SOFC systems both fed by natural gas. The monitoring routine is based on a fuel cell system grey box model which contains an explicit formulation of physical phenomena.

Black box model based algorithms:
Recurrent Neural Networks (RNN) derive from static neural networks by considering feedback connections among the neurons. Thus, a dynamic effect is introduced into the computational system by a local memory process. Moreover, by retaining the non-linear mapping features of the static networks, RNNs are suitable for black-box nonlinear dynamic modelling. The Eq. 4 expresses the nonlinear dependence of RNN output on current (i.e. at time t) and past information (i.e. from time t-1 to time t-m) on the values of the input variables y. Eq. 4 also highlights how the dynamic effect is introduced by providing also, as inputs, information on previous simulated values of the output variables (i.e. from time t-1 to time t-n).

Eq. 4

When training and developing a RNN model, one of the most troublesome tasks is the selection of the best network structure, both in terms of past input information (see Eq. 4) and number of hidden neurons. In this work, a trial and error procedure was set-up to determine the best network structure per each available data-set. The algorithms used to train and validate RNN models are based on the work done by the authors from the Department of Industrial Engineering at the University of Salerno over the last decade towards the development of both static and dynamic neural networks for the simulation of complex energy systems. Among others, the virtual sensors for modelling, control and diagnosis of internal combustion engines are of relevance for the purpose of the GENIUS project. Figure 20 shows the experimental curves and trajectories simulated by the RNNs trained for the Topsoe (i.e. RNN1) and the HTceramix stacks (RNN2) tested by VTT, respectively. The comparisons shown in Figure 20 indicate that both RNN1 and RNN2 achieved quite a high accuracy level (i.e. with error bounded below 2 %).

(a) (b)
Figure 20. Comparison between measured and simulated stack voltage on the test-sets provided by Topsoe and VTT-HTceramix, respectively.

Furthermore, an RNN was trained and successfully tested against data-sets provided by Wärtsilä. A dedicated RNN model was developed per each stack the Wartsila sub-system consists of. Afterwards, one of the above RNN was embedded into an-online diagnosis algorithm. The results presented in WP5 final report highlight the reliability of the RNN-based approach to perform on-field fault detection for complex SOFC systems.

Statistical tools for SOFC behavior (UNISA)
A stepwise multiple regression analysis can be useful to identify the most relevant factors (such as temperatures, current density, etc.) for cell/stack output voltage. It introduces some automatic procedures to select the most significant regressors X (typically influencing factors and some functions involving them) for a measured quantity Y. For instance, in an experiment depending on the values of 4 factors, the measured quantity Y can be modeled as a function of direct effects X1, X2, X3, X4 and their main interactions according to the model in equation Eq. 1.
This approach has been applied to the data set provided by VTT-HTceramix, consisting of measures performed at 21 different operational points: 16 points given by a 24 full factorial DoE and 5 points in the center of the domain according to a model which equation is given in Eq. 1, where the number of parameters to be estimated from the n = 21 observations equals p = 11, namely Y0 and the aij coefficients.
Indeed, the least square estimates of said parameters can be computed by Eq. 3:
While a confidence interval (CI), at a given level 1 – #, can be computed for every parameter as:
Eq. 5

Where the standard deviation is computed as the square root of the variance estimated by its unbiased estimator:
Eq. 6

In a regression analysis, the i-th coefficient is statistically significant if its CI does not include 0: this approach is equivalent to a t-test with the null hypothesis a #_i=0. It implies that the corresponding factor or interaction in Eq. 5 is statistically significant to model the dependant variable Y. On the contrary, ith factor/interaction is not relevant to model the behaviour of Y.

The stepwise approach to multiple regression analysis exploits this idea by adding or removing independent variables (i.e. influencing factors) in order to select an adequate model for Y by a sequence of t-tests (or F-tests) to include or exclude single variables or some variables.
Therefore, the stepwise regression analysis can be adopted to model SOFC stack's steady-state behaviour. In particular, the SOFC stack's (output) voltage Y was considered. By selecting a p-value for entrance equal to 0.05 and a similar exit p-value for every independent variable, we deduced that highly significant influencing factors for stack voltage are current density J, interaction between J and temperature T, the interaction between T and fuel utilization FU, and the interaction between J and FU. The coefficient of determination corresponding to the empirical model involving only those factors is R2 = 0.986, as depicted in Figure 21. Besides the most relevant factors and interactions, it points out that the lambda CPO seems to have no significant influence on the stack voltage. Similar results (not shown) have been obtained for single cell voltages.

