Uncertainty and Sensibility Analysis of Loss-of-Forced-Cooling Accidents for 150-MWt Molten Salt Reactors

Authors: Wang, Kai, Wang, Chaoqun, Yang, Qun, He, Zhaozhong, Wang, Naxiu, Wang, Naxiu

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Abstract

Molten salt reactors (MSRs) are a promising candidate for Generation IV reactor technologies, and the small modular molten salt reactor (SM-MSR), which utilizes low-enriched uranium and thorium fuels, is regarded as a wise development path to accelerate deployment time. Uncertainty and sensitivity analyses of accidents guide nuclear reactor design and safety analyses. Uncertainty analysis can ascertain the safety margin, and sensitivity analysis can reveal the correlation between accident consequences and input parameters. Loss of forced cooling (LOFC) represents an accident scenario of the SM-MSR, and the study of LOFC could offer useful information to improve physical thermohydraulic and structural designs. Therefore, this study investigates the uncertainty of LOFC consequences and the sensitivity of related parameters. The uncertainty of the LOFC consequences was analyzed using the Monte Carlo method, and multiple linear regression was employed to analyze the sensitivity of the input parameters. The uncertainty and sensitivity analyses showed that the maximum reactor outlet fuel salt temperature was 725.5℃, which is lower than the acceptable criterion, and five important parameters influencing LOFC consequences were identified.

Full Text

Uncertainty and Sensitivity Analysis of Loss of Forced Cooling Accident in a 150MWt Molten Salt Reactor

Kai Wang,[1],[2] Chaoqun Wang,[1],[2] Qun Yang,[1],[2] Zhaozhong He,[1] and Naxiu Wang[1],†

[1]Shanghai Institute of Applied Physics, Chinese Academy of Sciences, Shanghai 201800, China

[2]University of Chinese Academy of Sciences, Beijing 100049, China

Abstract

Molten salt reactors (MSRs) have been identified as one of the most promising Generation IV reactor technologies. The small modular molten salt reactor (SM-MSR), which utilizes low-enriched uranium and thorium fuels, represents a prudent development pathway to accelerate deployment timelines. Uncertainty and sensitivity analysis of accident scenarios provides crucial guidance for nuclear reactor design and safety assessment. While uncertainty analysis helps determine safety margins, sensitivity analysis reveals correlations between accident consequences and input parameters. Loss of forced cooling (LOFC) constitutes a key accident scenario for SM-MSRs, and its study yields valuable insights for improving physical, thermal-hydraulic, and structural designs.

This paper focuses on the uncertainty of LOFC consequences and the sensitivity of related parameters. The uncertainty of LOFC outcomes was analyzed using the Monte Carlo method, and multiple linear regression was employed to assess the sensitivity of input parameters. The uncertainty and sensitivity analysis demonstrates that the maximum reactor outlet fuel salt temperature reaches 725.5°C, which remains below the acceptance criterion. Additionally, five critical parameters influencing LOFC consequences were identified.

Keywords: molten salt reactor, LOFC, uncertainty analysis, sensitivity analysis

INTRODUCTION

Molten salt reactors (MSRs) have been selected as one of the promising candidate Generation IV reactor technologies [1-3] due to their inherent safety advantages [4–9] and high economic efficiency [10–14]. In 2011, the Chinese Academy of Sciences (CAS) launched the Strategic Priority Research Program on Future Advanced Nuclear Fission Energy, with the molten salt reactor as one of the project options. Subsequently, a small modular molten salt reactor (SM-MSR) was proposed [15]. Safety analysis plays a pivotal role in molten salt reactor design, ensuring that the reactor meets relevant safety requirements established by operating organizations and regulators while also supporting design optimization and safety performance improvements. One critical event in safety analysis is the loss of forced cooling (LOFC) accident, which is essential for verifying that the design adheres to prescribed and acceptable limits for radiation doses and releases under various plant conditions.

The use of best-estimate codes combined with uncertainty evaluation—so-called BEPU methodologies [16]—represents an accepted procedure among regulatory authorities for conducting deterministic safety analysis. At the end of the 1980s, the US Nuclear Regulatory Commission decided to permit the use of best-estimate methods with uncertainty quantification for reactor safety analysis, replacing the earlier licensing practice that employed deterministic methods with conservative assumptions to address uncertainties [17]. The BEPU approach calculates the uncertainty associated with values provided by a best-estimate code to realistically estimate safety margins for safety criteria. When combined with sensitivity studies, this approach can identify and quantify the significance of input parameters.

