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Radiation Embrittlement Prediction Models and The Impact of Irradiation Temperature

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ABSTRACT

A new methodology is developed for the prediction of RPV embrittlement that utilizes a combination of domain models and nonlinear estimators including neural networks and nearest neighbor regressions. The Power Reactor Embrittlement Database is used in this study. The results from newly developed nearest neighbor projective fuser indicate that the combined embrittlement predictor achieved about 67.3% and 52.4% reductions in the uncertainties for General Electric Boiling Water Reactor plate and weld data compared to Regulatory Guide 1.99, Revision 2, respectively. The implications of irradiation temperature effects to the development of radiation embrittlement models are then discussed.

1. Introduction

There have been several domain models that capture various aspects of material behavior; these models are designed by the domain experts to capture various critical relationships. At the same time, conventional non-linear estimators - while requiring very limited domain expertise - can model relationships that are not readily apparent. Consequently, there has been a profusion of methods with complementary performance with no single method proven to be always better than all others. Our goal is to develop an effective methodology by combining the domain models with the nonlinear estimators including, neural networks and nearest neighbor regressions to exploit their complementary strengths. We have previously developed a large Power Reactor Embrittlement Database (PR-EDB) [1] for U.S. nuclear power plants. Subsequently in cooperation with the Electric Power Research Institute, additional verification and quality assurance of the data were performed by the U. S. reactor vendors. PR-EDB is used in this study to predict the embrittlement levels in light water reactor pressure vessels. The results from newly developed nearest neighbor projective fuser indicate that our combined predictor achieved about 67.3% and 52.4% reductions in the embrittlement uncertainties for General Electric Boiling Water Reactor plate and weld data compared to Regulatory Guide 1.99, Revision 2, respectively.

2. New Methodologies for Developing Radiation Embrittlement Models

2.1 Background

The complex nonlinear dependencies observed in typical material embrittlement data, as well as the existence of large uncertainties and data scatter, make the modeling of material behavior (such as embrittlement prediction) a difficult task. The conventional statistical and deterministic approaches have proven to result in large uncertainties, in part because they do not fully exploit the domain specific knowledge. The domain models built by researchers in the field, on the other hand, are not able to fully exploit the statistical and information content of the data. As evidenced in previous studies, it is unlikely that a *single* method, whether it is statistical, non-linear or domain model will outperform all others. Considering the complexity of the problem, it is more likely that certain methods will perform best under certain conditions. In this paper, we propose to combine a number of methods such as domain models, neural networks, and nearest neighbor regressions. The combined system has the potential to perform at least as well as the best of the constituents by exploiting the regions where the individual methods are superior. Such a combination of methods became possible due to recent developments in measurement-based optimal fusers [2-4] in the area of information fusion.

The problem of estimating nonlinear relationships from noisy data has been well studied in the area of statistical estimation [5]. The nonlinear statistical estimators such as the Nadaraya-Watson estimator and regressograms [6] essentially rely on the properties of regressions. While neural networks and statistical estimators are general, the domain models developed by the material scientists specifically capture the critical relationships in the data that are not easily amenable to general methods. Such models are typically based on a combination of linear and nonlinear models, which are carefully chosen through an understanding of experimental data.

Particularly among the models developed for embrittlement data, there is unlikely to be a single winner, and different models perform well under different conditions. By discarding one or more models, one stands the risk of not characterizing certain critical performance. We propose to combine various methods using isolation fusers [5]. The most important part of these fusers is that the combined system can be guaranteed to be at least as good as the best individual estimator with a specified probability. Furthermore, fusion of no proper subset of the models performs better than the fused system based on all models. This way the positive aspects of *all* individual estimators can be exploited without discarding any single estimator. The deployment of these fusers on various models will ensure that the fused model is at least as good as the best of the individual models, irrespective of their individual performances. However, the general results on fusers do not specify the actual performance gains that may be achieved in a particular application. We show here that significant performance improvements are indeed obtained by employing fusers to combine various embrittlement models.