Figure 21. A graphical output of a Matlab tool implementing the proposed stepwise approach applied to the stack voltage from VTT data set.

Classification model based on neural network (FCLAB):
A fuel cell stack degradation is usually attributed to improper operating conditions caused by BoP failures (such as temperature control fault, fuel leakage, air blower failure...). At the beginning of operation under these faulty conditions, the stack performance degradation is not quite visible until considerable damage occurs. It is thus necessary to perform an early diagnosis on the fuel cell stack to examine its actual operating condition. To achieve this, an NN model can be set up to distinguish faulty operating conditions from the nominal ones, used as a classifier. Two faulty operating conditions for SOFC stack were considered: operation in a high temperature gradient environment, which leads to mechanical damage (e.g. delamination) in the fuel cell and anode re-oxidation, which accelerates the SOFCs degradation. Under each operating condition, two classes, “no degradation” and “degraded”, were defined to describe the actual state of health of the stack. Hence, there are 4 faulty operation modes to consider.
The NN model consists of two parallel sub-networks: one is composed of 4 perceptron networks, each of them representing one faulty operation mode (simply labelled by a number from 1 to 4); the other is a two-layer forward neural network used to estimate the matching degree to the class. When all the perceptron networks give null output, it means that the SOFC stack operates in proper operating condition and without degradation. On the contrary, when the stack is operated improperly, one of the perceptron networks will produce a “1”, indicating the faulty operation mode. This NN model was trained with the experimental dataset from RealSOFC project, which aimed to understand the degradation mechanisms of SOFC stacks. These data were recorded on the HEXIS 5-cells test rig at which 4 long-term (more than 6000 hours) experiments were carried out on 4 stacks of the same type and manufacturing technology. Redox cycling and/or thermal cycling were simulated during some of these experiments. The former were simulated by switching off the gas and the current at constant temperature. The latter were realized by abruptly shutting down the system, which also caused indirect redox cycling due to the current vanishing.

Signal / Pattern recognition based algorithms:
In the real world, when equipment is operated improperly, interferences arise in the whole system and result in considerable noises. Conversely, when these noises appear and can be recognized, we could detect the presence of a problem in the system and figure it out. The noise can manifest acoustically as a sound or is present in image, for example, as “snow” on a television. If it is neither audible nor visible, we can also observe it in electrical signals.

Signal is a coded message that conveys information on the behavior or the status of a physical system. For a FC system, the diagnosis can be implemented through analyzing the voltage signal of the FC stack.
Basically, a signal can be decomposed into two parts: a fundamental part (linear, non-linear or oscillating) and a fluctuating part. The former is the principle waveform of the signal which is considered as the essential representation of the information to be analyzed, whereas the later, at high frequencies and, in most of cases, with relatively low amplitudes, is viewed as unwanted disturbing component (or noise) to filter out.

Figure 22: Signal decomposition.

In fact, the fluctuations of a signal also contain useful information and have great value in some special applications. For example, in GENIUS, the diagnosis is asked to be achieved at the early stage of system failure. During this period, the degradation of FC's output voltage is too little to notice. That is, the fundamental component of the voltage signal will be approximate to a horizontal line, especially in the case where the signal is measured with a very low sampling rate. For this situation, the fluctuating part of the signal seems more interesting for information extraction.
Essentially, a fault in a FC system can induce considerable disturbances to the electrochemical process taking place in the FCs. These disturbances will influence the system stability and result in abnormal fluctuations in the FC stack's voltage signal. Conversely, the fluctuating pattern of the signal allows us to assess the FC stack's operation and thus the system's state. The signal-based diagnosis algorithm was developed on the basis of this principle. This algorithm uses an effective and fast transform technique to process the signal and derive its fluctuating component.
The new representation of the signal allows the extraction of 3 parameters that are sensitive to the FC stack's operation. The validation results demonstrate that these parameters are indicative not only to the FCs operating conditions but also to their state of health. In other word, these indicators are discriminative enough for effectively distinguishing the system/BoP fault from the FC failure.

