CMM Perturbation Theory and AI Engineering Design Optimization

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INTRODUCTION

Based on the past experiences practiced on BWR fuel design optimization, this paper presents a new concept to build an Artificial Intelligence （AI） fuel design engineer with Combined Micro and Macro (CMM) perturbation theory. CMM perturbation theory will be briefly reviewed first, then it will be explained how CMM perturbation theory provides a way to digitize physics laws of a design object, thus building a big data, a way to search and scan over the whole design range, and a way to optimize a design object with a unique strategy of macro and micro change rates, self-learning, knowledge center and its update, limiting maps etc. Thus, an "Cmm Artificial Intelligence Design Engineer", i.e. CAIDE, can be created. Finally, the possible applications will generally be discussed.

CMM PERTURBATION THEORY

Macro Variables & All Time All Space Conditions

Combined Micro and Macro parameter perturbation theory [1] [2] is a large-scale perturbation theory to cover all the engineering design ranges and has been used for BWR fuel assembly lattice design and optimization [3] [4]. It can deal with massive design variables, either continuous or discrete, even different shapes of design. For example, BWR 10x10 fuel lattice designs have approximately 200 micro variables (each fuel pin's enrichment and Gd weight) and 3 macro parameters (average enrichment, average Gd weight and total number of Gd pins), see Figure 1. Micro variables are basic design variables, which have local impacts to design performance, but also are accumulated into or contribute to global impacts. Macro parameters (or called integral parameters, global parameters) are usually functions of micro variables, thus are dependent on micro variables. Macro parameters have global impacts and are the most important to the design performance [3]. However, macro parameters are dependent functions of micro variables that are independent, and then macro parameters are usually not considered as variables, i.e. not independent. Furthermore, macro parameters do not appear in physics equations as variables. For examples, neutron transport equation does not include the total mass of U-235, but have the local distribution of U-235, i.e. micro variables included. The total mass of U-235 will have the impact on the solution of neutron transport equation through the local distribution, but not directly. Taylor series has the same way that does not include the information of global or macro parameters, that is, all the derivatives are with respect to independent variables. Although the macro parameters are most important to design goals, they are not directly involved in physics equations or Taylor series. To overcome this theoretical dilemma and to numerically involve macro parameters into engineering design, CMM makes the following assumptions: macro parameters are independent variables, and their functions of micro variables are all time all space conditions to guarantee the true physics of original problems, see references [1] & [2]. The all-time all space conditions together with initial conditions and boundary conditions should be satisfied by the solutions, especially the all-time all space conditions must also be satisfied by any numerical operations. From now on, macro variables are used, instead of macro, integral or global parameters. Both micro and macro variables are design variables and should be optimized. Of course, any set of micro and macro variables should always meet the respective all-time all space conditions.

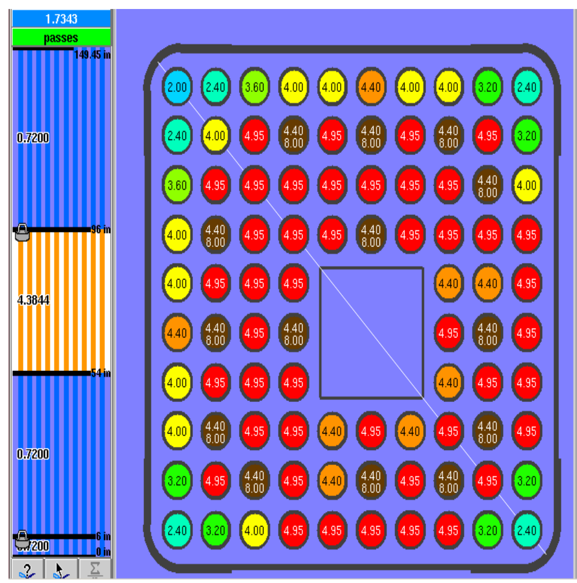

Figure 1 - A 10x10 BWR Lattice with a Water Channel (Each Fuel Pin has an Enrichment Number and a Weight Number of Gd as lower one if Gd Weight is Not Zero)

CMM Perturbations

CMM performs two steps of perturbation: micro perturbation with respect to micro variables and macro perturbation with respect to macro variables, and combines them together. Micro perturbation performs each single micro variable perturbation without interaction with others, which means ignoring all the partial derivatives of multiple variables if Taylor series considered here as an example. Of course, for massive variables it will cause big errors, i.e. high cut off errors. Actually, macro variables are collective variables of micro variable groups respectively and good measures of global impacts for these micro variable groups. CMM reasonably assumes macro perturbation should reflect a massive interaction among all the micro variables (including each micro variable itself higher orders) in each group, and then defines macro perturbation is equal to the cut off error of micro perturbation for the group. In this combined way of micro and macro perturbations, CMM achieves zero cut off errors. This accuracy has been proved in BWR fuel assembly lattice design and optimization, ALADIN/BALO/FLS [5] [6].

Macro-Micro Space and Plib

CMM is a large-scale perturbation theory since macro variables can be set up to cover all the design range. CMM is a direct perturbation that all design targets including curves and single values are directly calculated from perturbation of micro and macro variables. Therefore, first thing is to construct a perturbation library Plib [1] that is a big data of values of design targets and the corresponding values of micro and macro variables at all reference points in the micro and macro variable spaces. Usually, micro spaces are built on each macro space point, which, of course, meet the all-time all space conditions. A macro space is often multidimensional, and a micro space is usually massive dimensional, such as above BWR example has approximately 200 dimensional. Each macro space point has its own corresponding micro space, which means that each value of macro variables on this macro space point and the values of micro variables of each group satisfy all time all space conditions respectively, otherwise not valid. All the interactions' information among macro variables, micro variables and macro-micro variables are contained in Plib, which reflects the physics laws.

