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Comparison of Direct and Metamodel Based Optimization in the Coolant Jacket Design of an IC Engine

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Abstract

This paper focuses on the conjugate heat transfer analysis of an I4 engine, and discusses optimization of the coolant passages in engine coolant jackets. Direct Optimization approach integrates an optimizer with the numerical solver. This method of optimization is compared with a metamodel-based optimization in which a metamodel is generated to aid in finding an optimal design. The direct optimization and metamodel approaches are compared in terms of their accuracy, and execution time.

1. Introduction

Increased customer demands combined with stringent fuel economy regulations have driven the need for higher power density engines. Higher power generation is associated with increased heat released. Increased heat release demands effective and efficient rejection of heat to meet the thermal management as well as temperature distribution requirement. One of the critical components of the thermal management system is Internal Combustion Engine. To maintain the engine components at acceptable temperatures the generated heat needs to be removed in an effective manner.

Heat generated by the IC engine is removed by coolant circulating through passages in cylinder head and engine blocks termed as coolant jackets. Due to complicated topology of these passages, designing the water jackets for optimum coolant flow and velocities is a very challenging task. An ideal water jacket would have sufficient amount of coolant flow rate in critical areas to remove heat and result in desired temperature distribution without adversely affecting pressure drop. A higher pressure drop across the water jacket results in overall increase of power consumption. Higher component temperatures compromise structural integrity of the engine which results in Thermomechanical fatigue failures.

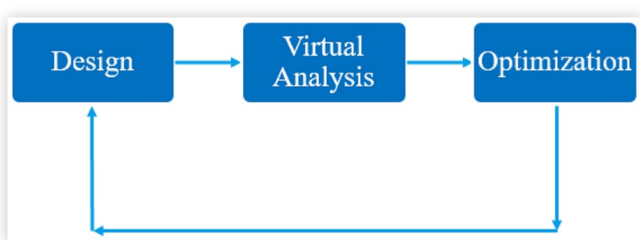
Conjugate Heat Transfer (CHT) analysis has been successfully employed recently in automotive industry for numerical prediction of metal temperatures in IC engines [1-6]. In CHT analysis, thermal field of engine is predicted by solving energy equation for fluid and solid domains simultaneously. Multiple commercially available softwares are capable of predicting entire thermal map of an engine using CHT.

The possibility of predicting coolant and metal thermal map simultaneously using CHT has made it a powerful tool in early design phase and throughout development of IC engines. CHT coupled with optimization tools opens a gateway for upfront design of coolant jackets. Due to stringent target requirements on flow and temperature, coolant passage design optimization often turns out be a multi-objective problem. The conflicting goal of maximizing flow, and minimizing pressure drops makes this a very intriguing problem in Optimization field. Optimization has widely been used in design and development of engines and vehicles [8-17].

As shown in the flowchart below (Figure 1) design and optimization of water jacket is a multistep process. It starts with a design typically based on past experience, manufacturing feasibility and meeting minimum design requirements. This design is evaluated via CHT for temperature distribution and analyzed to determine any shortfalls. The design then goes through optimization process resulting in a product which meets all the requirements and design targets.

The optimization process starts with a well-established baseline analysis. Based on the resulting temperature map, areas of concerns such as high temperature zones and enablers, such as coolant passages, gasket holes, for improvement are identified. The enablers, known as design parameters form the input to the optimization study. To fully comprehend the influence of design parameters, a full factorial study which entails modifying each parameter at a time, is required. This approach is time consuming and hence has limited applications, especially as the number of parameters increase.

FIGURE 1 Design optimization process workflow



An alternative to this approach is to discretize the design space using space filling techniques, evaluate minimum required design points and use that information to get the optimized design.

Metamodel based optimization and direct optimization are the two common approaches employed in coolant jacket design of IC engine. Metamodel based optimization is comprised of three unique steps. First step is spatial discretization of the design space using Design of Experiments (DOE). This is achieved using space filling techniques such as Optimal Latin Hypercube, which ensures the designs evenly span the entire design space. Once the designs are identified, they are evaluated in CFD code to obtain the desired outputs. Finally, a metamodel, which is a mathematical relation between inputs (design parameters) and output responses, is built. This inexpensive metamodel is then used to evaluate additional designs to using multiple optimization techniques to identify the optimized design.

Direct optimization, as the title suggests uses a more direct and a closed loop approach. Instead of discretizing the entire design space, it generates a few designs based on initial values for each parameter, evaluates them in CFD code and compiles all the output responses. It then looks at the responses, based on the specified objectives and constraints, decides the next generation of designs. This process repeats till a design meeting all the criteria is identified.