Several researchers have engaged in uncertainty and sensitivity analysis of molten salt reactors. X.W. Jiao et al. [18] adopted RELAP5/MOD4.0 to study the significance of trip setpoints in a reactivity-initiated accident and provided sensitivity rankings of the trip setpoint parameters. X.W. Jiao et al. [19] also investigated the sensitivity of initial conditions during a reactivity-initiated accident under low-power conditions of a molten salt reactor, finding that the consequences of reactivity insertion events exhibit low sensitivity to temperature coefficients of reactivity. M. Santanoceto et al. [20] studied the uncertainty and sensitivity of the molten salt fast reactor steady-state using a polynomial chaos expansion method, with analysis of the entire temperature field indicating that the heat exchanger may be a critical component. J.J. Wang et al. [21] examined the uncertainty of heat transfer in the TMSR-SF0 simulator, with simulation results indicating that the uncertainty propagated to the core outlet temperature is approximately $±$10°C with a 95% confidence interval for steady-state operation. While previous studies have explored uncertainty and sensitivity analysis in molten salt reactors, most have concentrated on steady-state conditions or specific parameters, leaving comprehensive uncertainty and sensitivity studies of accidents insufficiently addressed thus far.

This study focuses on the comprehensive uncertainty of LOFC consequences and the sensitivity of related input parameters.

II. DESCRIPTION OF SM-MSR

Fig. 1 [Figure 1: see original paper] illustrates the schematic design of the SM-MSR, and the main design parameters are listed in Table 1 . The reactor adopts a double molten salt circuit design. The primary circuit components include a reactor core, intermediate heat exchangers (IHX), control rods, a primary pump, and pipelines. The reactor core consists of open-celled graphite elements forming 241 molten salt channels and six functional channels for control rods. The fuel salt, composed of LiF-BeF_2-ZrF_4-UF_4-ThF_4, enters the reactor at approximately 629°C through the lower plenum, ascends through the reactor core where nuclear fission reactions occur and the fuel salt is heated, and finally exits the reactor core at approximately 700°C [15].

The secondary circuit consists of a secondary pump, molten-salt-air heat exchangers (AHX), and pipelines. The coolant salt is made of LiF-NaF-KF, and it is pumped into the tube side of the primary heat exchanger to remove heat from the primary circuit, then discharges this heat to the Brayton cycle system through the molten-salt-air heat exchanger. Finally, nuclear power is converted into electrical energy via the Brayton cycle turbine.

To mitigate accident consequences, a natural circulation flow loop is implemented for decay heat removal, formed between the hot core and heat exchangers (PHX) of the pool reactor auxiliary cooling system (PRACS). During normal operation, the PRACS flow path is partially blocked by a check valve, which exhibits much larger loss coefficients for reversed flow compared to forward flow. The PHX modules transfer heat from the primary salt to the buffer salt, which is then cooled by direct reactor auxiliary cooling system (DRACS) modules. The DRACS transfers heat through natural circulation from the buffer salt to molten salt-air heat exchangers (ADHX), and finally dissipates heat to outside ambient air. Notably, all components in contact with molten salt are constructed from Hastelloy-N.

III. METHODOLOGY

Currently, two general approaches exist for uncertainty analysis: propagation of input uncertainty and extrapolation of output accuracy [22, 23]. Extrapolation of output accuracy requires extensive experimental data. Given the limited number of current molten salt reactor experiments, this study adopts the propagation of input uncertainty approach, which is based on Monte Carlo methods. This approach involves two elements: associating uncertainty with input parameters and performing multiple executions of the best-estimate code. A flowchart for performing the SM-MSR LOFC accident uncertainty and sensitivity analysis is illustrated in Fig. 2 [Figure 2: see original paper].

A. Uncertainty Parameters

The uncertainty of input parameters stems from imprecise knowledge of actual values, with sources including reactor system data, structural material properties, and best-estimate code correlations. Uncertain parameters for the LOFC accident were selected using the phenomena identification and ranking table (PIRT) approach. The primary approach for quantifying input uncertainty includes both probabilistic and deterministic methods. Probabilistic methodologies utilize statistical elements to characterize and combine input uncertainty, while deterministic methodologies use reasonable ranges or bounding intervals and combine input uncertainty based on maximization and minimization of output values [24–26]. The probabilistic approach is currently the most widely adopted procedure and is endorsed by industry and regulators. Limited detailed information about certain aspects of the SM-MSR presents a significant drawback. To minimize this impact, a list of input parameters along with their associated density functions was adopted using a probabilistic methodology. Quantification of uncertainty parameters was established through previous studies, experimental data, and expert judgment. In this study, 30 uncertainty input parameters were identified, and Table 2 shows these parameters and their probability distribution functions.