DIGITIZING PHYSICS LAWS & BIG DATA

The total reference points will be huge and some time it may be impossible to build such Plib because it need huge number of case calculations to create these reference target values, and each case calculation often take several hours to several days depending on multi-physics models & accuracy requirement. This is an unavoidable step, which is here called as digitizing physics laws. Once this big data, i.e. Plib is built, it represents its physics laws of the object. Any solution for any sets of micro and macro variables can be obtained from this big data with CMM, including optimized solutions searched by engineers. Because CMM is direct perturbation, it is superfast. For example, for above BWR case, CMM take six second for a case solution, vs. 3 hours of CASMO4 [7] normal calculation on the same computer net.

INTELLIGENCE & CAIDE

After physics laws are digitized, all the necessary information for optimization will be included in this big data, Plib. It's then possible to build an CAIDE' brain, i.e. an AI code to search the most optimized solution based on the inputted requirements, such as for above BWR example, e^{SAVING} model for cost optimization, e^{SAFETY} model for safety margin optimization or other. AI code should build at least two centers as in above BWR example, **Knowledge Center (KC)** and **Self-Learning Center (SLC)** [4] [5]. KC is always updated by SLC during optimization process. KC should include all target value changing rates with respect to all micro variables, as well as all target value changing rates with respect to all macro variables. The changing rates could be respective to continuous or discrete variables, or any countable shape. With these changing rates AI code will evaluate the importance of all the design variables, and to choose the best values for each design variable, one by one and in the order of importance, to achieve the optimization targets. All these steps cannot be done manually or just automatically since these changing rates are not fixed, and must be learned or tested during the process, and the **importance maps** and **limiting maps** of all design variables are constantly changed and need be automatically updated by AI code itself. Although some of these have been proved by BALO [6], many new advanced searching technologies and algorithms, such as scan to choose promising regions etc., may be adopted into AI code for engineering design optimization. For convenience of discussion, we call the AI code as CAIDE as above, named from "Cmm and AI Design Engineer".

DISCUSSION AND CONCLUSION

CMM provides accurate and superfast solutions for modern engineering design, as well as the way to digitizing physics laws, and all necessary information needed for AI optimization of engineering design. However, different engineering disciplines have different physics laws, and the digitized big data will be different. Even for the same physics laws, but different designs differed by geometry and/or materials (if they are not input variables) etc. need different digitized big data. For example, PWR is different from BWR. For BWR, 10x10 design is different from 12x12. Actually, each individual type of designs probably needs different Plib. Therefore, digitizing is a big challenge, supercomputer or cloud computing may be the best way to resolve this problem. Fortunately, once Plib is built, it can be forever used for the type of project. Also, Plib can be automatically created by a simply script or code.

Digitizing physics laws need a set of software for numerical solutions, and different software gives different accuracy that will determine the Plib's accuracy, as well as solution's accuracy. CAIDE only guarantees the accuracy consistent to the set of software that is used to digitizing physics laws. If one need more accuracy for CAIDE design, one may need more accurate software. Also, the uncertainty of CMM perturbation theory will be same as the set of software that is used to create Plib since both of them have the same accuracy.

Another challenge of digitizing physics laws is how much fine for the digital net world, that is, how fine of the macro space meshes and micro space meshes are. In general, finer meshes get more accuracy, but need more time for digitizing. Usually, under certain accuracy requirement, excessive finer net meshes are not necessary, because CMM has not only reached the accuracy requirement that is consistent to the set of digitizing software, but also limited further improvement to this accuracy. Therefore, CMM determines the accuracy, so for the best sizes of the space net meshes. This has been discussed in ref. [1].

CMM is a direct perturbation, and only based on the results that are calculated from numerical calculations vs. input variables as discussed above. However, if the results can be corrected from experiments, such as from medicine or chemical experiments, or plant operations, CAIDE could also be designed for experiment or operation analysis for optimization if Plib is big enough to cover the ranges interested. However, all these are built on a big true physics data that represents the physics laws involved for the objects. Therefore, with this big data CAIDE can get the insights of objects and find something new that human can't see manually, then innovate a true best design with fast speed and precisely aiming to the best target like precision guided bomb, which human engineer can't achieve. This has partially been proved by BWR fuel design optimization [4], as briefly described below.

As a BWR project mentioned above, it partially developed some AI with CMM into a computer package ALAADIN/BALO/FLS. Based on this package, we list its comparison, "AI vs. T", "T" is the team design.

ITEM	SPEED	ACCURACY	SAVING/SAVETY Improve
a case	6 s vs. 3 hr.	same	2,160,000 times fast
a lattice (optimization)	hr. vs. wks.	same	enrich. saving 0.02-0.03 MPP 1% improved Feff 1% improved MH saving ≥37 times

MPP is Maximum Pin Power that is related to power cost and safety issues; Feff is a CPR correlation factor that is related to the fuel safety. MH is man-hours.

SUMMARY

Many papers in LWR core design optimization have been published [8] [9] [10], including fuel assembly lattice design and optimization [11] [12]. This paper generalizes CMM perturbation theory specially with AI to create CAIDE for possible wide applications. Although several keys of intelligence concepts have been practiced and proved for BWR [4] [5], it is needed to further develop algorithms and expand it to other disciplines if possible, and to use supercomputer or cloud computing for Plib that author has been looking for more than one decade.

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