The current paper focusses on comparing the two methodologies in terms of results, efficiency and inherent pros and cons. While each methodology has its own advantages and disadvantages, they still enable proactive design of water jackets in a very effective and timely manner. Finally, the temperatures from the optimized design are compared to temperature measurements from a dyno test. Commercial CFD code StarCCM+ is used for CHT simulations. Commercially available tool "ISight" and "Design Manager", both provides variety of design optimization routines/codes, are used in this study

2. Methodology

Optimization plays a crucial role in designing of water jackets. With the current high density engines, heat needs to be removed in an efficient and timely manner. A well-established baseline is a cornerstone for the optimization study. This is followed by identifying the input parameters which have a significant impact on the resulting temperature distribution. The last step is the implementation of optimization techniques to meet the objective function.

2.1. Conjugate Heat Transfer Analysis

Numerical methods have been successfully employed to predict thermal behavior of IC engines. Conjugate heat transfer analysis to predict temperature map of engines is described in detail in Iqbal et al. [1]. The analysis involves predicting of both metal and coolant temperature. In the current study, a set of inputs which includes heat load (3D spatial distribution of convective conditions obtained from a combustion simulation), coolant flow rate at a given temperature and appropriate ambient and oil convective conditions are used for baseline and all consecutive designs. Commercial CFD tool StarCCM+ was used to carry out the conjugate heat transfer analysis.

2.2. Metamodel Based Optimization

Metamodel based Optimization is described in detail in Annabattula et al. [8]. The first step involves identification of design parameters which have a significant influence on the objective function, followed by discretization of design space, generating design matrix, evaluating the designs, constructing metamodel and finally performing the task of optimization.

2.2.1. Spatial Discretization of Design Space

To fully understand the effect of all design parameters of a design a full factorial, which involve modifying each parameter, one at a time and evaluating the corresponding change in output responses is required. However, due to practical limitations of resources and time, that approach is seldom used involving complex 3D simulations. Instead various discretization schemes which effectively distribute a given number of design points throughout the design space are employed. Techniques such as Box-Behnken Technique, Central Composite Design Technique and Face-centered Central Composite Design primarily focus on the extremes of the design space [need a reference here]. Hence, the interior of the design space is often missed. Other techniques such as Sphere Packing Design, Random Latin Hypercube, and Optimal Latin Hypercube Technique depart from the full factorial by strategically distributing the sample points throughout the design space [9]. They use space-filling techniques to spread the design points evenly to capture the entire design space, while eliminating the necessity to evaluate the complete domain.

Optimal Latin Hypercube discretization technique is used for the current study. Figure 2a and 2b show the Latin Hypercube and Optimal Latin Hypercube respectively for two parameters in 2-dimension design space with 9 design points. While the design points are placed randomly in the former technique, they are distributed uniformly in the later.

FIGURE 2 Sampling techniques; a. Latin hypercube b. Optimal Latin hypercube

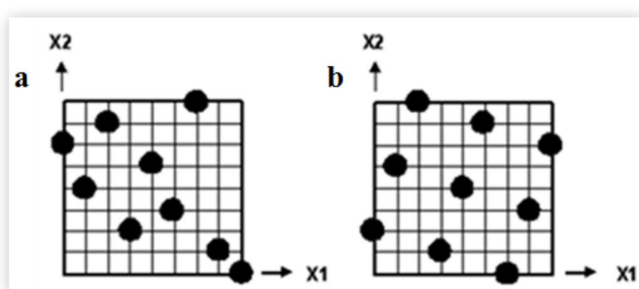
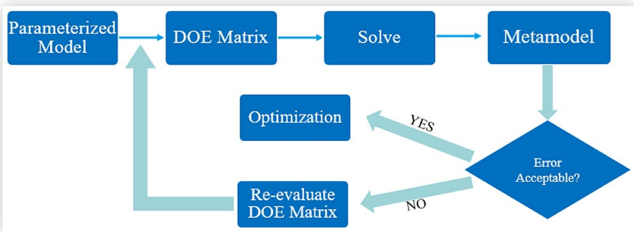


FIGURE 3 Flowchart of metamodel based optimization



2.2.2. Construction of Metamodel

Once all the designs are evaluated and desired output responses are extracted, next step is constructing a metamodel. The metamodel characterizes relation between the inputs and outputs. It can be imagined as an empirical mathematical formulation of inputs and outputs. Figure 3 shows work flow of this process.