B. Best-Estimate Code

The RELAP5 code is a transient analysis code designed for light water reactors, developed by the U.S. Nuclear Regulatory Commission (NRC) for various applications such as rule-making, licensing audit calculations, and evaluation of operator guidelines. It employs one-dimensional and two-fluid thermal-hydraulics models. The latest version, RELAP5/MOD4.0, was developed by Innovative System Software (ISS) specifically for nuclear power plant analysis [27].

In RELAP5/MOD4.0, an uncertainty analysis package has been incorporated, following the methodology developed by Gesellschaft für Anlagen- und Reaktorsicherheit (GRS) [24]. This methodology integrates order statistics and Wilks' formula [28, 29] into the propagation of input uncertainty approach. Since heat transfer coefficient correlations and coolants for the SM-MSR are not available in the current RELAP5/MOD4.0, new correlations [30] and coolants applicable to MSRs have been inserted, resulting in the updated code named RELAP5-TMSR [31–33].

Considering that the uncertainty analysis package can only be employed for partial analysis of light water reactors, an uncertainty analysis package for molten salt reactor systems was developed during this study. It can propagate uncertainties associated with molten salt properties and uncertainties related to the inserted heat transfer correlations applicable for fuel channels in the reactor core and heat exchangers of the SM-MSR.

C. Sensitivity Analysis Method

Sensitivity analysis assesses the impact of varying independent variable values on a particular dependent variable within defined assumptions. In other words, it studies how uncertainties from various sources in a mathematical model contribute to overall model uncertainty.

Linear regression [34–36] utilizes a straight line to describe relationships between variables. It identifies the best-fit line in a dataset by searching for regression coefficient values that minimize the total model error. The model' s equation presents clear coefficients that clarify the influence of each independent variable on the dependent variable. Two primary types exist: (1) Simple Linear Regression, which involves only one independent and one dependent variable, and (2) Multiple Linear Regression (MLR), which involves multiple independent variables and one dependent variable. This study adopts the multiple linear regression (MLR) method. The equation for multiple linear regression is shown in Eq. (1), where y is the dependent variable, x are independent variables, β_0 is the constant, and β are coefficients.

A systematic sensitivity analysis process based on MLR is shown in Fig. 3 [Figure 3: see original paper], proposed by G. Manache [37] and also applied in the functional reliability analysis of a molten salt natural circulation system [38]. The adjusted coefficient of determination (R^2{adj}) *is used to evaluate* *whether the linear model is acceptable* (R^2{adj} ≥ 0.7 indicates an acceptable model). The collinearity problem in multiple linear regression is addressed by calculating the variance inflation factor (VIF) for each parameter, where VIF ≤ 5 indicates weak collinearity. If the linear model exhibits strong collinearity, a significance test of the semi-partial correlation coefficient (SPC) is used for ranking input uncertainty parameters; otherwise, the standardized regression coefficient (SRC) is used for significance testing [38].

IV. ANALYSIS AND RESULTS

A. Thermal-Hydraulic Model

Fig. 4 [Figure 4: see original paper] shows an overview of the RELAP5-TMSR nodalization of the SM-MSR. The entire system consists of four coupled parts: (1) the primary circuit, including the downcomer, reactor core, lower plenum, upper plenum, primary pump, pipes, and IHX tube side; (2) the secondary circuit, including pipes, secondary circuit pump, IHX shell side, and AHX tube side; (3) Brayton cycle modules, including air inlet volume, AHX shell side, and air outlet volume; and (4) the passive residual heat removal system consisting of DRACS and PRACS, including pipes, PHX, ADHX, and air cooling loop.

B. Uncertainties and Sampling

Wilks' formula has been frequently used to quantify the minimum computational effort required to meaningfully assess a model' s uncertainty by specifying acceptable tolerance limits on model output parameters [39]. A fundamental advantage of Wilks' formula is that it imposes no limit on the number of uncertainty parameters considered in the analysis. The number of code runs required for uncertainty analysis depends only on the statistical features of the imposed tolerance limits, including percentile tolerance interval, confidence interval, and order, and is independent of the number of uncertain parameters [28, 29]. The number of code runs for a one-sided tolerance interval can be calculated using Eq. (2), where γ is the percentile tolerance interval, β is the confidence interval, N is the number of input samples (or code runs), and m is the order.

Table 3 shows the number of code runs based on Wilks' formula, varying with percentile tolerance and confidence intervals at different orders. In this study, the upper tolerance limit' s percentile and confidence were set to the standard 95%/95% at the 5th order, requiring a minimum of 181 code runs according to Wilks' formula.

