Abstract: A new kind of statistical fuel failure analysis procedure has been developed at VTT Technical Research Centre of Finland. For reactor safety considerations, it is essential to have a calculation tool for the evaluation of the number of fuel rods expected to fail in the course of an accident. Particularly, the safety regulations in Finland require that the number of failed fuel rods in the most limiting design basis accident scenario would be less than 10 % of all the rods. Statistical best-estimate methods have acquired an established position in this field worldwide during the past two decades. These methods are based on the selection and variation of parameters that are important in accident conditions. The accident scenario is simulated with a designated computer programme several times with different parameter values between simulations, and that way an estimation of the number of failed rods is obtained. An enormous number of simulation runs is needed in order to the results to be statistically reliable. Thus the analysis requires a lot of computer resources, and this has been a limiting factor for the breakthrough of these methods. Different approaches have been used to reduce the number of simulations.

Since 2006, a calculation system for statistical fuel failure analysis has been under development at VTT. The calculation procedure introduces neural networks as a new way to reduce the number of simulations. Neural networks are familiar from other applications in nuclear plant modelling but the concept is a novelty in this context. The developed method utilizes the results of nonparametric statistics, the Wilks’ formula in particular. With the help of neural networks, the number of fuel performance code calculations can be substantially reduced from what would be necessary if all the rods in the reactor were to be simulated 59 times as required by the Wilks’ formula. A neural network is trained with results from stacked fuel performance code calculations, and then the network is used as a substitute for the analysis code. Neural networks are chosen for this purpose because those are more flexible than the alternative technique, the response surfaces. The applied analysis programme is the coupled fuel performance – thermal hydraulics code FRAPTRAN-GENFLO. Here the FRAPTRAN code provides the criteria for fuel failure. The system has been successfully tested with a small-scale analysis with a loss-of-coolant accident (LOCA) scenario which is considered to be the worst design basis accident in PWRs. The system is now ready for full reactor scale applications.

Keywords: statistical analysis, Wilks’ formula, neural networks, fuel failure, LOCA

1. INTRODUCTION

In safety assessments the estimation of the fraction of failing rods is conventionally based on conservative analyses, but this approach has several downsides. Sometimes it is hard to judge whether the assumptions are conservative because the phenomena in the reactor are highly nonlinear [1]. Additionally, conservative methods often lead to excessive margins and that way to economic losses. The development of statistical fuel failure analysis started worldwide when the U.S.NRC revised its rules in 1988 to allow realistic best-estimate methods complemented with uncertainty analysis alongside with the old conservative approach [2]. The so called CSAU (Code Scaling, Applicability and Uncertainty) methodology has been widely used as a standpoint for these analyses [3]. With the contribution of U.S.NRC, a group of experts developed this three-step method in 1989 to meet the new regulations.

In the first phase of CSAU, the accident scenario is divided to distinct segments by place and by the course of the accident, and then important phenomena are recognized for each place and time. The second phase consists of the evaluation of the fuel performance code and its ability to model the identified phenomena. Also the distributions of the related parameters are qualified. The third task is to combine the uncertainty distributions with a chosen method. The statistical procedure developed at VTT follows the main guidelines of this methodology.

Before the current efforts in this field at VTT, there has not been a statistical or any other systematic tool in Finland for the evaluation of the number of failing rods. The Regulatory Guides on nuclear safety set by the Finnish nuclear safety authority STUK introduce a number of design criteria that the utilized fuel has to fulfil in accident
conditions [4]. The following criteria are applicable for LOCA conditions (Class 2 accident):

- less than 10% of the rods in the reactor are allowed to be damaged
- coolability of the fuel shall be ensured
- external and internal oxidation of the cladding during the accident and the preceding normal operation shall not embrittle the cladding excessively
- limit for peak cladding temperature: 1 200 °C
- the amount of hydrogen produced in coolant – cladding chemical reactions shall be less than 1% of the amount of hydrogen produced if all the active cladding surrounding a rod would react with the coolant

Limits for cladding burst, collapsing and oxidation are not fixed in the regulations but those have to be experimentally determined.

The statistical calculation system has to show that the number of failing rods does not exceed the allowed limit. The premise of the current analysis is that the fuel performance code which is appropriately modelling the accident behaviour should indicate the fuel rod failure and therefore no additional failing criteria are needed. Thus the essential output from the calculations is the binary information whether the rod fails or not.