2.2 Approach

We employ neural networks, nearest neighbor regressions, and domain models, based on the PR-EDB data, to predict the transition temperature shift of RPV materials, which is a measure of the material embrittlement. From past experience [7], the boiling water reactor data has larger uncertainty compared to the other power reactor data. In this study, we only focused on the boiling water reactor data.

The first task is to create unbiased training and test sets. The General Electric (GE) boiling water reactors' (BWR) surveillance data (listed in PR-EDB) were preprocessed and streamlined. The final processed GE BWR data were compared with that of the ASTM E10.02 subcommittee embrittlement database for consistency in the surveillance information, such as irradiation temperature, chemical composition, Charpy impact test data fitting methodology, and power time history, etc. The processed GE BWR data has essentially the same neutron fluences, chemistry, and irradiation temperature data compared to that of

ASTM E10.02 database, with minor difference of transition temperature shift (within a few degree F). The GE BWR's data values were then scaled to the interval [-1, 1] using a Linear Max/Min transformation. This ensures that no one component in the data dominates the parameter optimization scheme. Then the data were randomly partitioned into training and testing sets.

The second task consists of determining a number of estimators for this problem. For each method, a criteria function and optimization routine will be selected that consistently produces stable results. For statistical estimators, we will follow the procedure described in the literature. For artificial neural networks (ANN), one hidden layer and eleven hidden nodes were chosen with 2000 epoch iteration. A random generator was used to generate the initial weights for ANN modeling. Four sets of ANN models were tested. We then combine the statistical and deterministic estimators using information fusion techniques.

An optimal projective fuser [3] proposed earlier was based on the lower envelope of error regressions of the estimators. In most practical cases, however, the error regressions are not available and only a finite sample is given. Consequently this fuser is hard to implement and furthermore provides only asymptotic consistency. In this paper, we propose a projective fuser based on the nearest neighbor concept [8], which is easy to implement. The combined system is guaranteed to perform at least as well as the best of the constituents by exploiting the regions where the individual methods are superior.

A novel methodology is developed here for inferring nonlinear relationships that are typical in material behavior prediction. A tool based on this methodology is also implemented for the embrittlement prediction of NPPs. This tool could be expanded and adapted for use in other areas in which nonlinear material properties are important, such as failure analysis of an earthquake event, airplane safety analyses, and others.

2.3 Embrittlement Prediction Models

In this section we briefly described various models used for embrittlement prediction, which will be combined in the next section.

ORNL Embrittlement Prediction Models – The residual defects in materials due to neutron induced-displacement damage are a function of neutron energy, neutron flux, exposure temperature, and the material properties that determine how neutrons interact with atoms and how defects interact within the material [9]. Thus, temperature, neutron flux, neutron energy spectrum, and material composition and processing history all contribute to the radiation embrittlement process [10]. Insufficient consideration of these factors may result in misleading correlations and, thus, incorrect predictions of material state and material behavior, as well as incorrect end-of-life determinations.

The development of new embrittlement prediction equations [7,11] stem from a series of studies on radiation embrittlement models, such as Guthrie's model [12], Odette's model [13], Fisher's model [14], B&W Lowe's model [15], the French FIM model [16], etc., and several other parameter studies on the PR-EDB. Although the copper-precipitation model has been extremely successful in explaining many aspects of irradiation embrittlement, it is becoming increasingly evident that other elements also contribute to the embrittlement of the RPV steel, such as Ni, P, Mn, Mo, and S. Theoretically, all the impurities in low alloy steel are candidates to be included in the modeling. For example, C, Si, Mn, Mo, S, etc., were investigated in the test run, but including or excluding these elements did not affect the overall outcome of the statistical parameters significantly; therefore, these parameters (or elements) were not incorporated into final governing equations. Thus, Cu, Ni, and P were tentatively selected as key elements and were incorporated into the formula of the new prediction equations. Furthermore, the reason for separating weld and base metals is because the welds tend to show enhanced degradation, the welding process presents a possible region of physical and metallurgical discontinuity, and offers added chances for the introduction of defects and undesirable components or stresses.