Fig. 5 [Figure 5: see original paper] shows the cobweb plot of the 181 random samples for the 30 parameters, where the x-axis displays uncertain parameters and the y-axis shows normalized sample values. Based on Fig. 5, the achieved sample population is well representative and meets the requirements of the LOFC uncertainty study.

C. Safety Variables and Acceptance Criteria

Safety variables and their acceptance criteria are crucial in SM-MSR safety analysis. The primary circuit boundary serves as the principal safety barrier against radioactive leaks, making the performance of Hastelloy-N—used as the structural material for the primary circuit—critical to reactor safety.

Temperature is a pivotal indicator of Hastelloy-N' s performance, with studies confirming its ability to maintain mechanical properties at 800°C [40]. Considering the direct contact between fuel salt and Hastelloy-N structural materials, the reactor outlet fuel temperature (T_{out}) with a limiting value of 800°C was selected as the criterion for this study.

D. Uncertainty Propagation Results

Once the code run numbers and sets of uncertain input parameters were established, input uncertainty was propagated through the RELAP5-TMSR code. During normal operating conditions, core flow is driven by the pump at approximately 1000 kg/s. However, following an LOFC event, the pump stops, causing a decrease in core flow and a consequent increase in T_{out}. Simultaneously, the reactor protection system sends a shutdown signal, the control rods drop, power coasts down, and this causes T_{out} to decrease.

Under the combined influence of changing core flow and nuclear power, T_{out} reaches its first peak at approximately 10 seconds and a second peak at approximately 200 seconds. The second peak represents the maximum temperature, after which T_{out} changes slowly and finally reaches a safe, stable temperature where decay heat continues to be removed by PRACS and DRACS.

The evolution of T_{out} for the 181 code runs is shown in Fig. 6 [Figure 6: see original paper], while Fig. 7 [Figure 7: see original paper] shows the maximum reactor outlet fuel salt temperature (T_{{{out}}{{max}}}) for the 181 cases. All results remain below the acceptable criterion of 800°C, with the maximum T{{{out}}{{max}}} value being 725.5°C and the minimum being 715.4°C. Fig. 8 [Figure 8: see original paper] shows the upper and lower uncertainty bands; the maximum difference between the upper and lower bounds is 18.5°C during the initial temperature ascent phase. In the base case, the maximum temperature increase of reactor outlet fuel salt (ΔT{out}) is 22.2°C compared to the initial condition. In the upper limited case, ΔT_{out} is 25.5°C, representing a 26.2% increase relative to the base case, while in the lower limited case, ΔT_{out} is 15.4°C, indicating a 23.7% decrease relative to the base case.

E. Distribution Identification of T_{{{out}}_{{max}}}

Fig. 9 [Figure 9: see original paper] shows the histogram and probability density function obtained from 181 simulations for T_{{{out}}{{max}}}. The points roughly follow a bell curve shape, indicating a normal distribution. In this study, the Shapiro-Wilk (S-W) test [41] is adopted to assess whether the calculated

T{{{out}}_{{max}}} follows a normal distribution. The S-W test compares the observed dataset to the expected normal distribution to determine normality. The test statistic for the S-W test is shown in Eq. (3), where x represents ordered random sample values, $\bar{x}$ is the sample mean, and a are constants that are functions of n.

The null hypothesis for the Shapiro-Wilk test states that the variable is normally distributed. If $p < 0.05$, the null hypothesis is rejected; otherwise, it is accepted. Statistical analysis yields a p-value of 0.197, which exceeds 0.05, so the null hypothesis of normality is acceptable.

The quantile-quantile (Q-Q) plot is a graphical technique for determining whether two datasets come from populations with a common distribution [42]. In a Q-Q plot, normally distributed data points align on a straight diagonal line; conversely, significant deviation from this line indicates non-normality. Fig. 10 [Figure 10: see original paper] shows the Q-Q plot for T_{{{out}}_{{max}}}, where points mostly lie along the straight diagonal line with minor deviations in the tails.

Based on the above analysis, T_{{{out}}*{{max}}} follows a normal distribution. Table 4 shows the main statistical results and T*{{{out}}_{{max}}} values at different percentiles according to the probability density function.

F. Sensitivity Analysis

This paper adopts the multiple linear regression (MLR) method following the steps outlined in Fig. 3 [Figure 3: see original paper] to ascertain the importance of input parameters. The F-test is used to assess whether the MLR models comply with statistical laws. The acceptance region is defined by an F-value greater than 1.83 at a significance level of 0.01. Table 5 lists the F-values and R^2_{adj} values, showing that the model follows a convincing linear hypothesis relationship.