In this paper, the developed statistical procedure is presented, and description of the theoretical basis behind it is briefly summarized. The complexity of statistical fuel failure analysis is brought forth. Testing of the procedure is conducted with a proof of concept case; yet further validation with relevant power reactor applications is required in order to verify the functionality of the system.

2. METHODS FOR STATISTICAL ANALYSES

There are various approaches for the statistical fuel failure analysis. The analysis methods do not exclude each other, and they can thus be used in parallel to diminish the amount of required computer code simulations. The constant growth in computer resources has affected and will continue to affect the choice between different statistical methods.

2.1 Classification of initial parameters and definition of their distributions

The initial parameters of statistical analysis can be divided by their range to two groups: local and global. Global parameters have an effect on all the rods in the reactor, whereas local parameters bring variation to individual rods. As an example, the model parameters of a fuel performance code are global, whereas fuel manufacturing parameters are local. The division of parameters to global and local should someway be taken into account in the analysis because the fuel rods have some correlation with each other. However, the magnitude of the correlation is unknown because it is not precisely known which parameters have the biggest influence on the integrity of the rod during an accident.

Before performing the actual statistical analysis, the varied parameters have to be chosen and their distributions defined. The selection can be conducted by means of a sensitivity analysis with fuel modelling codes and by searching specific variation ranges from open literature, but much of expert judgment is still needed. Fuel manufacturing parameter ranges are usually provided by the fuel manufacturer. The choice between different statistical methods can also limit the number of parameters that can be included in the analysis. This is the case if one uses for instance response surfaces for combining the uncertainties. Typically the parameter values are normally distributed around the nominal value, but in some cases other distributions like uniform or triangular distributions are closer to reality and should be preferred.

2.2 Different approaches for reducing the number of simulations

The established methods with a view to reduce the amount of required simulation code calculations include the use of response surfaces [3, 5], grouping of the rods [6], direct Monte Carlo sampling, and applying results of tolerance interval theory [5, 7]. The last mentioned is presented in more detail in the next subsection as it is adopted as the basis of the procedure developed at VTT. Each method has its own pros and cons and none seems to be totally superior. In any case, the lack of statistical accuracy could be compensated by introducing some conservative assumptions.

The use of response surfaces is the approach of the original CSAU methodology. Response surfaces are low-order polynomial fits between initial and result parameters. With the simulations, one initial parameter at a time is varied and a connection to one or more result parameters is created. These connections are again gathered as a polynomial fit. The polynomial fit can then be used to replace the actual fuel performance code calculations, as new initial parameter values are randomly sampled and the polynomial fit is applied to predict the results. This method is useful when the relationship between initial and result parameters is simple enough, but it cannot predict for example the possible branching of the accident sequence to different directions when the safety systems are activated. In addition to that, the number of initial parameters included has to be quite small to keep the number of simulations in a reasonable measure. More enhanced methods to utilize response surfaces exist, e.g. employing a generalized regression algorithm in the procedure [8].

Another approach to the analysis is to sample the values of initial parameters from their distributions using direct Monte Carlo sampling. Here the division to global and local parameters is neglected, and that means loss of statistical reliability to some extent. Further, the number of simulations that are needed to reach a certain confidence level remains unknown.

It is also possible to group rods with characteristics like burn-up, power level and thermal hydraulic conditions. One can then pick an arbitrary amount of rods from each group

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1 The criteria are given generally for all postulated accidents. Accidents are further divided to Class 1 and 2 according to their initiating event frequency: $10^{-2}$ – $10^{-3}$/year in Class 1, and less than that in Class 2. The criteria are set separately for the two classes.
2.3 Tolerance interval method

The tolerance interval theory gives the means to determine the number of simulations that are needed for the statistical analysis when the intended probability content and confidence level are predetermined. For instance, nuclear industry corporations Westinghouse [9, 10] and Areva NP [11] both have developed their statistical methods based on the CSAU procedure with the results of nonparametric statistics chosen to be the final step to combine the uncertainty distributions.