A nonlinear-least-squares fitting Fortran program was written for this study. The development of the parameters for this new embrittlement model is based on statistical formulation chosen by computer iterations. To some extent, the physical mechanisms are embedded in the equations, such as the formulation of the fluence factor. Two new prediction models for the GE BWR data were developed, where the fluence rate effect was considered in the second prediction model and are described below:

Model 1:

$$\Delta RTNDT(Base) = [-94.8 + 411.9Cu + 247.3\sqrt{CuNi} + 498P/Cu]\, f^{0.3216 - 0.001003\ln f} \quad (1)$$

$$\Delta RTNDT(Weld) = [420.9Cu + 134.6\sqrt{CuNi} - 25.94P/Cu]\, f^{0.2478 - 0.01475\ln f}$$

Model 2

$$\Delta RTNDT\ (Base) = \left[(13.62 + 318.1Cu - 58.75\sqrt{NiCu} - 151.4\,P/Cu)\ f^{-0.4354 - 0.1285\ln f}\right]$$
$$+\left[(18.44 - 49.13\sqrt{CuNi} - 17.22Cu - 97.57P/Cu)\ f\ (-8.344 - 0.7045\ln f)\ln(t_i/600000)\right] \quad (2)$$
$$\Delta RTNDT\ (Weld) = 1.075\left[(1580\,Cu - 86.06\sqrt{NiCu} + 43.55\,P/Cu)\ f^{0.6523 + 0.02866\ln f}\right]$$
$$-2.23\left[(4.193\,Ni - 45.54\,Cu)\ f\ (-11.63 - 0.4554\ln f)\ln(t_i/600000)\right]$$

where ΔRTNDT is the transition temperature shift in °F; and neutron fluence f is in unit of 10^{19} n/cm² (E > 1 MeV), effective full power time, t_i, is in hour, and Cu, Ni, P. are in wt %. The residuals, defined as "measured shift minus predicted shift," for ORNL Model2 are illustrated in Figs. 1-2 for base and weld, respectively.

Regulatory Guide 1.99, Revision 2's Model – The transition temperature shift of Reg. Guide 1.99, Rev. 2's model [17] was also used in this study for comparison, which is described as below.

$$\Delta RT_{NDT} = (CF)\, f^{(0.28 - 0.10\log f)} \quad (3)$$

where, ΔRT_{NDT} is the transition temperature shift in °F, CF(°F) is the chemistry factor (given in the Table 1 and Table 2 of Reg. Guide 1.99, Revision 2), which is a function of copper and nickel content, and neutron fluence f is in unit of 10^{19} n/cm² (E > 1 MeV).

The residuals for Reg. Guide 1.99, Rev. 2's model are illustrated in Figs. 3-4 for base and weld, respectively.

Eason's Models – The developed embrittlement model by E. D. Eason et. al. (Eason's model) [18], was used in this study. The Eason's trend curve of transition temperature shift was developed based on the power reactor data, and is described below. The residual of Eason's model are illustrated in Figs. 5-6 for base and weld, respectively.

$$\Delta T_{30p} = ff_1(f\,t) + ff_2(f\,t)\ f(cc), \quad [°F]$$
$$ff_1(f\,t) = A \bullet \exp\left[\frac{1.906 \bullet 10^4}{T_c + 460}\right](1 + 57.7\,P)\left[\frac{f\,t}{10^{19}}\right]^a$$
$$ff_2(f\,t) = \frac{1}{2} + \frac{1}{2}\tanh\left[\frac{\log(f\,t + 5.48 \bullet 10^{12}\ t_i) - 18.29}{0.600}\right] \quad (4)$$
$$ff(cc) = B(Cu - 0.72)^{0.682}(1 + 2.56\ Ni^{1.358})$$
$$\text{where, } a = 0.4449 + 0.0597 \bullet \log\left[\frac{f\,t}{10^{19}}\right], \quad f\,t = \text{fluence}$$
$$\text{Welds}: A = 1.10 \bullet 10^{-7},\ B = 209,\ \text{Plates}: A = 1.24 \bullet 10^{-7},\ B = 172$$
$$\text{Forgings}: A = 0.90 \bullet 10^{-7},\ B = 135,\ T_c\ \text{is coolant inlet temperature}, °F$$

