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Derivation of empirical equations for neutronic performance in a thorium fusion breeder with various coolants using regression analysis

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ABSTRACT

In this paper, regression analyses (RA) are presented for the neutronic calculation of ThO_2 mixed $^{244}CmO_2$ fuel with different neutronic parameters for various coolants, natural lithium, $Li_{20}Sn_{80}$ and Flinabe, respectively. The tritium breeding ratio (TBR), energy multiplication factor (M), total fission rate (Σ_f) and ^{232}Th(n, γ) reaction is computed by XSDRNPM. In addition, this numerical results are estimated by RA depends on neutronic parameters and the empirical equations for neutronic performance are acquired. The results obtained by using XSDRNPM and the results of the RA, obtained empirical equations, are compared. The empirical equations indicate that RA can successfully be used for the prediction of the neutronic performance parameters in the hybrid reactor with a high degree of accuracy. In addition, correlation matrix is calculated to determined statistical relationships between variables TBR, M, Σ_f, and ^{232}Th(n, γ).

1. Introduction

In nuclear engineering applications, there has been a significant interest on the use of fuzzy logic, neural network, regression analysis, analysis of variance analysis (ANOVA) (Acır, 2009; Acır, Alakoç, & Yıldız, 2009; Boroushaki, Ghofrani, Lucas, Yazdanpanah, & Sadati, 2004; Nissan, 1998; Übeyli & Übeyli, 2007, 2008; Uhrig & Tsoukalas, 1999). These functions are widely used in many applications. Recently, the neutronic performances in a hybrid reactor were predicted by using RA (Acır et al., 2009) and ANOVA was applied to investigate the effect of the neutronic parameters of neutronic performance characteristics (Acır, 2009). Moreover, the estimation neutronic parameters in the hybrid reactor technology using artificial neural networks (ANNs) were investigated (Übeyli & Übeyli, 2007, 2008). In literature, regression analysis was used for prediction in a widely variety of fields. However, it has been shown that RA method in nuclear energy technology is very limited as a statistical approach (Acır, 2009; Stocks & Faulkner, 1980). The burning and/or transmutation of ^{244}Cm nuclear wastes of hybrid reactor were suggested by different researchers in earlier studies (Şahin & Al-Kusayer, 1986; Yapıcı, Genc, & Demir, 2004; Yapıcı & Übeyli, 2003). There have been a number of studies carried out on hybrid reactors with different fuels (Şahin, Acır, Altınok, & Yalçın, 2008; Şahin & Al-Kusayer, 1986; Şahin, Al-Kusayer, & Abdul Raoof, 1986; Übeyli & Acır, 2007; Yapıcı et al., 2004; Yapıcı & Übeyli, 2003). However, regression analysis and correlation matrix used for prediction and defining statistical relationships of neutronic performance were not used in earlier studies. Regression analysis and correlation matrix are statistical procedures used to investigate the relationship between a dependent variable and one or more independent variables and determine the degree of relationship between two or more variables. Therefore, in a nuclear engineering applications, the statistical relationships of neutronic performance between TBR, M, Σ_f fission rate and ^{232}Th(n, γ) are very important.

The main objectives of this study are:

1. Obtaining empirical equations for prediction of neutronic performance in a hybrid reactor with ThO_2 mixed $^{244}CmO_2$ fuel using regression analysis with different neutronic parameters for natural lithium, $Li_{20}Sn_{80}$ and Flinabe coolants.
2. Deriving correlation matrix for determination of the effect of the statistical relationships of neutronic performance characteristics between TBR, M, Σ_f fission rate and ^{232}Th(n, γ) reaction.

In this study, the calculation procedure of XSDRNPM and geometric design are indicated in the following section. In the third section, the results of the regression analysis are discussed. Details of regression equations, performance measures, and correlation analysis are presented.

This paper is organised as follows. Section 2 provides a brief description of the hybrid reactor structure. In Section 3, we describe the architecture of the regression analysis. Finally, Section 4 makes concluding comments.

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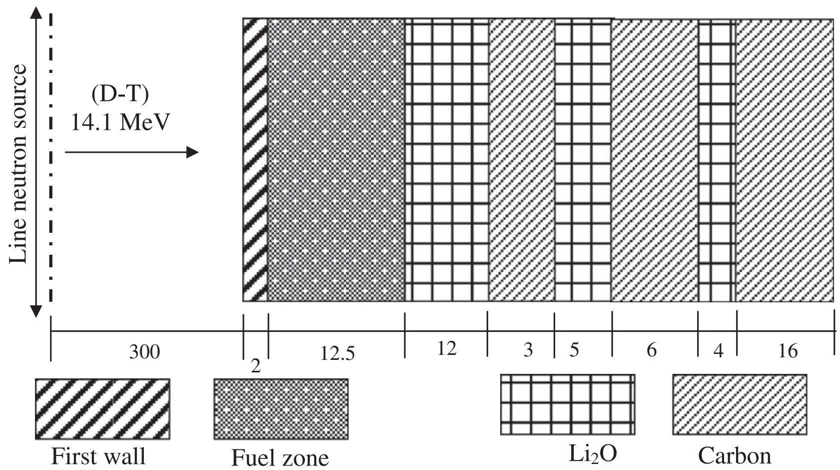

Fig. 1. Structure of the investigated one dimensional blanket (dimensions are given in cm).