Theoretical basis of the tolerance interval method was set by S.S. Wilks in 1941 [12]. The starting point of the problem setting is that N sets of initial parameter values are sampled from their corresponding distributions. These sets are used as simulation code inputs, and as a result there will be N values of a result parameter, accordingly. The distribution of the result parameter is an unknown function (hence the appellation nonparametric), here denoted by f(y). With tolerance interval method, the upper and lower limits in the distribution f(y) are to be chosen so that a given probability content γ would be inside those limits with a confidence level $\beta$. The above mentioned is mathematically expressed as [5, 13]:

$$\beta = 1 - \left( \prod_{j=1}^{N} (1 - \gamma)^{s-j} \right).$$

Equation (1) can be written:

$$\beta = 1 - \sum_{j=1}^{N} \left( N \right) j \Gamma(1 - \gamma)^{N-j}.$$

In case of one-sided tolerance interval, the lower bound L is chosen to be $\propto$ (r=0) and the upper bound U is the highest value in the random sample picked from the distribution (s=N). Thus, inserting $r=0$ and $s=N$ into Equation (2), one gets the relation known as the Wilks’ formula (for one sided tolerance limit):

$$\beta = 1 - \gamma^N.$$

When this formula is applied to safety evaluations, the generally acceptable level is 95 % probability with 95 % confidence that the number of failed rods would not overstep the allowed limit. When the corresponding values are inserted into Equation (3), thus $\gamma = 0.95$ and $\beta = 0.9515$, the number of cases comes out as 59. This figure applies when there is only one result parameter but the analysis can be broadened out: if one would like to examine multiple output parameters, more calculations are needed. On the other hand, the number of calculations is independent of the number of initial parameters included to the analysis. In practice when using the Wilks’ formula, one can state that when all the rods in the reactor are simulated 59 times with global variation between each of the 59 scenarios, and if the number of failed rods in the worst case is below the allowed limit, then the safety requirements are rightly met with the probability of 95 % and with the confidence level of 95 %.

2.4 Neural networks

With the analysis procedure developed at VTT, neural networks are used in the same way and for the same purpose as response surfaces. Neural network approach is chosen instead of response surfaces because it is a more sophisticated tool for describing nonlinear phenomena. Compared to response surfaces, it is also more flexible because it is less confining with respect to the number of initial parameters to be included to the analysis. Naturally this approach also has its own downsides which are highlighted later on. Neural networks are used in many applications in nuclear plant modelling [14-20], but those are a novelty in fuel behaviour analyses [21, 22].

3. DEVELOPED ANALYSIS PROCEDURE

In the spirit of the CSAU methodology, the problem setting in the calculation system developed at VTT is split in distinct steps. Firstly, there are several ways to conduct the statistical analysis depending on the setup of the accident scenario and on which phenomena are to be included. It is important to decide how to take into account the propagation of modelling uncertainties throughout the calculation system. Namely, the boundary conditions of a fuel performance code come from a system code and/or from a neutronics code, and those have their own uncertainties. The source and the form of boundary conditions can thus vary, and that poses an extra challenge for the first phase of the analysis. As this first step is in a sense that ambiguous, the calculation system cannot be made fully solid but must be adapted from analysis to analysis. In this point, the possible symmetry of the accident could be made use of to reduce the number of simulations.

Secondly, the distributions of the chosen parameters are defined. In the third phase, the uncertainties are combined with the result of nonparametric statistics introduced by Wilks. There are several ways, however, to apply this result of “59 calculations” to practice.

3.1 Alternative approaches for the analysis

There are different paths that the statistical analysis could proceed depending on the setup of the analysis. As an example, let us first have a look at a situation in which the course of the accident is predetermined but no boundary conditions are calculated or known beforehand. To perform the analysis rigorously, one should calculate the boundary conditions 59 times with a system code like e.g.
APROS [23]. Then there are 59 global variations of the accident and the fluctuations in boundary conditions are taken into consideration as a source of uncertainty. Naturally, also the global parameters in the fuel modelling codes contribute to this group of 59 global variations. Next for each global case, a large number of cases with different local parameter values are calculated. The number of calculations could be for example 1000 for each global variation. In practice, simulation of the accident 59 times with a system code may be too time-consuming, and consequently the objective could be that some of the cases are left outside the analysis. This delimitation should be done in a conservative fashion but it is recognized that the conservatism is here hard to be distinguished a priori. Again, if the boundary conditions are fixed from the start, then that source of error is out of scope of the analysis and the problem setting is simplified.