The generic formulation of the approximation model is as follows:

If y is the design response of interest and x_1, x_2 and x_n are independent design parameters, then

$$\{y\} = F\alpha + \varepsilon \tag{1}$$

where, $F = \begin{bmatrix} f_1(x_1) & \cdots & f_m(x_1) \\ \vdots & \ddots & \vdots \\ f_1(x_n) & \cdots & f_m(x_n) \end{bmatrix}$,

the coefficient vector $\alpha = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_m \end{bmatrix}$, and ε is the random error assumed to have probabilities that follow a Gaussian distribution with zero mean and variance equal to σ^2.

The coefficient matrix can be estimated by covariance of least squares estimators:

$$cov(\alpha) = \frac{\sigma^2}{n} M^{-1} \tag{2}$$

Where the information matrix, $M = M(D_n) = \frac{1}{n} F^T F$

The robustness of the metamodel is indicated by minimizing the random error ε of the approximation as defined above. There are different algorithms available in literature such as Kriging Model, Chebyshev Orthogonal Polynomial Model, Radial and Elliptical basis function model.

One of the most widely used algorithms for approximation is "Radial Basis Function". "The Radial basis functions (RBF) are a type of neural network employing a hidden layer of radian units and an output layer of linear units. These are characterized by reasonably fast training and reasonably compact networks" [19].

The Mathematical formulation of RBF model, as documented in Isight manual [18, 19], is reproduced here as follows:

If $x_1, \ldots, x_N \in \Omega \in R^N$ be a set of given nodes and $g_j(x) \equiv g(\|x - x_j\|) \in R, j = 1, \ldots N$, be a set of any radial basis functions, where $\|x - x_j\|$ is the Euclidian distance given by $(x - x_j)^T(x - x_j)$

Given interpolation values $y_1, \ldots y_N \in R$ at data locations $x_1, \ldots, x_N \in \Omega \in R^N$, RBF interpolant,

$$F(x) = \sum_{j=1}^{N} \alpha_j g_j(x) + \alpha_{N+1} \tag{3}$$

Is obtained by solving the system of $N + 1$ equations

$$\sum_{j=1}^{N} \alpha_j g_j(x_i) + \alpha_{N+1} = y_i, i = 1, \ldots N \tag{4}$$

$$\sum_{j=1}^{N} \alpha_j = 0 \tag{5}$$

One critical step in accepting the metamodel is to verify the fidelity of the model. This is done by quantifying error of the model. This can be done error analysis. This entails removing one data point at a time, using the metamodel to recompute the point and compare it to the original values. This is done for all the points

2.2.3. Optimization

The general mathematical formulation of a constrained optimization problem is as follows [22]:

Find X, which minimizes/maximizes the objective function ($F(\{X\})$) subjected to inequality constraints

$$G_a(\{X\}) \le 0 \text{ where}, a = 1, 2, \ldots m \tag{6}$$

and equality constraints

$$H_b(\{X\}) = 0, \text{where}, b = 1, 2, \ldots n \tag{7}$$

within the bounds,

$$\{X\}^{LB} \le \{X\} \le \{X\}^{UB} \tag{8}$$

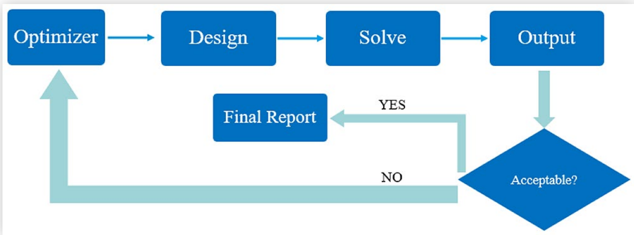
{X} is the set of independent design variables and the functions G {F, G and H} depend upon these variables.

The optimization algorithm searches for set of design variables {X}, which leads to the best possible design objective, either minimum or maximum, while adhering to the bound constraints.

Depending on the nature of the problem and its formulation, traditional methods, such as direct search methods and gradient based methods, or modern evolutionary techniques are used to solve an optimization problem. Direct search methods work with the actual objective function value, whereas multiple function evaluations are performed aiming to reach the minimum or maximum value. The gradient based methods use first or higher order derivatives information of the objective function. These are efficient and faster than direct search methods, however due to the requirement of derivatives, cannot be applied to functions which are discontinuous or noisy.

