A Machine Learning-Based Approach to the Prediction of Accidental Source Term

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1. Introduction

After the Fukushima Daiichi Nuclear Power Plant (NPP) accident caused by the Great East Japan Earthquake on March 11, 2011, Awareness increased towards preventing of nuclear disaster. The countries reviewed existing monitoring framework, and many radiation-monitoring posts have been added or set up around nuclear facilities to control the radioactive release. In addition, emergency countermeasures for radiation and nuclear accident within the country revised and updated. However, research on the detection of radioactive releases in the case of a nuclear accident in neighboring countries and early warning of this has rarely been carried out. The severe accident at the Chernobyl NPP located in Ukraine led to significant contamination not only outside the evacuation zone, but also in many European countries, especially in neighboring countries [1]. Likewise, modeling the effects of a cooling system failure in spent fuel storage pools showed that this failure could lead to a fire, and a huge amount of ^{137}Cs would be released to the environment and contaminated large areas of Japan, north Korea and China [2]. Source term of accident is very important factor during emergency to estimate the amount and path of radioactive material release in accident scenarios; referred to as accident source term, is a pivotal point for decision-making in the nuclear emergency response. The estimation result provides necessary input for dispersion simulation of fission products, public dose evaluation and then corresponding emergency response actions determination, such as whether people should evacuate or shelter in place, and for rating the significance of the accident according to INES. The aim of this study is predicating the amount of radioactive material inside the core of VVER-1200 during two design basis accidents, long term station blackout (LTSBO) and loss of coolant accident (LOCA) by using CART regression model. In this study, the new Russian reactor VVER-1200 which is one type of Generation-III+ reactors where build in ELDABAA Egypt is the case study. It has thermal power 3212 MWth, 163 fuels assembly with Max burnup 70,000 MWd/t. [3]The code that used in two accidents simulation is RASCAL 4.3.3. RASCAL is abbreviation for Radiological Assessment System for Consequence Analysis. It evaluates releases from nuclear power plants, spent fuel storage pools and casks, fuel cycle facilities, and radioactive material handling facilities. Developed for the U.S. Nuclear Regulatory Commission, Source term calculations in RASCAL estimate the amount of radioactive material released based on a wide variety of potential radiological accident scenarios.

2. Methods and Results

The method that used in this paper divided to 2 steps, first step is using RASCAL to calculate the amount of radioactive materials in the VVER-1200 at different conditions, and then output data will treat by CART regression model in MINITAB software to produce model. This model can predict the amount of radioactive materials by using certain parameter as predicator. There are several important parameters shall consider during calculation source term and meteorological data for ELDABAA.

2.1 Meteorological data

Meteorological condition of ELDABAA considered from historical meteorological data analysis from jan-2011 until Oct-2020. This data collected from the nearest weather station to ELDABAA; the distance between this station and the ELDABAA is 20 km. The daily data was analyzing to determine wind speed, temperature, atmospheric pressure and wind direction, Fig. 1 explains the normality test graphs for temperature, atmospheric pressure and wind speed over approximately 10 years.

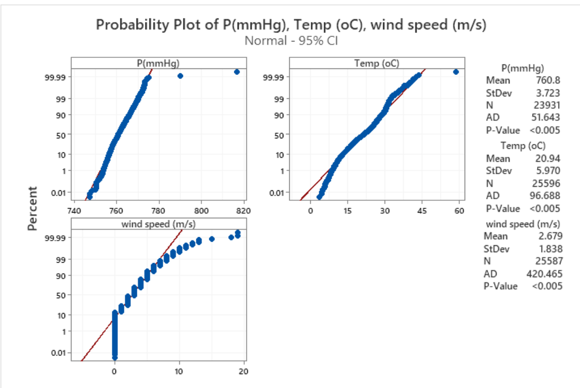

Fig. 1. Probability plot of temperature, atmospheric pressure and wind speed.

From the normality test for the data, P-value is lower than 0.05 for atmospheric pressure and temperature and wind speed, therefore the data not follow normal distribution and we used the median of data over 10 years; it is more statistically significant than the average. The median value of wind speed is 3.0 m/s, temperature is 21.1 °C and atmospheric pressure is 1.02 bar. These values used for each scenario. The second parameter in metrological data shall consider is wind direction. The wind direction data over 10 years is shown in Fig. 2. The predominate wind direction in ELDABAA is North West direction.