As neural networks at this point lack comprehensive validation in this context, two surveys are conducted: a conservative analysis and one with neural networks. This branching into two phases is schematized in Figure 1 where the flow chart of the calculation system is presented. In the first option designated as “Phase 1”, on the grounds of the above mentioned calculations, the worst global case is determined based on the highest number of failed rods. The number of failed rods in the worst global case can then be directly scaled to find out the number of failed rods in the whole reactor. This approach is on the conservative side because with a smaller number of cases, deviation of rod failure numbers grows, and thus, the biggest failure number is likely higher than what it would be if all the cases had been calculated instead of an extrapolation. And based on the tolerance interval theory, only the highest number of failed rods counts. In this case, sufficient number of cases need to be calculated to limit the deviation due to the extrapolation of the rod failure numbers. If one would like to make a more thorough analysis, one could sample the local parameter values for all the rods in the reactor and calculate all the rods in the worst global case.

Alongside with the method presented above, the same calculation results are utilized for a neural network analysis. This is designated as “Phase 2” in the flow chart. If one has calculated for example 59×1000 cases in the previous stage, one can now use these cases to train a network. This network is then used for the full analysis with both global and local parameter values sampled anew. It means that the trained network is used instead of a real fuel performance code to simulate all the rods in the reactor for 59 times. This is mathematically more justified than the conservative result because now all the simulations required by the Wilks’ formula are conducted. Additionally, neural network analysis would give a wider margin to the acceptance limit as it is more realistic than the conservative approach. The Phase 2 does not require notable additional effort as neural network simulations are fast to perform. The results from Phase 1 and Phase 2 would support each other.

At this point, the neural networks are considered to be used for a complementary analysis, and the analysis based on the high number of fuel performance code simulations (Phase 1) is the primary way. Before it can be stated that neural networks are suitable for performing these kinds of analyses, it should be made sure that they work as expected in different kinds of accident scenarios. It is not at all obvious that neural networks can be utilized in all cases and therefore it is desirable to have an alternative way to perform the analysis. As the experience grows with further analyses, more can be said about how well the neural networks could be utilized to cover different scenarios.

### 3.2 Applied codes and programmes

In order to attain the time-dependent boundary conditions for the fuel performance code calculations, the overall progress of the accident is simulated with the system code APROS. The APROS code is developed and maintained...
jointly by VTT and Fortum. The relevant boundary conditions are coolant mass flow and enthalpy at the channel inlet, pressure at the top of the channel, and rod power including the axial power profiles. Statistical version of APROS is under development, and that will ultimately enable the propagation of uncertainties from the system code level.

The steady-state initializations of the stacked calculations are performed with the U.S.NRC/PNNL FRAPCON code (version 3.3). An advanced statistical version of FRAPCON developed at VTT in 2003 is being used. It enables the variation of selected model and fuel manufacturing parameters (cf. Table 1).

The primary calculation tool is the coupled fuel performance–thermal hydraulics code FRAPTRAN-GENFLO [24]. FRAPTRAN (version 1.3) is a single-rod fuel performance code developed by PNNL and it is designed to model accident conditions specifically [25]. The general thermal hydraulics code GENFLO has been exclusively developed at VTT. The thermal hydraulics modelling in stand-alone FRAPTRAN has been found to be unsatisfying, and therefore the coupling with an external thermal hydraulics code has been introduced. For each time-step and axial segment, GENFLO calculates the coolant temperature and clad-to-coolant heat transfer coefficients. GENFLO is fast-running due to non-iterative solution of field equations [24]. The coupled code has recently been validated against results from the Halden Project IFA-650 LOCA tests.

The cladding failure is a FRAPTRAN output, and the code’s ballooning model is the one suitable for modelling the failure mode in LOCA. The model assumes that when the effective plastic strain in any axial segment of the cladding exceeds the instability strain given by the material properties package MATPRO, local non-axisymmetric cladding ballooning begins. In the current analyses, however, the calculation can be stopped and the cladding conservatively declared as having failed once the local ballooning model is called. In fact the possibility that the cladding would not fail once the instable ballooning has started is considered theoretical.

The actual calculation system consists of several small programmes that have been coded for data processing, writing inputs and steering the calculations. Some external programmes are also used, like the sampler programme USA (Software system for Uncertainty and Sensitivity Analysis) [26] developed by the German research organisation GRS. USA is utilized for generating random parameter values from specified distributions. For the conversion of the sampled data into the format used in the input generating programme, two auxiliary programmes coded in Fortran 90 are used. Parameter values are handled in Fortran NAMELIST format which makes the input files self-documenting.