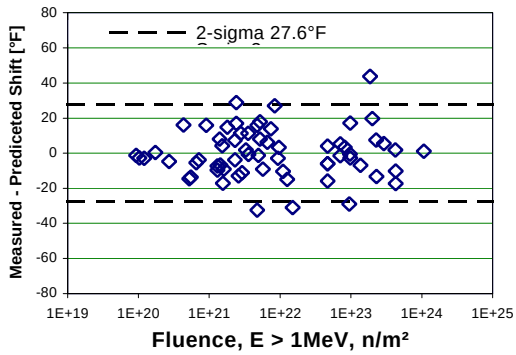

Fig. 1. ORNL Model 2 base residuals.

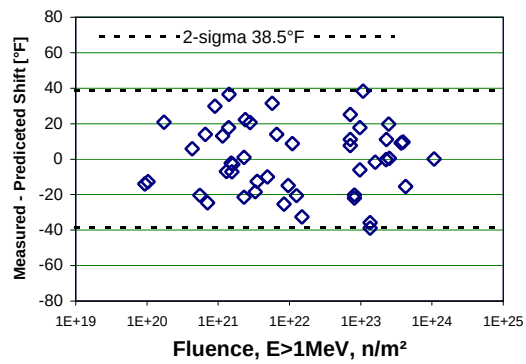

Fig. 2. ORNL Model 2 weld residuals.

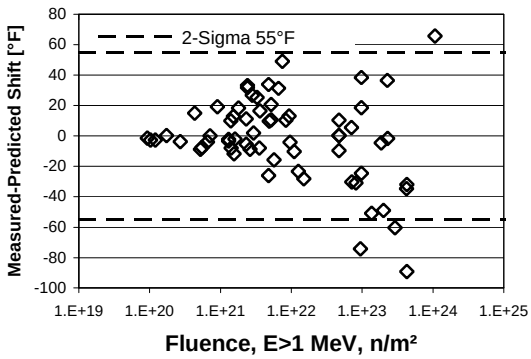

Fig. 3. R.G. 199/R2 base residuals.

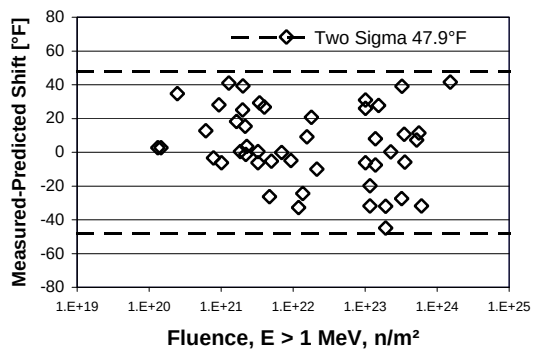

Fig. 4. R.G. 199/R2 weld residuals.

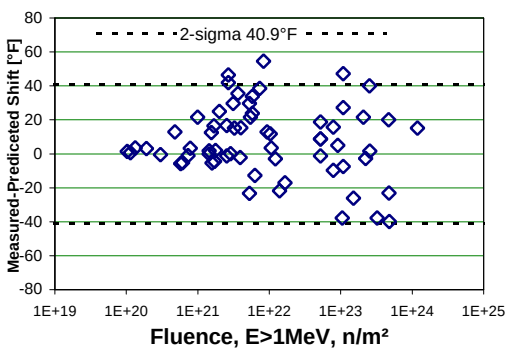

Fig. 5. Eason Model base residuals.

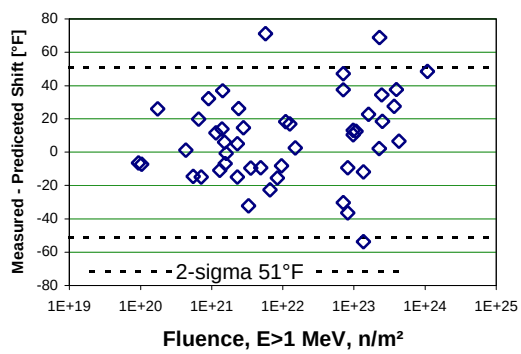

Fig. 6. Eason Model weld residuals.