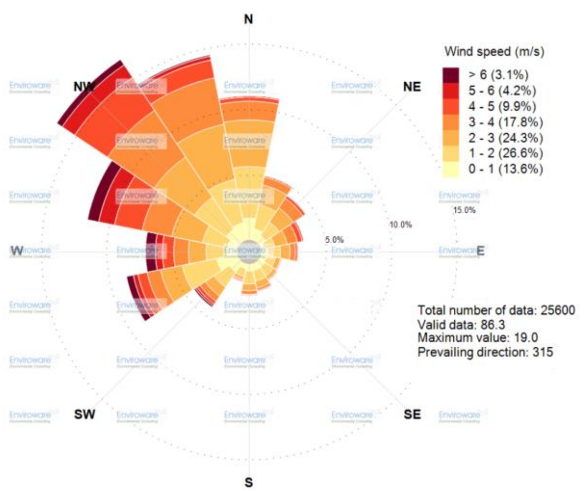

Fig. 2. Wind rose diagram at ELDABAA.

2.2 Reactor parameter

In this study, we use RASCAL code to build a generic model with VVER-1200 parameters as shown in Table I.

Table I: Parameters used in this model.

VVER-1200 RASCAL parameters	
Reactor power	3212 MWth
Average burnup	30,000 MWd/MTU
Containment volume [3]	4.04×10^4 ft^3
Assemblies in core	163
SG water mass [3]	63,000 kg

2.3 accidents scenarios

The source term is function of many parameters, like reactor power, reactor burnup, the condition of accident, how many hours the core is uncovered and the emergency core cooling system is available or not. The source term calculation of RASCAL based on NUREG-1465. RASCAL versions before RASCAL 4.3 didn't consider right time for core uncovered in the case of SBO accidents. After Fukushima accident, NRC updated RASCAL and add LTSBO option based on NUREG-1935 and NUREG/CR-7110. In this study, we will select LTSBO accident and LOCA accident for different parameters. The number of scenarios is 24 scenarios simulated, 16 scenarios for LTSBO and 8 for LOCA. In all scenarios, we assume the leakage rate is 10% per day, the core uncovered for 12 hour and the amount of radioactive materials calculated for each 15 mins until 96 hours. The source term calculated at four power steps that are 100%, 75%, 50% and 25%, with each power step, we assume the condition of emergency core cooling system and/ or containment spray system. Fig. 3 explained the probability tree that used in source term simulation for both accidents.

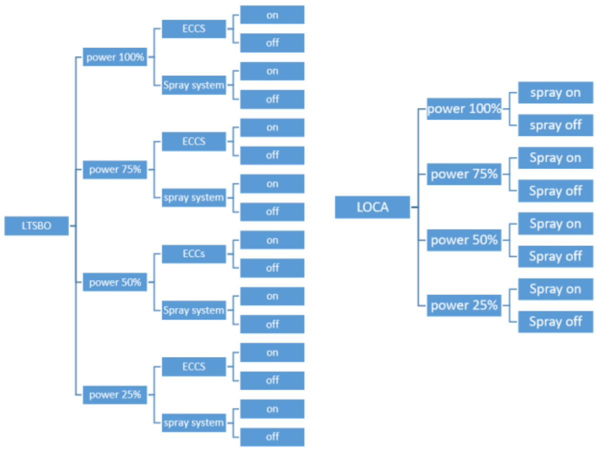

Fig. 3. Probability tree of LTSBO and LOCA.

2.4 Results

RASCAL output data is big data; it is greater than 600k rows. This data filtered and divided to groups. If the amount of radioactive material is lower than 1mCi, this value will be ignored. Under this condition, the amount of data was decrease to 271k rows. The radioactive isotopes that formed during the fission process in the reactor fuel and core can group into a small set of categories of elements with similar physical or chemical behaviors [4]. In this study, we are interested in Iodine group and Cesium group. The activity of radioactive materials inside the core not only the output of RASCAL, but also the total effective dose equivalent (TEDE) is RASCAL output. This dose calculated at the edge of Emergency Planning Zones (EPZ), which is 10 miles. Two CART regression model created. The first model to Cesium group data prediction. Amount of data used in this model is 23852 and 10-folds cross validation to validate the model. We used 9 predictors in this model. These predictors are nuclide name, TEDE (Sv), calculation time (min), type of accident, Leakage rate percentage, containment spray system status, power percentage, Emergency core cooling system status and release time (hour). Fig. 4 explained the relative importance of these predictors.