A Perl script has been written to steer the stacked FRAPTRAN-GENFLO calculations in a linux cluster. Major changes to the FRAPTRAN and GENFLO codes for the purpose of the statistical analysis were avoided at this stage. So far the model parameter values cannot be varied in FRAPTRAN because those values cannot be changed via the input file without changing the source code. With the predecessor of FRAPTRAN code, FRAP-T6, one could use in-coded automated uncertainty analysis option in which input parameter values were varied. This option was removed, however, when introducing FRAPTRAN because it was not used by the U.S.NRC, not being maintained nor verified [25]. If the development of a statistical version of FRAPTRAN is considered, it would require a careful analysis of the utilized models and their uncertainties in the code. At the moment, however, the fact that the code has not been changed eases the changeover to the new 1.4 version of FRAPTRAN. Meanwhile, the new FRAPCON version 3.4 has been modified to include the capabilities for statistical analysis. Most likely these new versions of FRAPCON and FRAPTRAN will be used with the subsequent analyses.

The neural network analysis is conducted using a MATLAB built-in neural network software package, the Neural Network Toolbox™. It is a general-purpose tool for neural network analyses, and its basic use is quite simple. Of course, as always when operating with neural networks, one has to take extra care when interpreting the results. Network overfitting could become a problem. The same may occur if one uses an insufficient amount of data to train the network in relation to the number of layers and neurons in it. Generally, one can use more complex network structures and get more complicated phenomena into view if a large data set for training is used.

Two MATLAB m-files have been written in which the neural networks are operated. The m-files have been coded in such a way that the recording and opening of the network is independent of the size and configuration of the network. The applied network type is a feed-forward backpropagation network. There are a number of training functions included in the Neural Network Toolbox™ but here the default function is used. The function utilizes the Levenberg-Marquardt algorithm for training. Other training functions could also be tested in the future. The default tan-sigmoid activation function has been used after each neuron and a linear function after the output layer.

3.3 Varied parameters and their distributions

The discussion about which parameters to include to statistical analyses has continued from the start of the development of the CSAU methodology. It is hard to give any general rules for the selection as the sources of uncertainty and their relative importance vary from code to code [27]. The parameters chosen to be varied in the VTT’s system are aggregated into Table 1. In some cases the lack of knowledge limits the precise definition of the corresponding uncertainty distribution. The uncertainties that are considered in statistical methods by other organizations are studied for example in the BEMUSE project [28, 29]. Application of those parameters with the codes and analysis here is not straightforward and needs adaptation. For example the uncertainties in thermal hydraulic parameters should be taken into consideration mainly in the system code APROS, and in addition to that, some parameter variations are possible in GENFLO. Meanwhile, fuel-related parameters are kept in their
Table 1 Varied parameters in the analysis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>FRAPCON</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global parameters</td>
<td></td>
</tr>
<tr>
<td>swelling parameter</td>
<td>normal</td>
</tr>
<tr>
<td>creep rate parameter</td>
<td>normal</td>
</tr>
<tr>
<td>fission gas parameter</td>
<td>normal</td>
</tr>
<tr>
<td>thermal conductivity</td>
<td>normal</td>
</tr>
<tr>
<td>cladding corrosion parameter</td>
<td>normal</td>
</tr>
<tr>
<td>GENFLO</td>
<td></td>
</tr>
<tr>
<td>basic drift flux velocity</td>
<td>triangular</td>
</tr>
<tr>
<td>drift flux separation</td>
<td>triangular</td>
</tr>
<tr>
<td>interphasial heat transfer</td>
<td>triangular</td>
</tr>
<tr>
<td>film boiling heat transfer</td>
<td>triangular</td>
</tr>
<tr>
<td>transition boiling heat</td>
<td>triangular</td>
</tr>
<tr>
<td>transfer tuning factor</td>
<td></td>
</tr>
<tr>
<td>Local parameters</td>
<td></td>
</tr>
<tr>
<td>cladding outer diameter</td>
<td>normal</td>
</tr>
<tr>
<td>cladding inner diameter</td>
<td>normal</td>
</tr>
<tr>
<td>fuel pellet outer diameter</td>
<td>normal</td>
</tr>
<tr>
<td>fuel pellet inner diameter</td>
<td>normal</td>
</tr>
<tr>
<td>cold plenum length</td>
<td>normal</td>
</tr>
<tr>
<td>fuel pellet density</td>
<td>uniform</td>
</tr>
<tr>
<td>grain size</td>
<td>uniform</td>
</tr>
<tr>
<td>flow area cross section</td>
<td>uniform</td>
</tr>
</tbody>
</table>

best-estimate values in the system code and varied only in the fuel performance codes. All in all, the discussion continues about how to take into account the inaccuracies in thermal hydraulic boundary conditions.

