Investigation of Data Exploration Method for Thermal-Fluid Simulation Results Using Proper Orthogonal Decomposition*

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Abstract
A data exploration method based on POD was investigated to get clues to improve actual-product designs from a small set of rough-design candidates. The current method is based on the Oyama method which was used to acquire design knowledge of Pareto-optimal solutions obtained by evolutionary approach with large set of simulation models. The expanded method adopted (1) 2 steps POD analysis, and (2) voxel representation for different topology models. These approaches enabled to evaluate rough-design candidates which had non-parametric structures and those were difficult to handle in the original method. Especially, for the case of handling rough-design candidates, there was no explicit rule for model number ordering at the "first" POD analysis. We found that reordering the model numbers based on the first POD result was important, and rich information was obtained from the expansion coefficient vectors that made it possible to classify the feature regions and to detect feature regions with complicated flow structures at the "second" POD analysis. The effectiveness of the expanded method was verified in a cooling design problem for an optical disc drive. We found that the expanded POD-based data exploration method is a promising method for detecting key factors for actual product designs.

Key words: POD, Voxel Representation, CFD

1. Introduction

Computer aided engineering (CAE) such as computational fluid dynamics (CFD) is regularly used in the field of product design. However, it needs to be used effectively in order to achieve high-performance and innovative product design in a short period. The recent advances in computer performance and open source/commercial CFD software have helped manufacturers to execute high-level computations within a reasonable cost and computing time. However, this has also led high-level competition among companies. Designers and researchers are therefore under great pressure to improve their ability to interpret simulation results and to increase their creativity in order to gain an edge on their competitors. One of the most important and time-consuming processes in product design is to find out the new key regions (design variables/features) to be modified. However, data exploration or data mining methods for this have not been sufficiently developed.
Oyama et al. proposed a new method using proper orthogonal decomposition (POD) (1). POD is a method of principal component analysis. The method is also known as the Karhunen-Loeve expansion in statistics. POD decomposes the original data set to orthogonal base functions and expansion coefficients, and extracts features in the original data. POD has been used to analyze unsteady flows in both experimental fluid dynamics (EFD) and CFD. Lumley was the first who used POD to identify the coherent structures in turbulent flows (2). Moin et al. applied POD to unsteady CFD results and extracted feature coherent structures from the turbulent flow in a channel (3). Matsuura et al. applied POD to compressible transitional cascade flows and extracted dominant behaviors of the unsteady boundary layers (4). Recently POD is also used in design problem (5)-(6). Rambo et al. used POD to create low dimensional models for the server rack optimal-cooling design from the CFD simulation results which were made in various simulation conditions such as fan flow rates (5). Toal et al. used POD to filter out undesirable or badly performing geometries from an optimization process (6). They used POD as a variable reduction technique for an optimization process.

Oyama et al. prepared 85 Pareto-optimal solutions of an aerodynamic transonic two-dimensional airfoil optimization problem and ordered them from the minimum-drag solution (model No.1) to the maximum-lift solution (model No. 85) (1). Then they showed that expansion coefficient vectors obtained from POD for the Pareto-optimal solutions indicate the feature structures of low drag and high lift airfoils and these features correspond to the well known “super critical wing section” (7). This means that principal component analysis of a simulation data set can potentially be used to find key features. "The Oyama method" is a novel approach to progress the simulation data exploration. Oyama et al. intended to acquire design knowledge from Pareto-optimal solutions obtained by a multi-objective evolutionary algorithm (MOEA) that requires large sets of CFD simulations for simple two-dimensional airfoil geometries. However, for actual product design problems, the number of design variables is too large to obtain Pareto-optimal solutions through an optimization process. In many cases, only small sets of rough-design candidates with non-parametric and different topology structures, are prepared and evaluated, and then feature regions that require modification to improve performance are identified. Generally, rough-design candidates are not Pareto-optimal solutions, then new issues causes to execute POD analysis and analyze the POD results. Thus, this study expanded the Oyama method to deal with a small set of rough-design candidates that has complicated geometries with different topologies. POD is used to analyze them and identify key features in order to find the next set of better candidates. Furthermore, in this study, a voxel representation based on a Cartesian grid system is used to handle different-topology models with complicated-geometries for POD analysis.

In this paper, a POD-based data exploration method is investigated for the rough-design candidates that have not been considered in the previous study. Furthermore, the method is applied for the actual product design. This paper is organized as follows: POD is introduced in section 2, and a POD-based data exploration method for rough-design candidates is introduced in section 3. Section 4 discusses the evaluation of the method for actual product design. The last section concludes the paper.
Nomenclature

\( a_i \) : \( i \)-th expansion coefficient vector  
\( a_{ik} \) : component of expansion coefficient vector  
\( B \) : eigenvector matrix for \( L \)  
\( d_{ij} \) : normalized data for \( i \)-th element and \( j \)-th model  
\( L \) : covariance matrix for data set matrix \( W \) in snapshot POD  
\( N \) : number of models  
\( P \) : number of elements  
\( p_i \) : \( i \)-th eigenvector, \( i \)-th POD mode function, \( i \)-th orthogonal base function  
\( R \) : maximum number of POD modes used to reconstruct data set  
\( u_{ij} \) : \( x \)-component of velocity vector for \( i \)-th element and \( j \)-th model  
\( V \) : covariance matrix for data set matrix \( W \)  
\( v_{ij} \) : \( y \)-component of velocity vector for \( i \)-th element and \( j \)-th model  
\( W \) : data set matrix  
\( w_i \) : data set vector for \( i \)-th model  
\( w_{ij} \) : \( z \)-component of velocity vector for \( i \)-th element and \( j \)-th model  
\( X \) : eigenvector matrix for \( V \)  
\( \Lambda \) : eigenvalue matrix  
\( \lambda_i \) : \( i \)-th eigenvalue  
\( \sigma_{ij} \) : component of covariance matrix \( V \) and \( L \)  

Superscripts

\( t \) : transpose matrix  
\( \sim \) : reconstructed value

2. Proper Orthogonal Decomposition Method

In POD, an original data set is decomposed to orthogonal base function vectors and expansion coefficient vectors that have a maximum variation in order to extract the dominant factors.

Here, a data set has \( N \) models and number of elements \( P \). Number of elements \( P \) is unified between \( N \) models. The data set is represented as matrix \( W \) with \( P \) rows and \( N \) columns in Eq. (1). Components of \( W \) are expressed by \( d_{ij} \), and \( w_i \) denotes the column vector in which data of model \( i \) are ordered longitudinally by element number, and \( d_{ij} \) is a normalized value in which the mean value is subtracted from the original data and the standard deviation is 1.

\[
W = [w_1, w_2, \ldots, w_N] = \begin{bmatrix} d_{11} & \cdots & d_{1N} \\ \vdots & \ddots & \vdots \\ d_{P1} & \cdots & d_{PN} \end{bmatrix} \tag{1}
\]

In the original POD, known as the direct POD, covariance matrix \( V \) is defined in Eq. (2). The eigenvalue problem for \( V \) in Eq. (3) is solved, and the \( i \)-th eigenvector \( p_i \) and the \( i \)-th eigenvalue \( \lambda_i \) are obtained in Eq. (4) and Eq. (5) respectively. The data set \( W \) is reconstructed as \( \tilde{W} \) in Eq. (6), where superscript \( \sim \) indicates the reconstructed value, and eigenvector \( p_i \) in Eq. (4) is the orthogonal base function vector (\( i \)-th POD mode vector; \( i \) is POD mode number), \( a_i \) is the expansion coefficient vector defined in Eq. (7), and \( R \) \((1 \leq R \leq P)\) is the maximum number of POD modes used to reconstruct \( \tilde{W} \). In Eq. (6), expansion coefficient vector \( a_i \) is an indicator of similarity between POD mode vector \( p_i \) and the \( i \)-th model.

\[
V = \frac{1}{N} WW^t = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1P} \\ \vdots & \ddots & \vdots \\ \sigma_{P1} & \cdots & \sigma_{PP} \end{bmatrix} \tag{2}
\]
In CFD simulations, the number of elements $P$ is generally of the order of $10^5$-$10^6$. For a large-scale simulation, number of elements $P$ often becomes of the order of $10^7$-$10^8$. Contrarily, the model number $N$ is of the order of $10^0$-$10^2$ at most; then a large gap in the order between $P$ and $N$ arises as $P >> N$. This makes it difficult to solve the eigenvalue problem numerically in Eq. (3), because the size of $P \times P$ matrix $V$ becomes too large. Sirovich proposed the snapshot POD method to avoid this problem (8)-(10). In the snapshot POD, covariance matrix $L$ is defined in Eq. (8), and the eigenvalue problem in Eq. (9) is solved. Here, matrix $B$ has a relation with matrix $X$ in Eq. (10), and matrix $X$ in Eq. (3) is obtained in Eq. (12) using matrix $B$.

\[ L = \frac{1}{N} W' W = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1N} \\ \vdots & \ddots & \vdots \\ \sigma_{N1} & \cdots & \sigma_{NN} \end{bmatrix} \quad (8) \]

\[ LB = BA \quad (9) \]

\[ B = W' X \quad (10) \]

\[ \Lambda = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_N \end{bmatrix} \quad (11) \]

\[ X = (NA)^{-1/2} WB \quad (12) \]

In the snapshot POD, the size of the matrix to solve eigenvalue problem $L$ is $N \times N$; thus, the matrix is sufficiently small to solve numerically in Eq. (9). In this research, snapshot POD was used for data exploration, and the eigenvalue problem in Eq. (9) was solved by using the Linear Algebra Package (LAPACK) (11).

3. Data Exploration Method Using POD for rough-design candidates

The schematic process of the proposed data exploration method is shown in Fig. 1. In step 1, a set of design candidates is prepared, and CFD simulations are executed for each model. At this stage, the design candidates are only rough plans; however they are selected keeping as much variety between them as possible; for example (1) new structures are adopted, (2) parts layouts are substantially changed, and (3) some parts are removed. Next, CFD simulations are executed for the design candidates.

In step 2, first POD analysis is executed for the set of CFD simulation results, and
expansion coefficient vectors and base function vectors are obtained. Oyama et al. analyzed Pareto-optimal solutions which were based on sufficient numbers of MOEA results (1). They ordered model numbers from No. 1 as the lowest objective function 1 to No. 85 (N) as the highest objective function 1 along the solutions, as shown in Fig. 2 (a). However, for rough-design candidates (not Pareto-optimal solutions) (Fig. 2 (b)), the model numbers cannot be determined straightforwardly. Therefore, the "first" POD analysis is executed using temporary model numbers based on the similarity of the model structures.

In step 3, expansion coefficient vectors and base function vectors obtained in step 2 are examined. If the output is too discontinuous for adjacent models, the model numbers are reordered taking the tendencies of expansion coefficient vectors and geometrical similarity into consideration. Then, the "second" POD analysis is re-executed, and feature regions extracted by grouping the expansion coefficient vectors are reflected in the model geometry. Finally, the effectiveness of each feature region is verified in terms of thermal-fluid design, and design regions are determined. Step 3 is one of the original features in this study.

Simulation data on all elements can be evaluated in the above process. This makes it possible to avoid oversights of important flow features in large-scale CFD simulations, and it simplifies the engineer's design works.

**Fig. 1 Schematic process of a data exploration method**
In POD analysis, the number of elements used to evaluate the candidates need to be the same even if the design candidates have structures with different topologies. Three grid systems are often used in general CFD simulation: (a) a boundary-fitted structured grid (b) a boundary-fitted unstructured grid, and (c) a Cartesian grid (Fig. 3). In a Cartesian grid system, a simulation region is divided into equal-sized elements for each x, y, and z coordinate, and each element is identified as a fluid/solid element whether an original body is inside or outside the element. Thus, a body surface is modeled by a staircase representation, as shown in Fig. 3 (c-2), and the fluid/solid elements are labeled, for example, flag 0 and 1, respectively. The each volume element is often called as "voxel", and data structure based on Cartesian grid and voxel-flags (0 or 1) is called voxel representation. Some CFD simulations using voxel representation have been reported for complicated geometries such as automobile (12) and aircraft (13).
simulation results based on a Cartesian grid system to execute POD analysis of various design candidates with complicated 3D geometries. Of course, a process in which CFD simulations are executed in a boundary-fitted grid, and POD analysis is executed in a Cartesian grid system, is possible by projecting the simulation data from the boundary-fitted grid to the Cartesian grid, as shown in Fig. 4. The important point is the use of voxel representation in the POD analysis. Voxel based simulations are well known for their simplicity and automated grid generation, but the compatibility of voxel representation for the data exploration is a latent advantage. We describe in this paper how CFD simulations were executed in a Cartesian grid system, which is referred to as "voxel CFD simulation," by considering the handling of complicated 3D geometries.

4. Verification of Cooling Design for Optical Disc Drive

4.1 Cooling Design Problem of Optical Disc Drive

The proposed data mining method in the previous chapter was applied to find the new cooling design of an optical disc drive (ODD) previously developed by one of the authors, and the results were used to verify whether reasonable features were extracted or not. The CFD simulation for the cooling design was done using a Cartesian grid. In the flow solver, the continuity equation and Navier-Stokes equation for an unsteady incompressible flow were solved by using the highly simplified marker and cell (HSMAC) method \(^{(14)}\) using a standard large eddy simulation (LES) \(^{(15)}\). The simulation results had already been validated by conducting experiments to take pressure and velocity distribution measurements using particle image velocimetry (PIV). Although some errors occurred because of the Cartesian grid, we confirmed that reasonable simulation results can be obtained when investigating the thermal design \(^{(16)}\).

In the optical disc drive shown in Fig. 5, a laser light is irradiated from the laser diode (LD) inside the optical pick-up unit (OPU) under the disc to the high-speed (9,000 min\(^{-1}\)) rotating disc that is 120 mm in diameter; then the data are read or recorded. The main thermal design points are the heat dissipation from the LD and the lifetime warranty period against temperature increases of the LD.
The Blu-ray Disc (BD) drive, which achieved BD 4X-speed recording and DVD-R 12X speed recording for the first time in the industry in July 2006, was selected in order to verify the validity of the data exploration method. One of the authors developed a new LD cooling structure using CFD simulations (17). The simulation results in Figs. 6 and 7 indicate that a high-speed flow induced by the disc rotation is blocked by the tray and the flexible cable, and does not directly reach the LD below the tray. The author also found that the low pressure region is induced by the disc rotation above the disc, and the region spreads locally on the tray, where it is just above the position of the LD. Then, an additional hole on the tray is opened, and a secondary upward flow is induced by the pressure difference between the upper and lower sides of the tray, and this promotes the cooling ventilation of the LD. The new structure achieves an approximately 2 K reduction in the temperature rise of the LD without needing any additional components such as a fan. This 2 K temperature reduction for a LD is significant considering that the LD temperature rise is often designed to be under 10-15 K in contrast to the reference air temperature in the drive.

![Fig. 6 Comparison of cooling structure for LD](image)

(a) Conventional structure (without tray hole)  
(b) Developed structure (with additional tray hole)

4.2 Design Candidate Models and CFD Simulation for POD Analysis

The optical disc drive model shown in Fig. 8 was used for CFD simulation. The model is based on the simplified geometry model used for the PIV verification experiments (16). The size of the body was the same as the original product model. In the PIV experiment, water was used as the working fluid instead of air because of the laser power of the PIV system and the selection of tracer particles. To match Reynolds number $4.8 \times 10^5$ in the actual product where the diameter of the disc is used for the reference length, the rotating-disc speed was set at 600 min$^{-1}$. The above conditions were used for CFD simulations in this study. Element sizes for the x, y, and z directions were uniformly 0.5 mm, 0.3 mm, and 0.5 mm, and there were 12.24 million elements in total. In the simulation, $\Delta t = 8 \times 10^{-5}$ sec was used for the interval of time integration, and 10,000 calculation steps were performed to prepare a quasi-steady flow field. Then, the next 10,000 steps were time-averaged for the evaluations. The 10,000 calculation steps are equivalent to 0.8 sec in physical time and 8 rotations of the disc. Time-averaged velocity vector data were used for POD in this study. For the velocity vector data, the $i$-th model data $\mathbf{w}_i$ is given in Eq. (13), where $u_i$, $v_i$, and $w_i$ are the x-, y-, and z-components of the velocity vector at element
1, and the size of the $w_i$ vector becomes $3P \times 1$. The matrix size of $W$ in Eq. (1) becomes $3P \times N$. For the solid elements, value 0 is given for the velocity vector components in order to maintain the consistency of the number of elements with different topologies.

$$w_i = [u_{i1}, u_{i2}, \ldots, u_{iP}, v_{i1}, v_{i2}, \ldots, v_{iP}, w_{i1}, w_{i2}, \ldots, w_{iP}]$$

(13)

In this study, 15 models (models 0-14) were prepared as design candidates (Fig. 9). Model 0 was the original design model and had no additional openings on the tray. Models 1 to 14 had additional openings on the tray to improve the airflow around the LD. Tray geometries and CFD simulation results (time-averaged velocity magnitude above the disc) are shown in Fig. 10. The flow direction changes slightly depending on the position of the opening. However, the difference in the main flow among the models is small, and it is therefore not easy to analyze the feature structures and relations among the models in a short time.

(a) Optical disc drive simulation model (simplified geometry model, top case is not displayed)  
(b) Time-averaged pressure distribution and grid (every 5th grid point is shown.)

Fig. 8 CFD simulation model and example of simulation result

(a) Example of design candidates
(b) Region and size of additional tray openings

Fig. 9 Design candidate models
Next, first POD analysis was executed for the data set composed of 15 models. Model 0, the original design model, was taken as the averaged model, and a normalizing process was carried out for all models. The eigenvalues and the normalized sum of the eigenvalues are plotted in Fig. 11. It is clear from this figure that the first nine modes reach a 90% contribution and that the eigenvalues of the first four modes are large relative to the other modes. Fig. 12 shows the POD mode functions above the disc from zeroth to sixth mode. Fig.13 (a) shows the expansion coefficient vectors. The original data can be reconstructed by linear combination of expansion coefficient vector $\mathbf{a}_i$ and POD mode function $\mathbf{p}_i$ in Eq. (6). However, the random tendency of the expansion coefficient vector $\mathbf{a}_i$ in Fig. 13(a) makes difficult to analyze feature flow structures and feature regions from these results in first POD analysis. In Oyama's result in reference (1), expansion coefficient vectors showed relatively smooth tendency, because they were based on Pareto-solutions with sufficient numbers and their model numbers were ordered in the rule from the lowest objective function 1 to the highest objective function 1. Contrarily, in our original models, the temporal model number ordering is only based on the model geometry shown in Fig.13 (a), and the model number ordering needs to be modified. In this study, the expansion coefficient vectors obtained by first POD analysis were used for model number ordering.
The expansion coefficient vectors shown in Fig. 13 (a) were analyzed for the first four modes, which had large contributions. The expansion coefficients of first and second modes change alternately with each model number. However, a relationship can be seen between the tendencies of models 3, 5, 7, and 9 and models 4, 6, 8 and 10. This indicates that the ordering of models was not adequate. Therefore, a modified order was investigated. The relationship seen in the first and second modes between models 3, 5, 7, and 9 and models 4, 6, 8, and 10 can be understood. This means ordering in the lateral direction on the geometry is adequate for models 3 to 10. In the original ordering of first POD analysis, the model numbers were ordered in a longitudinal direction. This ordering is inadequate from the viewpoint of the relationship of flow structures among the models.

Thus, the original model numbers 3, 5, 7, and 9 were reordered as the new model numbers 1, 2, 3, and 4, respectively. Next, the original model numbers 4, 6, 8, 10, and 14 were reordered as the new model numbers 5, 6, 7, 8, and 9. For the original model numbers 11, 12, 13, and 14, expansion coefficient vectors showed continuous tendencies. Then, considering the geometrical layout to the original model number 14, the original model numbers 13, 12, and 11 were reordered as the new model numbers 10, 11, and 12. Finally, for the original model numbers 0 and 1, expansion coefficient vectors showed similar tendencies, so the original model numbers 0 and 1 were reordered as the new model numbers 13 and 14, respectively.
Fig. 14 Regions grouped by POD analysis

(a) Expansion coefficient vectors

(b) Tray model

Fig. 15 POD mode functions below disc for reordered model numbers (Trays are displayed by semitransparent models. Contours are velocity magnitude and vectors show the component of the velocity vectors at the same plane of the contours. For the elements in which velocity vectors are not shown, the direction is downward in the mode functions.)
Consequently, the model numbers were reordered as shown in Fig. 13 (b). Second POD analysis was then re-executed, and new expansion coefficient vectors were obtained. Relatively monotonic results were obtained in Fig. 13(b). The tendencies of the expansion coefficients changed rapidly for some models. This indicates that the flow structures changed at these models, and the models can be classified at the changing models. Thus, the 15 models were classified into 5 groups (A to E) in Fig. 14 (a), and groups A to E are mapped onto the tray geometry shown in Fig. 14 (b).

The original velocity vector data were reconstructed by linear combination of the expansion coefficient vectors $\mathbf{\alpha}_i$ and POD mode functions $\mathbf{p}_i$ in Eq. (6). The POD mode functions $\mathbf{p}_1$, $\mathbf{p}_2$, $\mathbf{p}_3$, and $\mathbf{p}_4$ below the disc were shown in Fig. 15 for the reordered model numbers. For the group A in Fig. 14 (a), $\mathbf{\alpha}_1$ and $\mathbf{\alpha}_3$ were found to be dominant, then the POD mode functions $\mathbf{p}_1$ worked negatively and $\mathbf{p}_3$ worked positively by the sign of the expansion coefficient vectors $\mathbf{\alpha}_1$ and $\mathbf{\alpha}_3$. From the POD mode functions in Fig. 15, the region A1 in $\mathbf{p}_1$ and the region A3 in $\mathbf{p}_3$ generated downward flow through the tray openings. For the group B in Fig. 14 (a), $\mathbf{\alpha}_1$, $\mathbf{\alpha}_2$, and $\mathbf{\alpha}_3$ were dominant and these coefficients worked negatively for their POD mode functions. Then, the regions B1, B2, and B3 in Fig. 15 generated downward flow through the tray openings. For the group C in Fig. 14 (a), $\mathbf{\alpha}_2$ was dominant and worked positively for the POD mode function $\mathbf{p}_2$. Then the region C3 generated the downward flow through the tray openings. For the group D in Fig. 14 (a), $\mathbf{\alpha}_2$, $\mathbf{\alpha}_1$, and $\mathbf{\alpha}_3$ were dominant, and $\mathbf{\alpha}_2$ worked negatively for the POD mode function $\mathbf{p}_2$, and $\mathbf{\alpha}_1$ and $\mathbf{\alpha}_3$ worked positively for their POD mode functions. Considering the POD mode functions $\mathbf{p}_2$, $\mathbf{p}_1$, and $\mathbf{p}_3$, the regions D2, D1, and D3 generated downward flow through the tray openings. For the group E in Fig. 14 (a), $\mathbf{\alpha}_1$ was dominant and worked positively for the POD mode function $\mathbf{p}_1$. Then the region E1 generated upward flow through the tray opening.

The feature regions such as A1-A3, B1-B4, C1-C4, D1-D4, and E1 were found in the POD mode functions in Fig. 15, and they were almost common regions between the groups A-E. The detailed feature regions were detected by the above process. The easier detecting method was mapping the grouped regions in Fig. 14 (a) to the model geometry in Fig. 14 (b). The feature regions detected by the POD mode functions were almost same as the grouped-model structures that were differently designed. Therefore the expansion coefficient vectors $\mathbf{\alpha}_i$ had rich information to detect feature regions between the design candidates. The effectiveness of the feature regions detected by the above process for thermal-fluid design was investigated based on the objective functions such as the increase of flow rate around the heat generating parts. The effective regions for objective functions were finally recognized as the key design features.

The effect that the design of each group has in flow field, is discussed here taking past design knowledge consideration. As shown in Fig. 16, the additional openings of the group E and group A regions respectively result in an upward or downward flow due to the pressure difference of the tray surface, and these flows cool the laser diode. As shown in Fig. 17, the additional openings of the group C region cause a return flow at the end wall. This return flow can reach the OPU, especially on LDs mounted on the side, and this helps to cool the LDs. Groups E and C were confirmed to be key design features from the aspect of product design. This indicates that the current POD-based data exploration method can potentially be applied to detect feature-geometric structures coupled with feature regions of the flow field.
5. Summary

A data exploration method based on POD was investigated to get clues to improve actual-product designs from a small set of rough-design candidates. The current method is based on the Oyama method which was used to acquire design knowledge of Pareto-optimal solutions obtained by evolutionary approach with large set of simulation models. The expanded method adopted (1) 2 steps POD analysis, and (2) voxel representation for different topology models. These approaches enabled to evaluate rough-design candidates which had different-topology structures and those were difficult to handle in the original method.

Especially, for the case of handling rough-design candidates, there was no explicit rule for model number ordering at the "first" POD analysis. We found that reordering the model numbers based on the first POD result was important, and rich information was obtained.
from the expansion coefficient vectors that made it possible to classify the feature regions and to detect feature regions with complicated flow structures at the "second" POD analysis.

The effectiveness of the expanded method was verified in a cooling design problem for an optical disc drive. The feature regions extracted by POD-based method correspond to the past empirical design knowledge that was obtained by time-consuming and empirical works. We found that the expanded POD-based data exploration method is a promising method for detecting key factors for actual product designs.

References