Genetic Algorithms are evolutionary techniques based on the mechanics of natural genetics and natural selection. They mimic the survival-of-the-fittest principle of nature in their search process. Unlike the traditional methods, which work with a single point, these algorithms work with a population of points, hence the likelihood of obtaining a global

FIGURE 4 Flowchart of direct optimization



solution is high. In addition, since there is no usage of differentials, a discontinuous function can be handled similar to a continuous function. However, these methods are expensive compared to the above mentioned methods due to extensive usage of coding and computerized search techniques.

2.3. Direct Optimization

Direct optimization simulates each data point in real time and feeds the output to the optimization algorithm. It is essentially a closed loop feedback approach which eliminates the building of metamodel and any errors thereby involved. Commercial optimization and automation codes like Isight and Design Manager enable direct communication with the CFD software to carry out the simulation and extract the outputs. After collecting the outputs, the optimizer compares them against the targets specified and computes objective function and aims at minimizing it.

Figure 4 shows a typical direct optimization workflow. The loop continues till the desired objective is met and all constraints satisfied.

3. Computational Domain

The computational domain for this study consists of cylinder head assembly with valves, seats and guides, engine block assembly with liners and head gasket. The valves are simulated in their closed position to account for the heat conduction with cylinder head. Figure 5 and 6 below show solid

FIGURE 5 Computational domain: cylinder head with combustion chamber and seats

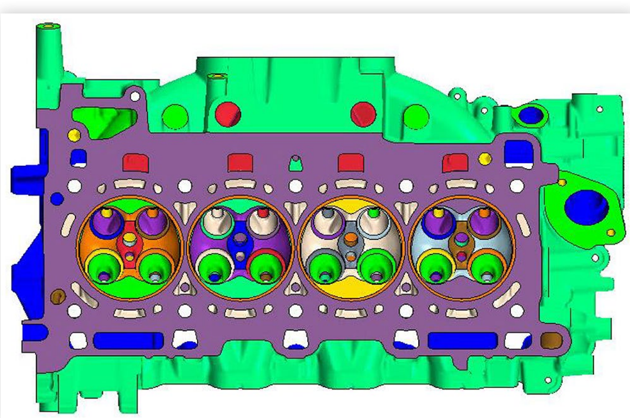
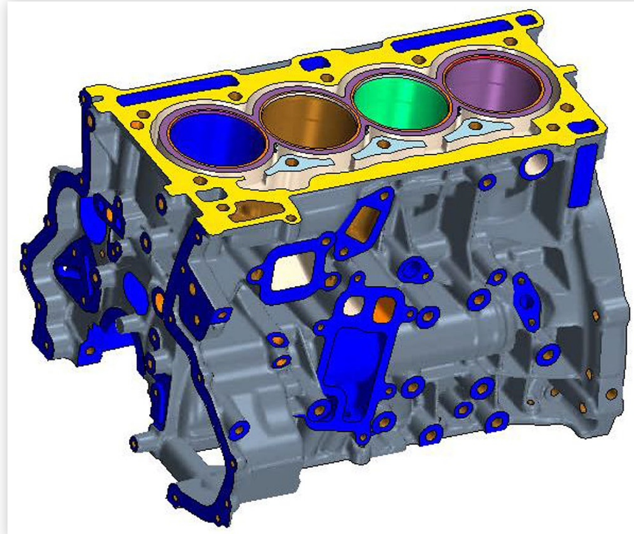


FIGURE 6 Computational domain: engine block



computational domain comprising cylinder head and engine block. Water jacket is shown separately in Figure 7. The head gasket coolant holes are shown in yellow. The cross section areas of the coolant holes are the design parameters for this study. The details of model building, choice of physics continuum, and solution algorithm are discussed in the studies by Iqbal et al. [1, 2]

Figure 8 shows the typical design targets for IC engines. The coolant temperature at all metal surfaces needs to

FIGURE 7 Coolant passages in engine block and cylinder head yellow regions are coolant transfer holes

