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An Approximation Method in Collaborative Optimization for Engine Selection coupled with Propulsion Performance Prediction

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Abstract

Ship design process requires lots of complicated analyses for determining a large number of design variables. Due to its complexity, the process is divided into several tractable designs or analysis problems. The interdependent relationship requires repetitive works. This paper employs collaborative optimization (CO), one of the multidisciplinary design optimization (MDO) techniques, for treating such complex relationship.

CO guarantees disciplinary autonomy while maintaining interdisciplinary compatibility due to its bi-level optimization structure. However, the considerably increased computational time and the slow convergence have been reported as its drawbacks. This paper proposes the use of an approximation model in place of the disciplinary optimization in the system-level optimization. Neural network classification is employed as a classifier to determine whether a design point is feasible or not. Kriging is also combined with the classification to make up for the weakness that the classification cannot estimate the degree of infeasibility.

For the purpose of enhancing the accuracy of a predicted optimum and reducing the required number of disciplinary optimizations, an approximation management framework is also employed in the system-level optimization.

Keywords: collaborative optimization, neural network classification, approximation management framework, engine selection, propeller design

1 Introduction

The preliminary ship design process goes through many design or estimation steps and there is frequent information exchange between the steps. The information flow is not unidirectional. A preceding step passes its output to the following steps and also requires outputs of the following steps as its input. Due to this coupled characteristic, the ship design traditionally uses an iterative approach, i.e., design-spiral approach for solving the large set of coupled relations. The approach provides a balanced solution to a given set of requirements. However, the balanced solution is also a solution that is not unique and not optimal (Neu el al 2000).

