Nuclear Engineering and Design 337 (2018) 66–73

Contents lists available at ScienceDirect

Nuclear Engineering and Design

journal homepage: www.elsevier.com/locate/nucengdes

Comparison of spatial interpolation approaches for in-core power distribution reconstruction

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ARTICLE INFO

Keywords:
Spatial interpolation
In-core power distribution reconstruction
RBF
SVR
TSA
DWA

ABSTRACT

This paper investigated the influence of various types of spatial interpolation algorithms in the reactor in-core power distribution reconstruction. These algorithms include different kinds of kernel function used in radial basis function (RBF) methods or support vector machine regression (SVR) methods, different orders of polynomial trend surface analysis (TSA), and various forms of distance weight average (DWA) methods, geo-statistics interpolation method. A typical pressurized water reactor core with 157 fuel assemblies and 33 measurement instruments located is analyzed. The validations of these methods under the measurement core status and predictive core status have been provided. The criterions of relative root mean square error (RRMSE) have been applied to guarantee the accuracy of these algorithms. The comparison of the different spatial interpolation algorithms shows that the DWA basis methods usually perform much better and stable than other methods. PEM and SVR methods have very poor performance in high signal deviation situation, but they can effectively eliminate measurement error in the opposite situation. The fitting methods TPS0, PEM4 could not be used in in-core power distribution reconstruction (IPDR). TPS1 is the best choice for no parameter RBF methods. While for other RBF basis methods, optimization algorithm should be used to search the optimized model parameters. The performance of RBF_TPS1, DWA_OK, SVR_Gauss, RBF_Gauss fall into a same group. Three-dimension surfaces of fitting results are compared. The factors are discussed that affect the reconstructed results of the methods, including detectors number, detectors design pattern and detector measurement properties, variability of the fitting surface. Suggestions to select an appropriate spatial interpolator method are provided.

1. Introduction

In-core flux mapping or core power distribution monitoring is one of the essential functional requirements in core surveillance and analysis. The detailed in-core flux and power distribution, as well as the parameter key to core safety analysis are calculated on-line. Most commercial nuclear power plants in operation are equipped with in-core detectors to obtain power distribution. Many kinds of the on-line Core Monitoring Systems (CMS), such as BEACON (Boyd and Miller, 1996), GNF-ARGOS (Tojo et al., 2008), and SOPHORA (Wenhuai et al., 2014) have been developed to best estimate in-core power distribution using fixed in-core detectors (FID) or movable in-core detectors combined with the other temperature and pressure measurement devices. Based on the “best estimate” core simulation, these CMS can survey core power distribution and thermal limits such as the minimum departure from nucleate boiling ratio, and detect the anomalies such as dropped/misaligned rods, fuel misloading and xenon oscillation.

Many computational methods have been developed for in-core power distribution reconstruction (IPDR). The coupling coefficient (CC) (Karlson, 1995) method is applied in the C-E CECOR (Terney et al., 1983) flux-mapping code to estimate the power distribution, and the two-dimensional assembly’s power coupling coefficients are pre-calculated. The three-dimensional coupling coefficient method (Jang et al., 2004) and the Lagrange multiplier method (Webb and Brittingham, 2000) are proposed, respectively to improve the reconstructed precision of the CC method. The MAPLE (Wenhuai et al., 2013) code proposed three methods to fit the 2D deviation between measured and predicted results, namely, weight coefficient method (WCM), polynomial expand method (PEM) and thin plane spline (TPS) method. The ordinary kriging (OK) method was proposed by Peng et al. (2014), which is one of the most common methods employed in geo-statistical. A kind of harmonics synthesis method (HSM) was proposed by Fu (1994) to express the flux distribution of the real core by the linear combination of higher order harmonics of neutron k-eigenvalue equation of the nominal core. However, the accuracy of HSM relies on the calculation precision of harmonics function. A least-squares method combining the coarse mesh

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https://doi.org/10.1016/j.nucengdes.2018.06.016
Received 19 March 2018; Received in revised form 6 June 2018; Accepted 12 June 2018
0029-5493/