ANN Models – An ANN is a parameterized nonlinear mapping from an input space to an output space [19]. An ANN realizes mapping from an m-dimensional input space to an n-dimensional output space and will have m nodes in its input layer and n nodes in its output layer. A multi-layer ANN (ML-ANN) is the most common architecture. This architecture has additional layers of nodes between the input and output layers. The information from each input-layer node is fanned out to nodes in the layer hidden between the input and output layers. The information entering a node in any hidden or output layer is the weighted sum of all information leaving the layer below it in the hierarchy. The node performs a non-linear/sigmoidal transformation on the weighted information it receives and fans out the result to all nodes in the layer above it in the hierarchy (except for the output layer). The weighting factors (weights) are free parameters that must be adjusted to some chosen criteria function using some optimization algorithm. In this way, ANNs are able to capture many higher-order correlations that may exist in the data. The relationship between the higher-order correlations produces a nonlinear mapping. This is the reason ANNs may offer a more

accurate prediction of material behaviors, embrittlement in this case. With methods like ANNs, one has a better tool to extract nonlinear relationships from embrittlement data to aid in the development of reliable maintenance and safety strategies and regulations in the nuclear industry.

The backpropagation algorithm is used to train the network with the data [19]. The training process determines the weights of ANN to fit a suitable nonlinear map. The backpropagation's flexibility in training an ANN is why it does a better job of modeling than linear regression, but this method has several weaknesses. The backpropagation algorithm is based on local descent and can get stuck in local minima, and as a result the predictive properties can be quite varied. Also, there are a number of tunable parameters such as starting weights and learning rates that have a significant effect on the weight computed by the backpropagation algorithm. Thus, when different ANN models are trained with the same backpropagation algorithm but with different starting weights and learning rates, the performance can be significantly different. These networks however can be fused to achieve the performance of the best ANN [4] creating a more robust architecture.

Six independent variables, namely, Cu, Ni, P, fluence, irradiation temperature, and effective full power time were used in the ANN models. A program written in C language was used in this study.

K-Nearest Neighbor Regression (K-NNR) Method – The nearest neighbor regression (NNR) [5] is also chosen to generate an embrittlement model. The algorithm is described below. Let x_1, x_2, x_3,…,x_n be a sequence of n independent measurements with known classifications, and x be the measurement to be classified. Among x_1, x_2, x_3,…,x_n, let the measurement with the smallest distance from x be denoted as x'. Then the nearest-neighbor decision rule assigns the classification of x' to that of x. As for K-NNR, it assigns to an unclassified sample point the class most heavily represented among its K nearest neighbors to x. In this study we chose the first three nearest neighbors with properly weighted function to represent the unclassified sample.

Six independent variables, namely, Cu, Ni, P, fluence, irradiation temperature, and effective full power time were used in K-NNR models. A second test K-NNR model, excluding irradiation temperature from the fitting parameter, generated a nearly identical trend curve as that with irradiation temperature. A program written in C language was used in this study.

2.4 Fusion of Embrittlement Models

The development of this model consists of identifying the error profiles of various estimators and the physical parameters of the underlying problem and designing the fusers for combining the individual estimators. Two types of information fusers were used in fuser model development, namely, linear fuser and nearest neighbor projective fuser.

Initially, we combined the statistical and deterministic estimators using the linear fuser, which is a special case of the isolation fusers [20]. The isolation fusers are shown to perform probabilistically as good as best estimator [5,21]. Given n estimators, $f_1(x)$,…, $f_n(x)$, the linear fuser is given by $f(x)=w_1f_1(x)+\ldots+w_nf_n(x)$, where $w_1\ldots w_n$ are the weights. We computed the weights for the fuser by minimizing the error of the fuser for the training set.