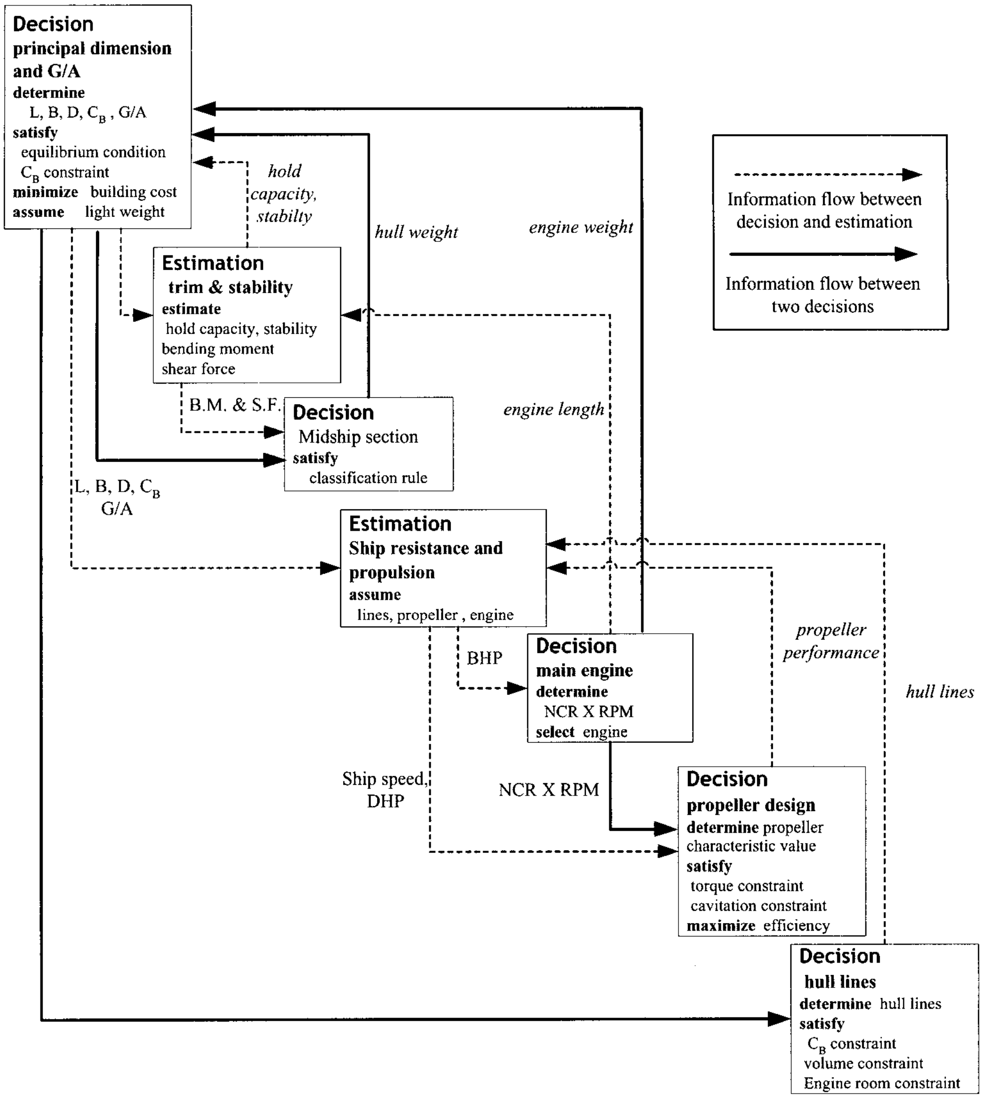


Figure 1: The information flow in the engine selection at the ship preliminary design stage

Figure 1 shows an example of the preliminary ship design process and information flow between the internal steps. The steps involved in ship design can be divided into estimation work and decision work. The estimation work is to compute or estimate ship performance based on mathematical theory or accumulated knowledge of ship design. The estimation of light weight, trim and stability, resistance, building cost, and so on belong to this category of work. Design specifications required for this estimation work should be given in advance. The decision work includes the determination of design specification or characteristic values of a ship such as principal dimension, hull lines, general arrangement, main engine, propeller and so on. This work is usually supported by the information obtained from the estimation work, design know-how of a shipyard, classification rules and so on.

Iterations can be also divided into two types; one formed between a decision step and an estimation step and the other formed between two decision steps as shown in Figure 1. In the first case, the estimation step can be regarded as dependent on the decision step because the estimation work only provides a certain type of result corresponding to input given by the decision step. For example, the determination of hull lines is based on the estimation of hull resistance. Since there is no conflicting interest, they can be easily integrated by automating the two modules themselves and the information exchange between the two.

The other iteration created in the interdependent relationship is that one's decision is influenced by the other's decision. For example, the design of hull lines has a strong influence on the design of propeller and is also affected by the result of propeller design. A traditional method to solve this coupled problem is to repeat the two decisions by assuming certain values required by a decision and comparing them with an actually determined value. The iteration is repeated until the difference between two values is within given tolerance. In order to minimize the number of iterations and obtain a balanced solution, initial assumption should be made as accurately as possible based on designer's experience. Differently from the first iteration, an additional work to coordinate the conflicting relationship is necessary. The field of Multidisciplinary Design Optimization (MDO) has emerged to develop approaches as an alternative to the iterative approach for efficiently optimizing the design of large coupled systems (Balling and Sobieszcznski-Sobieski 1996). The collaborative optimization is adapted in this paper for solving this problem.

Collaborative Optimization (CO) basically consists of a bi-level optimization architecture. It is the job of the discipline teams to satisfy constraints while working to define a design with which all teams involved can agree upon. The system team is in charge of adjusting the target values so that such agreement is possible while minimizing (or maximizing) the system level objective. This architecture is designed to promote disciplinary autonomy while maintaining interdisciplinary compatibility (Braun 1996, Kroo and Manning 2000). Due to this structure, CO is estimated to be more advantageous in its applications to practical engineering designs.