Nomenclature

CMS	core monitoring systems
FID	fixed in-core detectors
IPDR	in-core power distribution reconstruction
CC	coupling coefficient
WCM	weight coefficient method
PEM	polynomial expand method
TPS	thin plane spline
OK	ordinary Kriging
HSM	harmonics synthesis method
CMFD	coarse mesh finite difference
RBF	radial basis function
SVR	support vector machine regression
DWA	distance weighted average
IMQ	inversed multi-quadrics
LM	linear regression
IDW	inverse distance weight
IDL	inverse distance linear
IDS	inverse distance squared
IDF	inverse distance forth
KNN	K-nearest neighbor
MS	modified Shepard's method
IQW	inversed quantic weight
RRMSE	relative root mean square error
ARO	all rods out
FP	full power
BOC	begin of cycle
MOC	middle of cycle
CRDA	control rod drop into core accident
EOC	end of cycle
DMU	detector measurement uncertainty

finite difference (CMFD) form of the fixed-source diffusion equation and the detector response equation has been proposed (Lee and Kim, 2003). The reconstruction results of this method are accurate, but it could be used only in neutronics design codes that base on the finite difference method or CMFD method. A new intuitive method based on cross-section deviation (Jia, 2016) was proposed by searching cross-sectional parameters and solving diffusion equations which owing power deviation to assembly equivalence cross-section deviation. The essence of the method is to convert the power distribution reconfiguration to a search optimization problem, using the cross-sectional parameters as independent variables and the detector responding as the objective function. However, it's hard to find the right key factors in so many influences, which could lead to the deviation between calculated and measured values, such as xenon oscillation or inhomogeneous of inlet flow distribution.

In this paper, some spatial interpolation methods are introduced and applied in IPDR for the first time, such as surface fit basis on radial basis function (RBF) (Hickernell and Hon, 1999) or support vector machine regression (SVR) methods (Adankon and Cheriet, 2009). Numerous methods have been developed for spatial interpolation. Methods used in this paper are only those commonly used and could directly extent to IPDR studies. These spatial interpolation methods are briefly described. They are divided into categories: surface fitting methods and the distance weighted average (DWA) methods. In the context of spatial fitting approaches used in IPDR, no studies appear to compare various approaches that combine different variations of fitting method, and under various core operational conditions. The aim of this study is to test algorithms for spatial interpolation used for IPDR within these two approach frames. Several factors which could affect the performance of the reconstruction methods are also discussed. Different reactor core operation incidents have been analyzed to assess the ability to detect the core status anomalies. Another aim is to assess the performances of different spatial fitting method to eliminate detector measurement noise. Finally, recommendations are given for applying spatial interpolation methods to IPDR.

2. Computational model

SOPHORA system (Wenhuai et al., 2014) could process the measured signals on-line, including core condition parameters and the FID current reading. A predicted core is created by incorporating the measured core condition with the core follow power history. The difference between the measured and predicted FID current represents a bias between the measured core and predicted core, and is used to infer the predicted power distribution to a "best estimate" measured power distribution (Wenhuai et al., 2013). It is assumed that the ability of a nodal code such as COCO(Lu et al., 2012) to accurately predict the signal distribution should be equal to the ability of the same code to accurately predict the power distribution (Wenhuai et al., 2013). The ratios between the measured signal distribution and the predicted signal distribution stand for the ratios between predicted core power distribution calculated by algorithms and models used in nodal code and the real core power distribution.

2.1. Surface fit basis interpolation method

Let the ratio data be sampled at N location X_j, $j = 1, N$ and let the corresponding ratio values be p_j, $j = 1, N$. The value p at unknown location X is estimated as a function approximation of the form:

$$p(X) = T(X) + \sum_{j=1}^{N} a_j R(X, X_j) \tag{1}$$

where $T(X)$ is over-core trend function term, $R(X, X_j)$ is a kernel function term used to evaluate the contribution from sampled point X_j to unknown location X, a_j is weight coefficient. If a_j is zero, method could be equal to trend surfaces analysis (TSA) method. Under various assumption, different $T(X)$ and $R(X, X_j)$ could be raised up in RBF basis approaches or SVR basis approaches. In this study, different kernel functions were chosen including: TPS0 method as $\log(r)$; TPS1 method as $r^2\log(r)$; Linear method as r; Cube method as r^3; Gauss method as e^{-r^2/a^2}; inversed multi-quadrics (IMQ) method as $1/\sqrt{(r^2 + a^2)}$; Poly function as $(b + r)^a$, where a and b are the model parameters.

1) Radial basis function approaches

The RBF basis approaches contain the methods using radial basis function to fit an overall surface and then interpolate on the un-sampled points (Hickernell and Hon, 1999). Consider the three-dimension core power distribution interpolated, the trend function with first order polynomial is expressed as:

$$T(X) = b_0 + b_1 x + b_2 y + b_3 z \tag{2}$$

other constraints are expressed as:

$$\sum_{j=1}^{N} a_j = 0 \quad \sum_{j=1}^{N} a_j x_j = 0 \quad \sum_{j=1}^{N} a_j y_j = 0 \quad \sum_{j=1}^{N} a_j z_j = 0 \tag{3}$$

2) Support vector regression approaches

Support vector machine (Adankon and Cheriet, 2009) is a machine learning algorithm. SVR is formed based on statistical learn theory and the structural risk minimization, which improves the generalization ability (Cortes and Vapnik, 1995). For SVR fitting, the trend function is