The projective fuser [8] based on the nearest neighbor concept was also implemented in the study. This fuser partitions the space of domain X into regions based on the nearest to the sample. For each region an estimator with the lowest empirical error is used to compute the function estimate for all points in the region. This fuser is easy to implement and provides finite-sample performance bounds under fairly general smoothness or non-smoothness conditions on the individual estimator.

The program was written in C where the solution is based on solving a quadratic programming problem. In this study, we utilized the linear fuser and nearest neighbor projective fuser to develop the embrittlement models, six parameters, namely, Cu, Ni, P, fast

fluence, irradiation time, and irradiation temperature, were incorporated into model development. Eight different models were investigated including four neural network models, two ORNL models, the K-nearest neighbor regression method, and the Eason's model.

ORNL Fuser Model I – Linear Fuser was implemented into Fuser Model I development. The results of the linear fuser model indicate that this newly developed embrittlement model has about 56.5% and 32.8% reductions in uncertainties for GE BWR base and weld data, respectively, compared to that of Reg. Guide 1.99, Rev. 2. These are substantial improvements on the embrittlement predictions for the reactor pressure vessel steels. The plots of information model residual and its two-sigma uncertainties for base and weld materials are illustrated in Figs. 7-8, respectively.

ORNL Fuser Model II – Fuser Model II is a simplified version of Fuser Model I, excluding the irradiation temperature from the fitting parameter and excluding the Eason's model from the fusion modeling. The data scatter of residuals for Fuser Model II are essentially the same as that of Fuser Model I. The results of ORNL Fuser Model II indicate that it has about 55.2% and 28.8% reduction in uncertainties for GE BWR base and weld data, respectively, compared to that of Reg. Guide 1.99, Rev. 2's model. This indicates that fuser model I has marginal improved performance compared to that of fuser model II. Thus, the impact of irradiation temperature on embrittlement modeling for the GE BWR surveillance data can be considered as secondary.

ORNL Fuser Model III – Nearest neighbor projective fuser was implemented in Fuser Model III development. The results of the projective fuser model indicate that it has about 67.3% and 52.4% reductions in uncertainties for GE BWR base and weld data, respectively, compared to that of Reg. Guide 1.99, Rev. 2. These are significant improvements on the embrittlement predictions for the reactor pressure vessel steels. The plots of information model residual and its two-sigma uncertainties for base and weld materials are illustrated in Figs. 9-10, respectively.

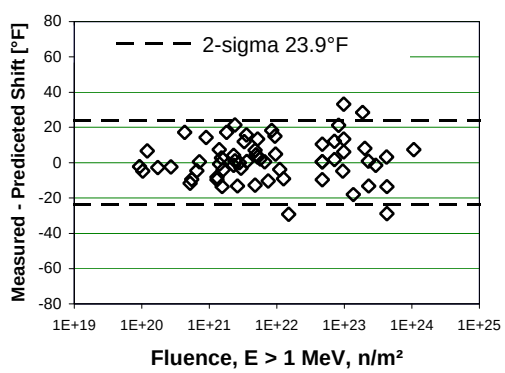

Fig. 7. Fuser Model I base residuals.

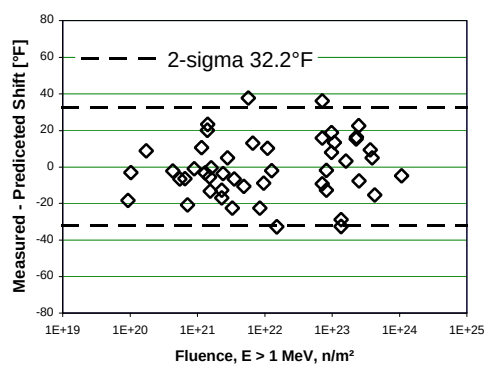

Fig. 8. Fuser Model I weld residuals.

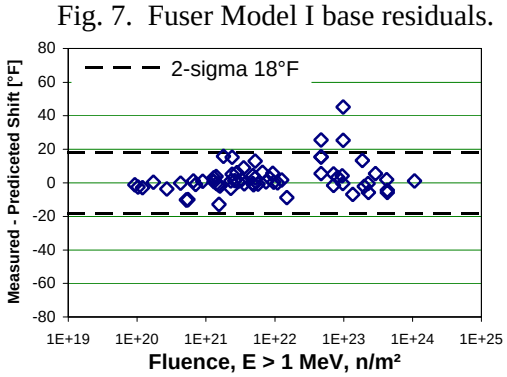

Fig. 9. Fuser Model III base residuals.

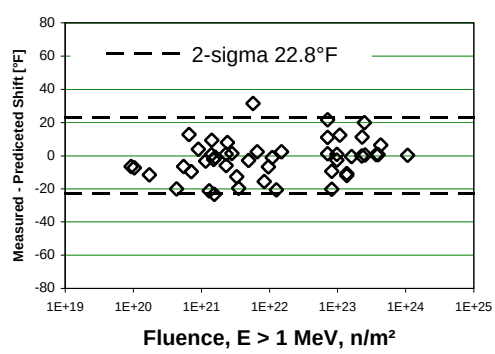

Fig. 10. Fuser Model III weld residuals.

3. Discussion

The comparison of the performance of the embrittlement models, based on the two-sigma uncertainty of residual values, is stated in Table 1. The Fuser Model III gave the best performance among all the embrittlement prediction models. ORNL embrittlement models indicate that ORNL Model II is superior to ORNL Model I by including irradiation time to simulate fluence-rate effect. Thus, the implication of a flux effect in BWR environment was revealed in the model development.

Table 1 - *Two-sigma uncertainty of the embrittlement models for GE BWR data*.

Embrittlement model	Parameters					Two sigma of residual (°F)	
	Cu	Ni	ϕt	t_i	T_c	Base (64 points)	Weld (48 points)
Reg. Guide 1.99, Rev. 2	x	x	x			55.0	47.9
ORNL Fuser Model I	x	x	x	x	x	23.9	32.2
ORNL Fuser Model II	x	x	x	x		24.6	34.1
ORNL Fuser Model III	x	x	x	x	x	18.0	22.8
ORNL Model I	x	x	x			39.6	41.8
ORNL Model II	x	x	x	x		27.6	38.5
Eason's Model	x	x	x	x	x	40.9	51.0
K-NNR Model	x	x	x	x	x	39.1	41.4
ANN-4 Model	x	x	x	x	x	56.4	78.8*

*| Residual | > 100°F are not included in two-sigma uncertainty evaluation.

The authors would like to point out that the fusion modeling developed here is based on GE BWR data, including 110 available sample data, where, Reg. Guide 1.99/R2 and Eason's Model were developed based on both PWR and BWR surveillance data. Thus, the superior prediction by ORNL Fusion model compared to that of Reg. Guide 1.99/R2 and Eason's models may be partially due to the subset of power reactor data used in the model development. However, by the same token, this study may also demonstrate the superiority and advantage of using subset data, for example, the vendor specific data, to develop power reactor embrittlement models. (The reason is explained in the next paragraph.) In general a large data set with similar characteristics or controllable parameters will generate a better trend prediction compared to its subset. But a misleading trend curve can result from a large data set built upon different bases and uncontrollable parameters, revealed by its large uncertainty.

The R.G. Guide 1.99/R2 was formulated based on Guthrie's model and Odette's model and no temperature effect was considered in embrittlement model development, where, the fluence factor (FF) and plates' chemistry factor (CF) are from Guthrie's model [17]. 177 surveillance data were used in Guthrie's model development, however, only 6 data are from BWR environment. Thus, BWR surveillance data may not be properly characterized from Reg. Guide 1.99/2's model. From ASTM E10.02 database, the mean temperature and one standard deviation of BWR and PWR data are 540.3 ± 13.6°F and 545.7 ± 10.4°F, respectively. Therefore, from the irradiation temperature variability point, the sample temperature environment of PWR and BWR are comparable. Currently, there are four major commercial power reactor vendors in the U.S., namely, Westinghouse, General Electric, Babcock & Wilcox, and Combustion Engineering. Each vendor has its unique designs and specific operating procedures. There are significant problems associated with insufficient information, such as the detailed irradiation temperature of surveillance specimen and the thermal gradient within surveillance capsules, and the lack of data in particular regions of interests to characterize the vendor's service environments. About 64% of PR-EDB data is from Westinghouse; thus, the trend curve of all the four vendors' data will closely resemble the Westinghouse reactor environment. Furthermore, B&W surveillance data appears to experience higher irradiation temperature (based on capsule melting wire) compared to other