The thermal hydraulic parameters chosen to be varied in GENFLO are at this point the three tuning factors for heat transfer and the two drift flux model parameters. In order to gain justifiable parameter ranges, previous validation reports of GENFLO were consulted. The parameter ranges were found in some cases too wide and GENFLO failed to calculate the transient through. Therefore, adequate variation ranges had to be searched by trial and error.

The variations in fuel manufacturing parameters are expected to have little influence on the fuel failures as the tolerances are quite small. Still, at least the gas gap size has a notable effect on the cladding temperatures [27].

4. TESTING THE PROCEDURE

As a proof of concept case for testing the calculation system, a large break LOCA in Loviisa VVER-440 type reactor is used. The boundary conditions were available from a prior APROS analysis. However, preliminary calculations of a single representative rod with FRAPTRAN-GENFLO showed that the cladding temperatures do not reach high enough values to result in a fuel rod failure. This is seen in Figure 2 where the cladding outer surface temperature is presented. There is a significant difference between the cladding temperatures calculated with APROS and FRAPTRAN-GENFLO, and the most significant cause for this arose from the degree of detail in modelling of the rod in a designated fuel performance code. In FRAPTRAN-GENFLO, the conductance of the pellet-to-cladding gap is calculated more realistically and will be determined to be higher during the transient than the constant value (3 000 W/m²/K) used in the simple fuel rod model of APROS.

Because of the substantial volume of coolant in VVER-440 core during a LOCA, rod failures are generally estimated to be unlikely in this type of reactor. With the boundary conditions of a more typical pressurized water reactor, rod failures may be more readily present in LOCAs. In order to have enough fuel failures with the stacked calculations to be used for training the neural network, the accident had to be artificially exaggerated by assuming an elevated power level during the accident, and by decreasing the gas gap conductance in the source code. In that way, higher calculated cladding temperatures could be produced as seen in Figure 2 (marked in the figure as “modified FRAPTRAN-GENFLO”).

The boundary conditions from the system code can be very demanding for the coupled fuel behaviour code. Owing to periodical pressure increase and decrease in the core region, the coolant flow tends to be reversed and go back and forth rapidly in the APROS simulation. If the coolant channel is empty for a prolonged time, GENFLO calculation fails. In these cases, careful evaluation of the boundary conditions is necessary, and resorting to filtering the boundary conditions is an option to be considered.

4.1 Performance of neural networks

After “dramatizing” the accident scenario, enough fuel failures were gained for the system testing. This was verified by preliminary calculations with FRAPTRAN-GENFLO, in which some 20 % of the 100 stacked example cases ended up with an indication of a rod failure. To test the neural networks in practice, a small-scale analysis consisting of a set of 900 stacked FRAPTRAN-GENFLO calculations was performed. Both global and local parameters presented in Table 1 were
The table, the error in predictions between simulation runs varied. When examining the calculation results, it can be stated that the time of failure is significantly scattered due to the variation in local and/or global parameters. Also the axial location of the failure somewhat varies. This may indicate that more than one of the varied parameters has an effect on the cause of the failure. For the neural network testing, it is good to have this kind of variation in the training data. A weakness in the current neural network analysis is that one cannot point out which parameter or combination of parameters caused the rod to fail. It requires additional analysis with the real fuel performance code to find out the reason(s) for rod failures.

At this point it is interesting to learn how accurately the network predicts the cases that were not used for training the network. Also the effect of changing the neural network configuration by adding neurons and layers is a subject of interest. To test the performance of a network, the fuel performance code calculations are divided to a training set and a test set. In this case, 33% of the cases were used as a test set. Thus the error in the test set predictions is under examination. One has to notice that the network may directly predict that the rod fails or remains intact, but the network result can as well be somewhere between these extremes. Below, a following (arbitrary) criterion is used: if the neural network prediction deviates more than 40% from the correct result, it is considered as a missprediction. Of course the missprediction can equally be on the conservative side, thus the neural network would predict the rod to fail even though the fuel performance code shows otherwise.