Fig. 11 [Figure 11: see original paper] shows the VIF values, all of which are less than 5; therefore, SRCs of the input parameters were selected for sensitivity analysis. The absolute values of SRCs provide a relative measure of parameter importance, and Fig. 12 [Figure 12: see original paper] shows the final absolute SRC values for the 30 input parameters.

Furthermore, a t-test is used to assess the significance of sensitivity coefficients. The acceptable range requires the absolute t-value to be larger than 1.66 with a significance level of 0.05. Finally, five important parameters considered to have significant contribution to LOFC consequences were identified based on the t-test and SRCs, as listed in Table 6 .

Unlike traditional pressurized water reactors, which utilize solid fuels with fission energy transferred from fuel pellets to cladding and finally to coolant, SM-MSR uses liquid fuel salt that also serves as the coolant. In this system, fission energy is directly transferred to the coolant. Therefore, reactor power, fuel salt flow in the reactor, and fuel salt properties are very important to LOFC consequences. Sensitivity analysis reveals that the volumetric heat capacity of the fuel salt (density × specific heat) stands out as the most critical input uncertainty parameter, as it affects both heat absorption and flow of fuel salt in the reactor core. Reactor power and reactor shutdown margin values influence heat generation after a scram, thus significantly impacting fuel salt temperature. The local resistance coefficients of the reactor core and primary circuit play crucial roles in affecting fuel salt flow, making them important to fuel salt temperature. Table 6 also shows the relationship between these five important input parameters and T_{{{out}}_{{max}}}. If an SRC has a negative value, this indicates a negative correlation, while a positive value signifies a positive correlation.

G. Parameter Prediction

Multiple linear regression can be used to predict the value of one variable using available information. Through this method, confident predictive values of T_{{{out}}*{{max}}} can be obtained without requiring numerous calculations. This paper conducted a preliminary study on predicting T*{{{out}}_{{max}}} using the five important parameters.

The weights used for prediction are shown in Table 7 . The SRCs of Cpv_{fuel} and _{shutdown} are negative, indicating a negative correlation with T_{{{out}}*{{max}}}, so weights are arranged from large to small. Conversely, the SRCs of P*{reactor}, f_{core}, and f_{primary} are positive, so weights are arranged from small to large to obtain a conservative prediction of T_{{{out}}_{{max}}}.

It has been proven that T_{{{out}}*{{max}}} follows a normal distribution (Section IV.E), and the significant statistical parameters used for prediction are listed in Table 4 . Fig. 13 [Figure 13: see original paper] shows the predicted values of T*{{{out}}_{{max}}} and the bounds of the 95% prediction interval. The predicted upper bound value for the 11th case is 752.2°C, slightly exceeding 750°C; from Table 7, the weights are 0.6 or 1.4, indicating a very large uncertainty range.

V. CONCLUSIONS

This paper presents uncertainty and sensitivity analysis of the loss of forced cooling accident in a molten salt reactor using Monte Carlo and multiple linear regression methods. An uncertainty analysis package for molten salt fluid systems was developed, and 181 samples of 30 input uncertainty parameters were propagated through RELAP5-TMSR, demonstrating successful execution of the uncertainty analysis package. According to the uncertainty analysis results, all cases remain below the acceptance criterion, with the maximum T_{{{out}}*{{max}}} value being 725.5°C and the minimum being 715.4°C. Additionally, distribution identification was performed, and statistical analysis confirms that T*{{{out}}_{{max}}} is normally distributed.

Statistical analysis demonstrates that the multiple linear regression method can be effectively used for molten salt reactor LOFC sensitivity analysis. Results show that Cpv_{fuel}, f_{core}, P_{reactor}, _{shutdown}, and f_{primary} are the most important parameters for LOFC consequences, and these parameters should be prioritized during the design and safety analysis of the 150MWt SM-MSR. Following distribution identification and sensitivity analysis, a preliminary study on predicting T_{{{out}}*{{max}}} using the MLR method was implemented. When the uncertainty of the five crucial parameters reached 40%, the predicted T*{{{out}}_{{max}}} was 752.2°C, which maintains a substantial safety margin compared to the acceptance criterion of 800°C.

Future research will focus on a comprehensive study of the uncertainty ranges of pivotal input parameters through a synergistic approach involving both experimentation and rigorous numerical analysis, with the ultimate aim of reducing uncertainty in accident consequences.

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Note: Figure translations are in progress. See original paper for figures.