However, quantitative information is not readily available as to demonstrate the merit. Although its several advantageous features have been demonstrated in (Braun et al 1996, Kroo et al 1994, Kroo 1997), CO is still relatively immature and is not applied extensively in an actual industrial environment. Some difficulties associated with the inherent features of the architecture have been reported. Numerical difficulties caused by certain mathematical details have been cited in (Kroo and Manning 2000, Alexandrov and Lewis 1999, Alexandrov and Lewis 2000). The use of quadratic forms for the system-level compatibility constraints has shown that changes in system targets near the solution have little effect on the constraint values. Specifically, the gradient approaches zero, leading to difficulties for many optimizers, especially the gradient-based optimization methods that rely on linear approximation of design constraints. This leads to slow rate of convergence of the system near the presumed solution.

In addition, the price that must be paid for the advantages of decomposition is increased computational time - some studies have cited extremely large computational time. This unexpected cost is mostly caused by the architecture that the discipline-level optimization is nested by the system-level optimization, that is, every disciplinary design should be performed once in order to evaluate the compatibility constraint of the system-level optimization. This is one of the reasons to hinder the application of CO to engineering design, especially when a disciplinary design cannot be automated or when it requires time-consuming analysis.

As an alternative to relieve the above-mentioned difficulties, the use of approximation model has been proposed in place of the disciplinary optimization in CO. The disciplinary optimization result, optimal discrepancy function value, is modeled as a function of the interdisciplinary target variables. This discrepancy function value is passed to system level and is used for checking the compatibility constraint as depicted in Figure 2. System level optimizer then uses this approximation instead of the disciplinary optimization. The target of the approximations is a decision-making itself, which is a different point from the traditional approximation concept to substitute a computationally expensive simulation. This concept was addressed initially by Sobiebski et al (Sobieski et al 1998). This concept is particularly appealing in CO for several reasons. Along with the usual approximation features that aid in parallel execution and load balancing, this approach enables very robust, but inefficient optimizers such as probabilistic optimization methods acceptable. Therefore, the convergence problem of CO can be eliminated (Kroo and Manning 2000).

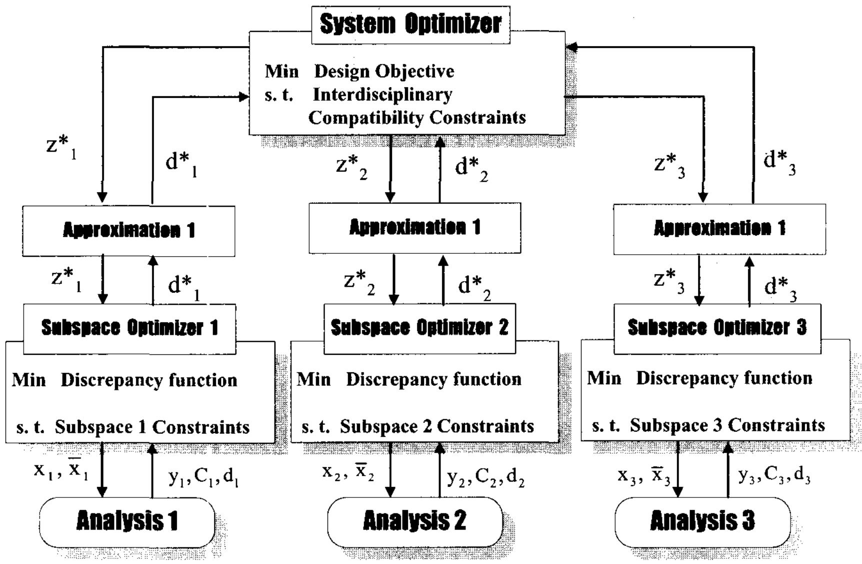


Figure 2: Use of approximation in CO.

However, there is a difficulty in the use of global approximation. Because of the peculiar form of the compatibility constraint, it is difficult to directly use the conventional approximation methods, such as response surface method, kriging, neural network, and so on. In this paper, neural network classification is employed as a classifier to determine whether a design point is feasible or not. Also, kriging is combined with the classifier in order to estimate the degree of infeasibility. Kriging, spatial correlation modeling, has been asserted to be an approximation technique and is more reliable for building accurate global approximations of a design space (Cressie 1993, Simpson 1998, Trosset and Torczon 1997).