Because of the intrinsic characteristics of neural networks, the performance of a network varies between simulation runs even if the training data is the same. Different network configurations were tested and as an example in Table 2, the percentages of falsely predicted rods in the test set are presented for two networks. Both networks have two hidden layers with 5 and 3 or 3 and 3 neurons. As one can see from the table, the error in predictions between simulation runs varies considerably. Still, it should be adequate that when the error is small, that particular network is recorded and used for the subsequent analysis. Thus, while a network structure with a low error fraction in its predictions is the aim, even the best structures have variation in their results. The smallest error in predictions in this case is 2.7%, a figure that already shows quite a good accuracy.

Among the experimentations, a small network that consists of two hidden layers with three neurons in both layers is found to have the steadiest performance. However, the most suitable network configuration should be sought each time an analysis is performed.

### Table 2: Examples of the percentages of falsely predicted rods in the test set with two network configurations

<table>
<thead>
<tr>
<th>Angle</th>
<th>5:3 –network [%]</th>
<th>3:3 –network [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1º</td>
<td>19.5</td>
<td>3.0</td>
</tr>
<tr>
<td>2º</td>
<td>4.7</td>
<td>4.7</td>
</tr>
<tr>
<td>3º</td>
<td>4.3</td>
<td>3.0</td>
</tr>
<tr>
<td>4º</td>
<td>19.2</td>
<td>2.7</td>
</tr>
<tr>
<td>5º</td>
<td>2.7</td>
<td>6.7</td>
</tr>
<tr>
<td>6º</td>
<td>4.0</td>
<td>3.7</td>
</tr>
<tr>
<td>7º</td>
<td>4.0</td>
<td>4.0</td>
</tr>
<tr>
<td>8º</td>
<td>8.1</td>
<td>5.1</td>
</tr>
<tr>
<td>9º</td>
<td>11.4</td>
<td>5.4</td>
</tr>
<tr>
<td>10º</td>
<td>2.7</td>
<td>11.1</td>
</tr>
<tr>
<td>11º</td>
<td>19.2</td>
<td>5.7</td>
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<td>12º</td>
<td>31.6</td>
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<td>13º</td>
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</tr>
<tr>
<td>15º</td>
<td>15.5</td>
<td>4.7</td>
</tr>
</tbody>
</table>
on the boundary conditions and the details of the accident scenario, the scripts will be modified accordingly.

The applied simulation codes are improved according to the arising needs. Development of a statistical version of the system code APROS is about to begin. The uncertainties propagating to the fuel performance code calculations via APROS boundary conditions can then be taken into consideration. Then again, the duration of a single system code simulation is so significant that the soundness of a statistical analysis with 59 APROS simulations included is a subject to be carefully assessed. Improvements to the GENFLO code are under way. After those the boundary conditions are separately given for water and steam at the channel inlet and outlet, so as to enhance the accuracy of thermal hydraulics modelling.

When advancing to full scale applications of the statistical method, the calculation scheme can be tested also with alterations. As an example, the neural network approach may be improved if the parameter values that are used for training the network would be sampled in the first phase of the analysis from uniform distributions instead of the more realistic distributions. In that way, more calculation cases would come from the edges of the distributions now covered by only a small number of cases. Consequently, neural networks would presumably have enhanced response in the Phase 2 when realistic distributions are used. Naturally the result of Phase 1 with uniform distributions would be unrealistic, but still conservative.

Feasibility of neural networks is examined as a part of the full analysis each time it is performed. The uncertainty related to neural network predictions is an important issue to be taken into account when evaluating the final result. Likewise the conservative proportion in the network uncertainty is to be quantified (i.e. when the network incorrectly predicts the rod to fail, contrary to the result of a fuel performance code calculation). It is easy to get bad results from the analysis if there is an insufficient amount of training cases, an unsuitable network configuration, or if one encounters problems with overfitting. Despite the challenges in this approach, it is a definite advancement from the traditionally used response surface method. The presented concept for analysing fuel failures in accident conditions is the first step in Finland towards systematic statistical procedure in this field.

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