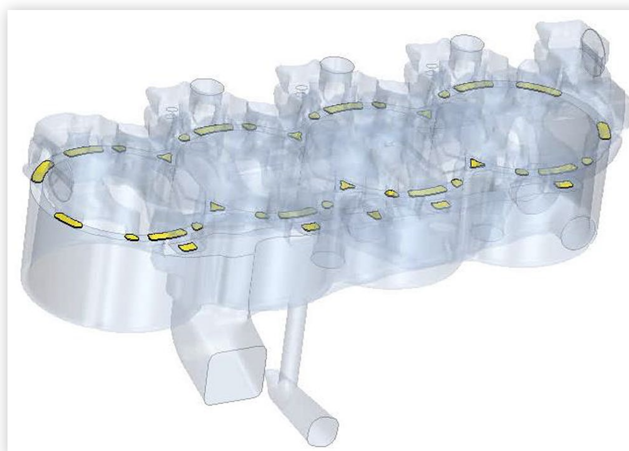


FIGURE 8 Design targets

Coolant temperature at all metal surfaces	< Target
Peak metal temperature	< Target
Cylinder to cylinder variation in peak metal temperature	< Target
Tangential coolant velocity	< Target

be within target to prevent boiling. Metal temperature needs to be within material limits to prevent any thermomechanical failures. Cylinder to cylinder variation in the peak temperatures should be within the limits to avoid structure displacement or expansion due to temperature difference. The coolant velocity also needs to be maintained within limits to avoid any material erosion.

4. Results and Discussions

The results section discusses and compares the aforementioned methodologies. Both the approaches start with an initial baseline design and input design parameters. Metamodel based optimization evaluates a set of predefined designs and creates an empirical mathematical model characterizing relation between the inputs and the outputs. Due to the inherent nature of approximation there is an error involved. The success of this approach is based on minimizing this error. Direct optimization analyzes initial set of designs, evaluates the output responses and dynamically determines the next group of designs. The fundamental benefit of this approach is the elimination of error associated with approximation.

For the metamodel based optimization it is critical to validate the metamodel. This can be accomplished through several metrics such as efficiency measures, residual analysis and error analysis. This study uses an error analysis metric known as cross validation [19]. This entails removing one design point at a time, recomputing the metamodel coefficients, and comparing the generated values with that of the actual values of the point. This is done for each design point in the entire design sample.

Figure 9 shows typical resulting plots from error analysis. The plot shows the comparison of the predicted value at the point and the actual value obtained from the CHT analysis. The plot on the left, which has the data sets clustered along the diagonal line indicate lower error and plot on the right side indicates a high error, where the predicted values and the actual values do not correlate with each other. The former model would be an accurate metamodel compared to the later.

Once the accuracy of the metal model is established, different optimization techniques such as direct search methods, gradient based methods and Genetic Algorithm techniques were evaluated. This problem was formulated as a

FIGURE 9 Error analysis (a) metamodel with low error (b) model with high error

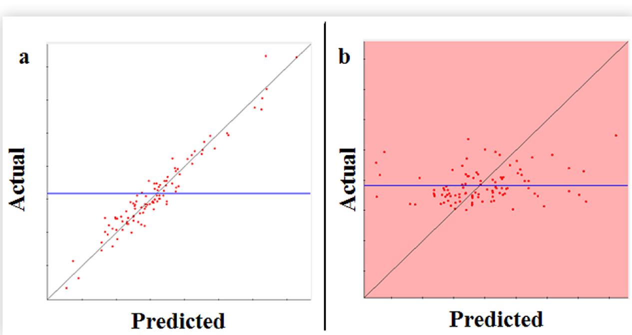
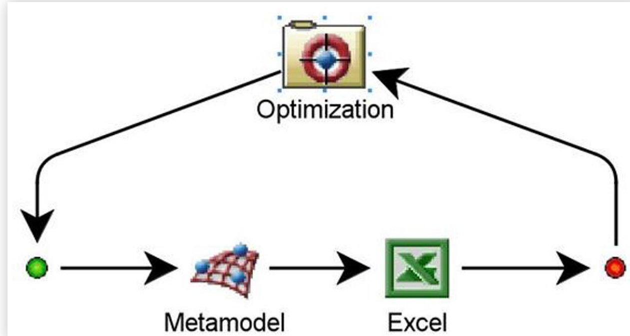


FIGURE 10 Workflow of metamodel based optimization



multi-objective study. The objectives include minimizing peak temperature in combustion chamber and engine block, maximizing flow through critical areas. Figure 10 shows workflow for this approach. The optimization component contains the information of the design parameters, objectives and constraints. The metamodel component contains information about the constructed mathematical model. The Excel component is used for performing calculations required for the study. For this study, Genetic algorithms had the best performance in predicting a design meeting all design targets.

Once the design parameters for an optimized design has been determined, it requires validation against the simulated model. A final design with optimized design parameters predicted by the optimizer is generated and evaluated. Figure 11 below shows the comparison between the predicted and the validated temperatures in critical zones. As can be inferred from the chart, the validated temperatures are in good agreement with the predicted values using the metamodel. This asserts the fidelity of the constructed metalmodel for this study.