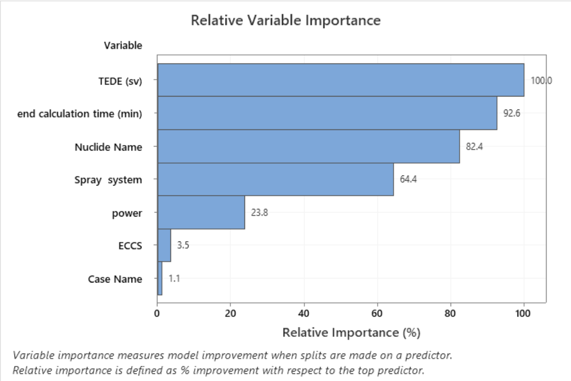

Fig. 4. Importance order of predictors for Cesium group.

The data divided to 70% to create the model and 30% to test the model. Fig. 5 explained the linear regression model between the real activity and the data predicated by CART model. The R-square is 0.982 and p-value=zero <0.05 which is mean strong linear relationship between the predicated data and real data.

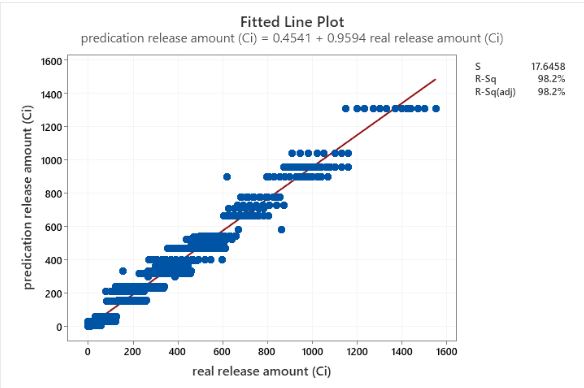

Fig. 5. Scatter plot between predicted activities and real activities for Cesium group.

The second model to iodine group. Amount of data used in this model is 19654 and 10-folds cross validation to validate the model. We used the same nine predictors in Cesium model. Fig. 6 explained the relative importance of these predictors.

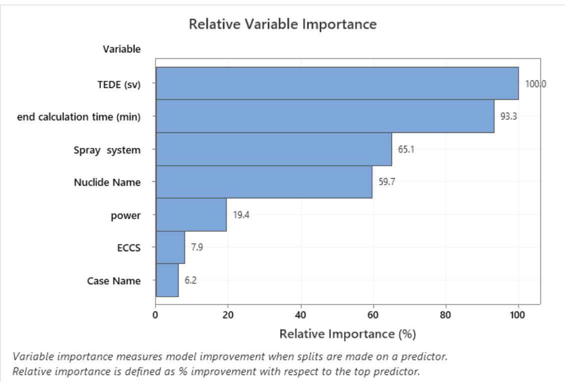

Fig. 6. Importance order of predictors for Iodine group.

The procedures followed in iodine group, the data divided to 70% for creating model and 30% for test. Fig. 7 explained the linear regression model between the real activity and the data predicated by CART model. The R-square is 0.989 and p-value=zero <0.05 which is mean strong linear relationship between the predicated data and real data.

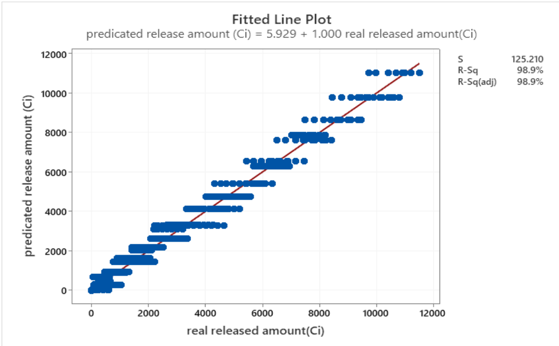

Fig. 7. Scatter plot between predicted activities and real activities for Iodine group.

3. Conclusions

From Fig (4) and Fig (6), we can conclude the TEDE and the calculation time for inventory are the most important predictors in predication model of source term. CART regression model can help us to know the source term in the reactor if I provide the model with TEDE, power percentage, calculation time (min), type of accident, condition of accident like, status of containment spray system, and Emergency core cooling system status.

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