Algorithms validation:

Overview:
In order to obtain the most generic diagnostic tool, we undertook to customize the different developed algorithms to each system. However, due to the nature and "quality" of accessible measurements and the characterization capabilities at each testing partner, three level of validation are considered:

"off-line" validation indicates that the validation was performed on data previously acquired that were split in two groups: one group for the model development and another for algorithm testing. But the algorithm was not operated continuously with incoming data.

"on-line ready" indicates that the algorithm was validated on previously acquired data but which were fed continuously to it, simulating a continuous flow coming from a monitoring system. But, no interface with a monitoring system was done and tested on field.

"on-line" indicates that the algorithm was tested during system operation with data coming from a monitoring system operating during the experiment.

The validation results are synthesized in Table 1, in which cross boxes indicate an absence of validation for the considered combination of experimental results and developed algorithms. Table 1 shows that several algorithms were successfully validated on at least two system and that at least 2 algorithms could be validated on each system. Therefore, this paves the way, on the basis of the developed generic approach, for the development of implementable diagnostic tool. But this implementation needs further customization by system manufacturers.

Table 1: Synthesis of algorithms validation's results.

Hardware modifications:
For the purpose of the on-line validation some system hardware/test bench modifications were necessary. For instance, for the on-line validation of both UNISA's and UNIGE's tool and as shown in Figure 23, EIFER modified the hardware of Gallileo Hexis system in order to mimic air leakage in

the cathode outlet pipe and stack internal resistance increase.

Figure 23: Hardware modification of Hexis system for algorithms validation at EIFER facilities

Validation results:
The neural network based classifier developed by the FC Lab was validated on a dataset of 639 samples. The ratios of correct classification are given in Table 2: the network was proven quite reliable in classifying faults 1 and 2, whereas further work is required to well classify fault 3 and 4.

	Fault 1	Fault 2	Fault 3	Fault 4
Description	OC1 + No degradation	OC1 + Degraded	OC2 + No degradation	OC2 + Degraded
Accuracy	88.75%	76.88%	32.81%	56.56%

Table 2: Accuracy of neural network based classifier. OC1 = high temperature gradient environment; OC2 = anode re-oxidation.

UNIGE focused on the enhancement and validation of grey box models while UNISA focused on black box models. All the achievements reached by both the partners in validation phase are collected in D4.6 Off-line enhanced System model. The efforts faced by UNIGE and UNISA in order to make their models ready for on-line diagnosis and the complete analysis of the validation task results are presented in D 4.8 Extension of Off-line System Model for on-line applications.
UniGE first validated off-line its algorithm on data coming from EBZ, Hexis and TOPSOE systems, while UNISA focused on the data provided by HEXIS and EBZ. Then, the diagnosis tools were developed focusing on two different kinds of systems: the EBZ test bed, placed in Dresden (Ger) and the GALILEO 1000N system developed by Hexis and tested in Karlsruhe (Ger) by EIFER.
A test bed has to perform repeatable tests allowing to control the input to the system and to monitor a wide number of parameters. This yields a large amount of data which allows realizing a model really close to the real system. As a matter of fact, the UniGE-EBZ model is dynamic and it is equipped with model for both the stack thermal losses and the pressure losses along the cathode side. On the other hand, UNISA developed a steady state map-based model through which the set points of the main monitored variables are simulated in accordance to the load value. As far as EBZ system is concerned, the last recorded data from the faulty stack were used for an off-line analysis. The data come from a low current test (2A), due to the reduced number of plausible values in the measurement: 1 degree of freedom is introduced in the energy balance for the UNIGE model. Therefore, just cell pack voltage distribution analysis was viable. The voltage distribution check detects correctly the abnormal distribution and it identifies the cells pack number 9 as the outlier. For the UNISA model, the reduction of the available monitored values hindered the possibility of perform a specific isolation process, but the diagnostic tool has been anyhow capable to detect an abnormal behavior.
On the other hand, the Galileo system is a combined heat and power generation one. It combines 1 kW SOFC with an additional burner and differently from a test bed it presents an integrated design. Furthermore, the number of measurement points is lower than the one of EBZ test bed. This introduces a lack of data for the validation. Therefore, for this system, the model only allows the simulation of steady state working conditions. The validation phase of the diagnostic tool was carried out at EIFER's laboratory in Karlsruhe, on a stack modified in order to mimic some faults (Cf. Figure 23). The on line tests were carried out by acquiring data with a fixed frequency, through a .txt file written by the HexisView, a software developed by Hexis, to acquire the measurements and to control the fuel cell. To easily acquire data, run the diagnostic code and display results, two graphic user interface (GUI) were created. From the UniGE interface (Cf. Figure 24) it is possible to set the sampling parameters, i.e. the frequency of the diagnosis calculation, 60 s for Galileo System, and to indicate the time span in which retrieve data looking back from last point. The retrieved data are averaged to reduce the measurement noise and displayed in the bottom plot, input display, which contains the main parameters made not dimensional to fit the plot. The input values are fed to the