As an effort to reduce the inaccuracy due to the use of approximations, this paper also adopts two approximation management frameworks for single objective and multiple objectives optimization problems. Their purposes are not only to reduce the computational cost but also to obtain a nearly true optimum or Pareto set by sequentially updating the approximations. The framework was proven to reduce the required function calls and to provide more accurate and optimal result than the method just using approximation without any updating process (Yang et al 2002).

The proposed optimization algorithm of CO procedure will be applied to a practical problem of engine selection at the preliminary stage of propeller design. It is important for the best overall performance of a ship to match the propeller characteristics with the engine characteristics for long years of ship service. The crucial role of the engine selection combined with optimum design of propeller geometry particulars is to provide the best performance of a particular ship.

The propeller design process as in most of engineering problems is associated with many disciplines such as hydrodynamics, structural integrity, manufacturing, vibration, noise, cavitation, and maintenance. Some disciplines for the particular design would be conflicting with other disciplines in order to satisfy a specified set of requirements and constraints. It is necessary to resolve these conflicts considering all constraints. Accordingly, the engine selection problem should be taken into account simultaneously in the propeller design.

The paper is organized as follows: in section 2, the overall approach concerning a combination of neural network classification and kriging is explained. A brief description of the approximation management strategy is also provided. An example to illustrate the use of the approximation management strategy in CO is discussed in section 3. In section 4, engine selection and propeller design problem is discussed based on both the traditional approach and the proposed approach. Conclusion is laid in section 5.

2 Managing Approximation in Collaborative Optimization.

2.1 Introduction of Classification Neural Network

In this subsection, the characteristic of the discrepancy function and the difficulty in its approximation are explained and classification neural network is newly employed.

The compatibility constraint of system level optimization (discrepancy function, $d_i = 0$) has a peculiar form compared to conventional inequality constraint ($g_i \leq 0$). It can take a non-negative value – positive in infeasible region and zero in feasible region, while the conventional constraint may take a negative value in the feasible region. Therefore, the trend of its response surface changes steeply at the boundary between feasible and infeasible region. For example, kriging model or response surface method produce "over-fitting" in feasible region. This may lead to seriously false approximation of the discrepancy function in the feasible region. Even if such an over-fitting could be avoided, it is practically impossible to completely avoid fitting error of the approximation in the feasible region. Even very small magnitude of error leads to regard a feasible design as an infeasible region because the feasible region is very sensitive to the magnitude of the fitting error.

In this paper neural network, multilayer perceptron (Haykin 1994), is employed as a classifier to decide whether a design point locates at the feasible region or not. The neural network classification approximates "region" itself while conventional approximation models "response value". Because of the different object of modeling, the inaccuracy of the approximation can be reduced considerably. The misjudgment of the feasibility may be limited to the neighborhood of the boundary between feasible and infeasible region. However, due to extra-points located along the boundary, the error of the judgment can be reduced further. The extra-points are special information to be exploited to reduce the number of required disciplinary optimization and improve the quality of approximation (Sobieski et al 1998, Sobieski 1998). A given disciplinary optimization yields values of $\{z\}$ for a given $\{z^*\}$. The key observation is that if a second disciplinary optimization were performed, where the target values $\{z^*\}$ were set equal to the optimal solution from the first disciplinary optimization (i.e. $\{z^*\} = \{z\}$), the resulting discrepancy function value would be equal to zero. Since the result is known a priori, there is no need to actually perform another disciplinary optimization; rather an extra disciplinary optimization solution is obtained implicitly, with no additional analysis.

Learning and mapping procedures are as follows. First, a sample point (i.e. a set of interdisciplinary target variables values) is given to a discipline, then, the discipline performs disciplinary optimization and yields an optimal discrepancy function value. According to the value, the sample point is classified into "feasible" or "infeasible" and assigned {1, 0} or {0, 1} as its output pattern, $\{O_1, O_2\}$, respectively. Neural network to be trained has the same number of input nodes as the target variables and two output nodes. After leaning, the neural network makes a decision by comparing the results obtained at the output nodes, $\{O_1, O_2\}$. It judges a certain design point feasible if its output results in $O_1>O_2$, otherwise, infeasible as shown in Figure 3.

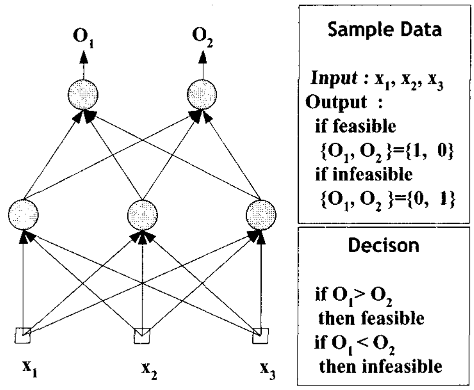


Figure 3: Multilayer perceptron as a classifier.

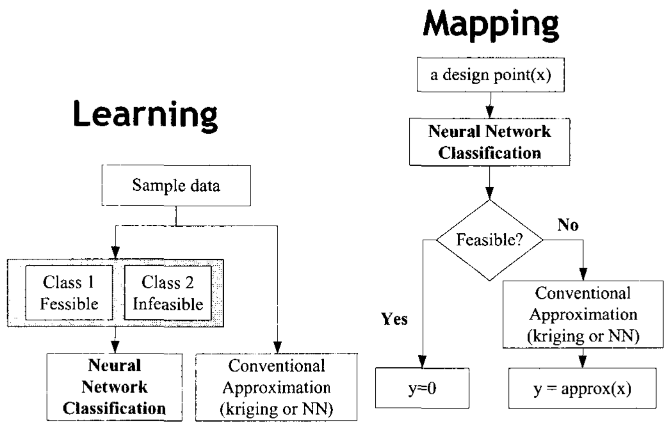


Figure 4: Leaning and mapping process of combined neural network classification - kriging model.

However, in spite of the above-mentioned advantage of the classifier, it cannot evaluate the degree of infeasibility for an infeasible design point. It just provides a judgment whether a design point is feasible or not. However, the information is important for any optimization algorithm, even for direct or global search methods like the simulated annealing or the genetic algorithm. In this paper, kriging is combined with the classifier in order to only estimate the infeasibility for a query point, once it is classified into infeasible class by the classifier. This process is explained in Figure 4. Sample data itself is used for building kriging and classified data is used for training the classification. When predicting the response of a query point, it is first filtered by the classification. If it is decided as feasible, its output is assigned zero, otherwise its infeasibility level is approximated by kriging or neural network. Since the response obtained in this way may have a discontinuity at the boundary of feasible and infeasible region, the genetic algorithm is thus used in this paper instead of the gradient-based search methods.

2.2 Managing Approximation Models in Optimization

In engineering problems, computationally intensive high-fidelity models or expensive computer simulations hinder the use of standard optimization techniques because they should be invoked repeatedly during optimization, despite the tremendous growth of computer capability. Therefore, these expensive analyses are often replaced by approximation models that can be evaluated at considerably less effort. However, due to their limited accuracy, it is practically impossible to exactly find an actual optimum of the original optimization problem. Significant efforts have been made to overcome this limitation. The model management framework is one of such endeavours (Booker et al 1999). The approximation models are sequentially updated during the iterative optimization process. The improvement in accuracy is concentrated on the region of interest. The models are modified by adding one or several sample points obtained from an optimization utilizing the predictive capability of approximation models.