The same multi-objective formulation was used for Direct Optimization approach. Figure 12 shows workflow for this approach. The Optimization component communicates the input design parameters information to the input component. It also communicates with output component to extract information related to output responses. Based on the proximity of the responses to each of its targets, the optimizer decides the direction of the subsequent designs. There is no requirement for any validation as the optimized design proposed by the optimizer would be the final design.

FIGURE 11 Comparison of metamodel predicted and simulation predicted temperatures for optimized design

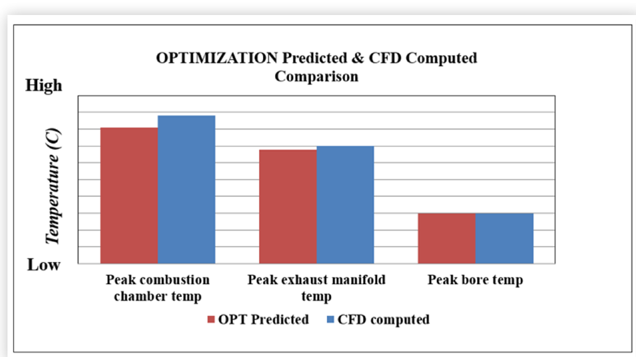


FIGURE 12 Workflow of direct optimization

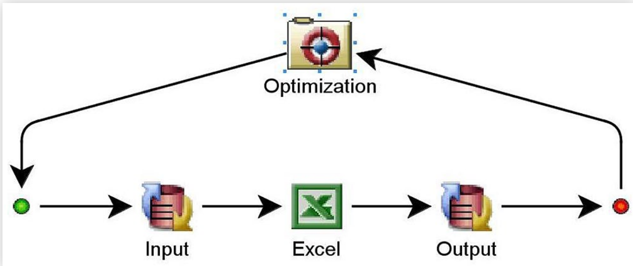


Figure 13 shows the temperature contour for combustion chamber. As shown in the figure the baseline design has relatively higher cylinder to cylinder temperature variation as well as higher temperature zones around the spark plug region. The final design obtained through metamodel based optimization approach has addressed both these concerns, i.e., all the cylinders have similar temperature distribution and the spread of peak temperature have also been reduced. The final design obtained through direct optimization has higher combustion chamber temperatures than metamodel based optimization design.

Figure 14 shows the temperature contours for engine block. Unlike the combustion chamber, engine block temperatures are very similar for the three cases.

The bar chart shown in Figure 15 compares the peak temperature in the combustion chamber and the engine block. Metamodel based optimization resulted in 10% lower peak temperature in combustion chamber compared to baseline, whereas, direct optimization results in peak temperature very similar to baseline values. The peak temperature prediction for both the methodologies is comparable to baseline for engine block.

Bar chart shown in Figure 16 compares cylinder to cylinder peak temperature variation in combustion chamber and engine bore and pressure drop across coolant jacket.

FIGURE 13 Combustion chamber temperature (a) baseline (b) metamodel based optimization (c) direct optimization

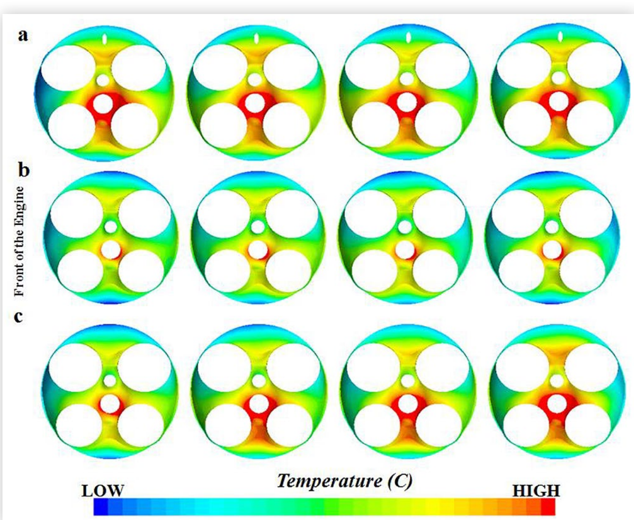


FIGURE 14 Engine block temperature (a) baseline (b) metamodel based optimization (c) direct optimization