diagnostic calculation, which give as output the absolute value of the residuals. The residual are turned into dimensionless residuals using the residual thresholds. These values are plotted as function of time in the non dimensional residual display. The last calculation is also displayed on a radar style plot, the features display. Finally the monitoring and diagnosis results are displayed as text in the warning box. A chronological record of the findings is written outside in a .txt file.

Figure 24 - UNIGE GUI of the diagnostic tool.

The UNISA GUI (Cf. Figure 25) allows the real-time evaluation of all the monitored variables and evaluates residuals from the acquired signals comparing them with the simulated variables. The inference process is made through the exploitation of specific thresholds defined with the threshold selection panel and, for each monitored variable, the current values of the acquired signal, the simulated one and the residual are displayed. If a variable is in faulty state the corresponding led turns red while, in nominal conditions, a green light is returned. Furthermore, the system status display warns about the system operating condition and, when a fault occurs, the fault number block returns the isolated fault number related to the fault description panel. As an example, the online detection and isolation of the CPO fault is presented in Figure 25.

Figure 25 - UniSA GUI of the diagnostic tool.

Potential impact and main dissemination activities and exploitation results

For HTc the immediate impact of the GENIUS results is restricted to development activities. The findings have some impact on the work in the on-going EU funded DESIGN project. Beside HTc, other GENIUS partners (EIFER, EBZ and UNISA) help to continue some part of the work started in the GENIUS project. For HTc the next steps would be: adopt the models and algorithms to their CHP-systems and implement the methodology into their own control software. To progress in this direction, HTc has applied for EU-funding of a related project in 2012 (without success) and is currently involved in the next attempt to launch a related EU-funded research project. An impact to their commercial products might be realistic earliest in 2014/2015. If an enhancement of the system reliability by implementing the monitoring tool will certainly enhance the competitiveness of commercial SOFC CHP systems.
For Hexis, the results on stack diagnosis achieved in the Genius project are interesting for future consideration in controlling a system/stack. However, for the present Galileo system, the achievements in Genius for monitoring the system/stack do not bring an added value for the company or the customer. In particular, the knowledge about the malfunction of the stack/system can just be seen as a first step to improve the robustness of the stack/system in the future, e.g. by using this information to act on the control of the system. However, at the moment the pressure in improving the monitoring or control of the system is low because the field tests show that the present solutions in the Galileo system are considered to be sufficient. Also note that a critical point for the implementation of a new controlling device in the future is that the control will act on parameters that are safety relevant. In that case, the new tool has to be intensively tested and CE certified which is a complex task and time consuming respectively. Therefore, the willingness of changing or introducing safety relevant parameters or components in the system is in principal rather low. With respect to that, we consider the technical uncertainty of a monitoring and controlling tool as high for the moment, due to the little experience. Therefore, the timeframe of implementing a monitoring and controlling tool in the Hexis system may be 3 to 5 years. As it turned out during the Genius project the demands of the industrial partners on the diagnosis and controlling tool are very different which makes it nearly impossible to design one generic tool for all partners. Therefore, Hexis prefers bi- or trilateral cooperation's, focused on the demands of the Hexis Galileo system. To continue the work on diagnosis and control started in Genius, Hexis is willing to further test the algorithm of UNISA.

Address of project public website and relevant contact details

Website address: http://genius-jti-project.eu/
Genius logo: