
Identifying Needed Fire Input Data to Reduce Modeling Uncertainty

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ABSTRACT:

Probabilistic risk assessments (PRA) of fires in nuclear power plants commonly use models to predict the conditions and expected damage from different plausible fire scenarios in order to quantify risk. In these analyses, fire model input varies from general behavior (overall heat release rate, combustion product yields, heat of combustion, physical size, etc.) to more detailed properties (thermal properties, pyrolysis kinetics, ignition temperature, *etc.*). Much of the data used to generate input for models is based on historical experiments that were conducted prior to many of the advanced measurement techniques in fire. The proposed research effort will identify the fire parameters that have the largest impact on fire conditions, quantify those parameters contributing to uncertainties in the fire data through Monte Carlo simulation results, and use statistical analysis and machine learning models from simulation results to assess existing data and recommend appropriate new fire tests to reduce uncertainties that are important to risk. Based on this research, we plan to develop a framework capable of determining the significant contributors to uncertainty in physical events that are relevant to the risk assessment and, then, determine the need for new experiments that would be of most value to reduce risk.

A database of existing fire test data will be created that will include the variation of different test parameters as well as the uncertainties associated with the measurements made during the test. To augment this database, a Monte Carlo analysis will be conducted using detailed computational models (Fire Dynamics Simulator – FDS) for fire and CONVERGE for explosions) where parameters are varied (fuel type and properties, exposure level, compartment size, *etc.*) and hazard conditions are simulated (gas temperatures, heat release rate, heat transfer, secondary ignition *etc.*). Statistical analysis will be conducted on the experimental data and simulation results using DAKOTA to identify the key parameters that most significantly impact the hazard conditions. A deep learning model will be created based on the simulation results and experimental data. Using the trained and tested model, analysis will be performed on the normalized hidden layer values to identify key parameters. The deep learning model will also be used in conjunction with other machine learning models to propose fire testing parameters that will span the required severity percentiles, which is currently not available with existing data. Additionally, a machine learning model combined with the deep learning model will be developed to provide a linkage between actual field conditions with the most relevant test data and simulation results. A final list of future test needs will be generated based on key parameters, uncertainty in existing test data, and potential impact on risk reduction. A general methodology based on the process in this research will also be developed for application to other hazard events relevant to PRA.