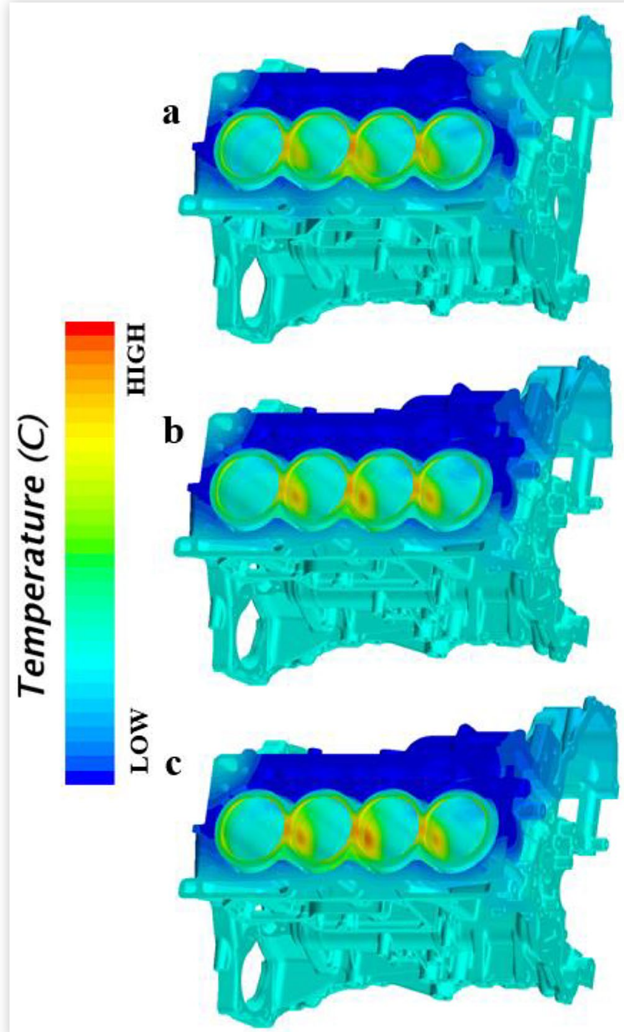
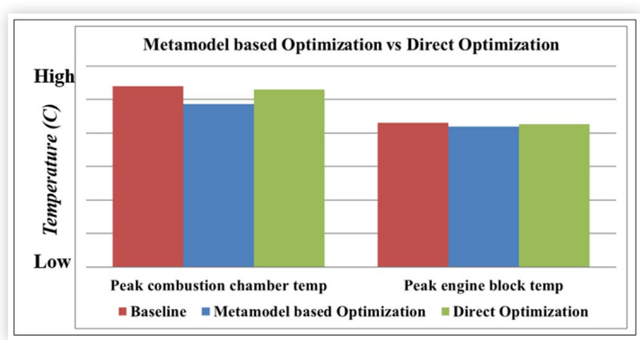
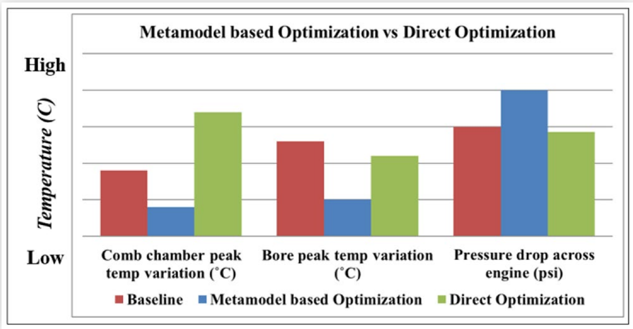


FIGURE 15 Result comparison of metamodel based optimization and direct optimization



The metamodel based optimization approach reduces cylinder to cylinder variation in peak temperature for combustion chamber and engine bore by 56% and 62% respectively. Direct optimization performs better for pressure drop across the engine resulting in 29% reduction.

FIGURE 16 Result comparison of metamodel based optimization and direct optimization



Although pressure drop is reduced by the design obtained through direct optimization, improved combustion chamber temperature design obtained by metamodel based optimization was chosen as the better design. This is due to the significance of having the metal temperatures below the target to avoid thermomechanical failure of the engine.

Metamodel based optimization has performed better than direct optimization for this particular application. The same number of designs has been evaluated for both the approaches using computationally expensive CHT simulations. For metamodel based optimization, multiple designs were numerically evaluated using the constructed metamodel. Since the designs are evaluated using a mathematical formulation, it is relatively quick and extremely large number of designs can be analyzed. This is the inherent benefit of metamodel based optimization. Direct optimization performance can be improved if additional designs are evaluated but it will be computationally expensive or problem formulation is modified at the cost of simplifying the problem than desired.

Metamodel based optimization also has benefits in terms of time. Since all the designs are predefined and are independent of each other, they can be evaluated in parallel, assuming the availability of necessary resources. The parallelization option is limited for the direct optimization, since the optimizer needs feedback from the initial designs to generate the subsequent designs. Though the computational time for both the studies was the same, the actual physical time was lower by approximately 50% for metamodel based optimization compared to direct optimization.

4.1. Temperature Correlation

Figure 17 shows temperatures in critical areas in combustion chamber compared to measured data. The measured temperatures were obtained from a dyno test with an engine instrumented with thermocouples. Figure 18 shows the location of thermocouples. The temperatures predicted using the metamodel based optimization are very close to the measured data.

FIGURE 17 Temperature comparison between test and CFD

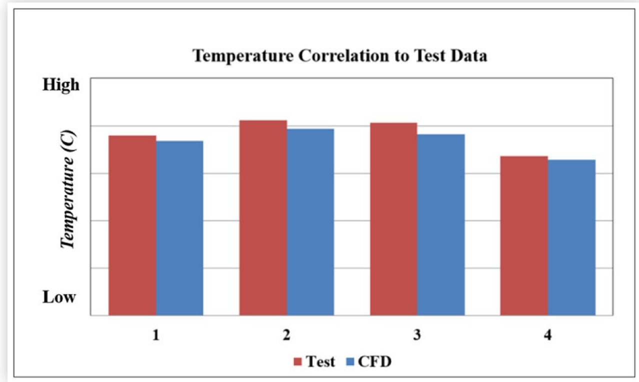
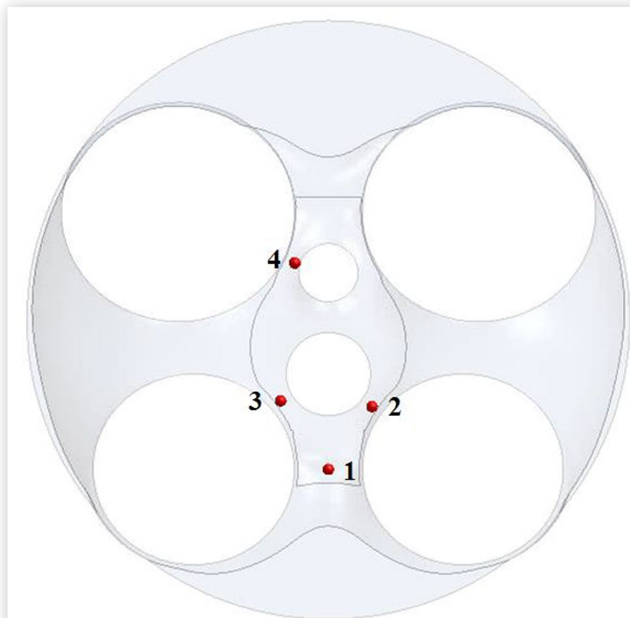


FIGURE 18 Thermocouple locations: 1, 2, 3 and 4



5. Summary and Conclusions

As the proposed goal of the study, the two approaches of metamodel based optimization and direct optimization are discussed and compared. Metamodel approach discretized the design space using Optimal Latin Hypercube and metamodel was constructed using Radial Basis Function (RBF). The optimization task was performed by formulating as a multi-objective problem of minimizing peak temperatures in critical zones while maximizing flows. Constraints were imposed on peak metal and coolant temperatures, cylinder to cylinder variation in peak temperatures and pressure drop. The design responses predicted by the optimizer were validated using a CFD simulation.

Direct optimization approach solves the same problem using a closed loop approach. It eliminates approximation and thus any errors associated with it. It is thus a better approach in terms of accuracy. However, metamodel based optimization is beneficial in terms of time due to the possibility of evaluating all the design points in parallel.

For the current problem, metamodel based optimization generates a better design compared to direct optimization. The time taken by the metamodel approach is also 50% less than direct optimization. The predicted temperatures also match with measured data.

Both the approaches demonstrated in this paper can be used as a powerful analysis tool in early design phase and throughout the development of an engine as it provides great insight into the behavior of the dynamics of the system without the need for physical testing. For this particular application metamodel based optimization approach outperformed direct optimization.

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Definitions/Abbreviations

DOE - design of experiments

CFD - computational fluid dynamics

IC - internal combustion

CHT - conjugate heat transfer

ANOVA - analysis of variance

RBF - Radial basis function