2. Calculation procedure and blanket structure

The calculation was performed with one dimensional XSDRNPM/SCALE5 neutron transport code using the 238-group library (Greene & Petrie, 2004; Landers & Hollenbach, 2004; Petrie, 2004) with BONAMI (Greene, 2004) and NITAWL (Greene & Westfall, 2004) modules for the resonance processing with full reactor power (plant factor, PF = 100%). Fig. 1 shows the blanket model of hybrid reactor (Şahin & Al-Kusayer, 1986; Şahin et al., 1986). The blanket consists of four sections radially, first wall, fuel zone, tritium breeding zone and reflector zone, respectively. $V_{moderator}/V_{fuel}$ is considered as 2 for neutronic calculation. Tungsten (W) is used as the first wall and clad materials. Li_2O and carbon are selected as reflector materials. Natural lithium, $Li_{20}Sn_{80}$ and Flinabe are used as coolants and ThO_2 mixed $^{244}CmO_2$ is used as fuel in the hybrid reactor is used. Atomic densities and materials using in the thorium fusion blanket are given in Table 1. The ^{6}Li fraction in the coolants is increased gradually from 7.5% to 30%, 60% and 90% in conducting the applications. Similarly, the ^{244}Cm fraction is increased gradually from 0% to 10% and stepped by 2%. Obtained neutronic results with XSDRNPM code depend on given previously determined parameters. Regression analysis, correlation procedures and other statistical analysis are performed by MINITAB 14 software for neutronic performance estimation.

3. Regression analysis

In real life, there exists some inherent relationships between the variables and in most cases we need to define these relationships to solve or model the problems. The relationship of a set of experimental data is characterized by a prediction equation. This equation is defined by the results of regression analysis. RA procedure estimates the dependent (outcome) variable, for various levels from the experimental information defined by the independent variables. In each regression equation a single dependent variable is expressed in terms of independent variables. It is desired that the exact values of the dependent variables are observed from the equations when the values of the independent variables are specified, but this is not possible in most analysis. It would be ideal to reach the dependent variables by the best estimates (Freedman, 2005; Mendenhall & Sincich, 1996; Montgomery & Runger, 2006).

In this study, the tendency of the dependent variables varies with the linear and non linear equations are considered systemically to obtain the best estimates for multiple regression. The model below gives the limited regression equation taken into account as the combination of independent variables (Freedman, 2005; Mendenhall and Sincich, 1996; Montgomery and Runger, 2006).

$$Y_i = \beta_0 + \sum_{j=1}^{m} \beta_j X_{ji} + \sum_{j=1} \beta_j X_{ji}^2 + \sum \sum_{j>k} \beta_j X_{ji} X_{jk} + \varepsilon_i$$
$$i = 1,2,\ldots,n,\ j = 1,2,\ldots\ldots,m,\ m = 5,\ n = 20$$

where Y_i is the ith observation of the dependent variable, X_{ji} is the ith observation of the jth independent variable, β_0 and β_j are regression coefficients, ε_i is the error term, m is the number of independent variables, n is the sample size.

3.1. Derivation of regression equations

In this paper, the goal of the RA is to predict the values of TBR, M, Σ_f fission rate and ^{232}Th(n, γ) reaction in the hybrid reactor. According to this goal, TBR, M, Σ_f and ^{232}Th(n, γ) are considered as dependent variables and ^{6}Li, ^{7}Li, ^{232}Th and ^{244}Cm are taken into account as independent variables. Descriptions of TBR, M, Σ_f fission rate and ^{232}Th(n, γ) reaction are given in Acır et al. (2009). The obtained TBR, M, Σ_f fission rate and ^{232}Th(n, γ) reaction numerical results by using XSDRNPM code are divided into two parts and these parts constitute training and testing data. Training data used in both empirical equations and neutronic performance estimation is evaluated by regression analysis depends on neutronic parameters. In other words, empirical equations for the estimation of TBR, M, Σ_f fission rate and ^{232}Th(n, γ) reaction by regression analysis are obtained. Testing data with obtained empirical equations are investigated for evaluating RA performances. Empirical equations derived from the RA model for different coolants are given below:

For natural lithium coolants:

Table 1
Atomic densities and materials using in the thorium fusion blanket.

Material	Density (g/cm^3)	Zone
ThO_2	9.86	Fuel
$^{244}CmO_2$	13.51	Fuel
Natural lithium	0.534	Moderator (coolant)
$Li_{20}Sn_{80}$	6.2	
Flinabe	2	
Li_2O	2.01	Tritium breeder
Carbon	2.26	Reflector
W (Tungsten)	19.25	First wall and clad