vendors., Combining low- and high-temperature data may bring further bias on top of bias from the modeling point. For example, from the trend curve of all the vendor data, the high irradiation temperature data shows negative bias (i.e. prediction model shows over-prediction) and low irradiation temperature data show positive bias. However, the overall bias (or uncertainty) will cancel each other resulting in a misleading statistical outcome, such as means and uncertainty.

Eason's model covers both PWR and BWR environment, where 96 BWR data were included in model development and coolant inlet temperatures were incorporated into governing equations to simulate temperature effect. In practice the coolant inlet temperature is incorporated into the embrittlement model to simulate the irradiation temperature for a pressurized light-water reactor. However, a past study [10] showed that a large bias can still be identified in Eason's model for surveillance data from a higher irradiation temperature environment and the bias is similar to that of Regulatory Guide 1.99, Rev. 2 [17]. This may indicate that the coolant inlet temperature is not equivalent to the irradiation temperature experienced by the surveillance specimens. Furthermore, from this study on fuser models, neither including or excluding coolant inlet temperature has a significant impact on the trend curve, which may further support the above statement.

For surveillance data, significant deviations of the measured shift from the trend curve (i.e., more or less than 34°F for plate materials) should be considered as a warning flag pointing to a possible anomalous capsule environment. The large uncertainties are the result of errors in the overall environment description. But, limited attention has been given to characterizing the irradiation temperature environment of the surveillance specimens. In general, the neutron environment, fluence and flux, can be determined fairly accurately and possible effects from these sources are relatively small in a power reactor environment. However, the temperature of surveillance capsules environments still heavily rely on the measurement of the melting wire. A more detailed analytical investigation of specimen temperature is needed based on detailed neutronic and thermal-mechanical analysis for specific capsule and specimen loading configuration, to facilitate the RPV surveillance program in confidence. Thus, in the current trend curve development, the most likely reason for deviations from the trend curve is the specimen temperature.

To develop a global embrittlement model for U.S. power reactors an independent investigation of each subgroup (each vendor) is recommended. Upon completing the investigations, if substantial improvement is achieved for each subset based on the proposed methodology, then an information fusion technique will be utilized to integrate all the subset models into a global RPV embrittlement model.

4. Conclusions

We described an information fusion method for the embrittlement prediction in light water reactor pressure vessels by combining domain models with neural networks, and nearest neighbor regressions. Our method resulted in 67.3% and 52.4% reduction in 2-sigma uncertainties compared to that of the Reg. Guide 1.99, Rev. 2's model for base and weld materials, respectively. This new approach combines the conventional non-linear methods and model-based methods into an integrated methodology applicable for modeling material aging processes. This approach can potentially assist the nuclear industry on the issues of safety and lifetime extension of aging commercial nuclear power plants. By using a wide spectrum of methods, the proposed tool can potentially handle the subtle non-linearities and imperfections and serve as a calibration and benchmark for the existing models. The predictions generated by our system have the potential for providing efficient, reliable, and fast results, and can be an essential part of the overall safety assessment of material aging research.

Future improvements of the proposed method can be made using the k-fold cross validation method [21]. In this method data is partitioned into k blocks, of which k-1 of them are used as the training set and the remaining as the test set. This process is repeated for all k

permutations of choosing the k-1 blocks for the training set. Thus, at the end of this exercise there are k accuracy estimates in terms of the average of test and training error. Using these k estimates we compute the average accuracy, variance and the confidence interval. Based on the results, one can assign weights to various blocks in proportion to test error. These weights will then be used in developing an i-neighbor version of the proposed fuser. More generally, the cross validation method can also be used to compare various methods in a statistically informative manner.

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