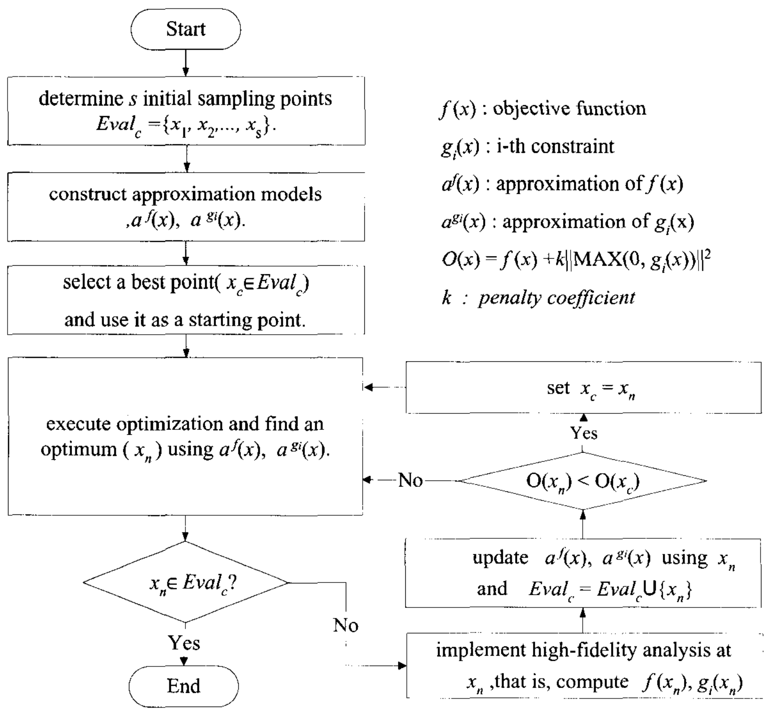


Figure 5: Adaptive Approximation in Single Objective Optimization

In a management strategy proposed in this paper, 'a predicted optimum' obtained from an optimization using approximation is used for the modification of the approximations. This method will be called Adaptive Approximation in Single Optimization (AASO) henceforth.

Figure 5 shows the algorithm of AASO. Detail descriptions are laid in (Yang et al 2000, Yang et al 2002). This strategy is applied to system-level optimization of CO and disciplinary optimization is replaced by the approximation.

3 Illustrative Examples

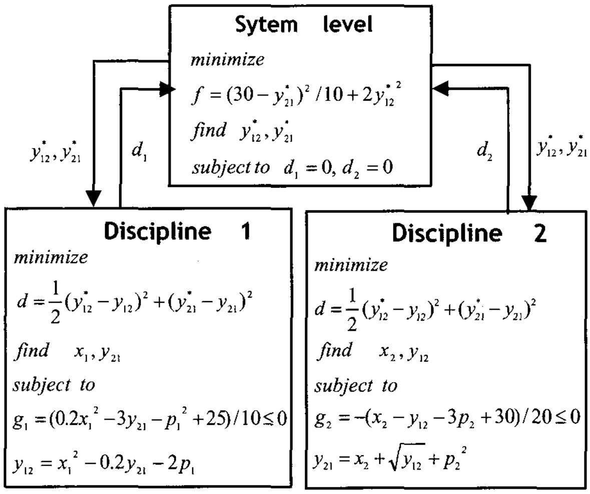


Figure 6: CO formulation of mathematical problem

This problem requires solving a coupled analysis to evaluate constraints and an objective function. System-level of a collaborative optimization coordinates the coupling by determining optimal target values of coupling variables linked between two disciplines, y_{12}^* and y_{21}^*. Three kinds of approximation methods are employed in place of two compatibility constraints (i.e. discrepancy functions): kriging, neural network, a combination of classification neural network and kriging. Here, the neural network is used just for the approximation of the response value itself, differently from the neural network classification. AASO strategy is also applied to reduce required sample points. Figure 7 shows nine initial sample points of 3×3 grid type and corresponding extra points along with the contour line of exact d_1.

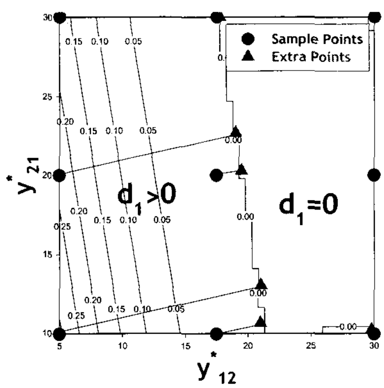
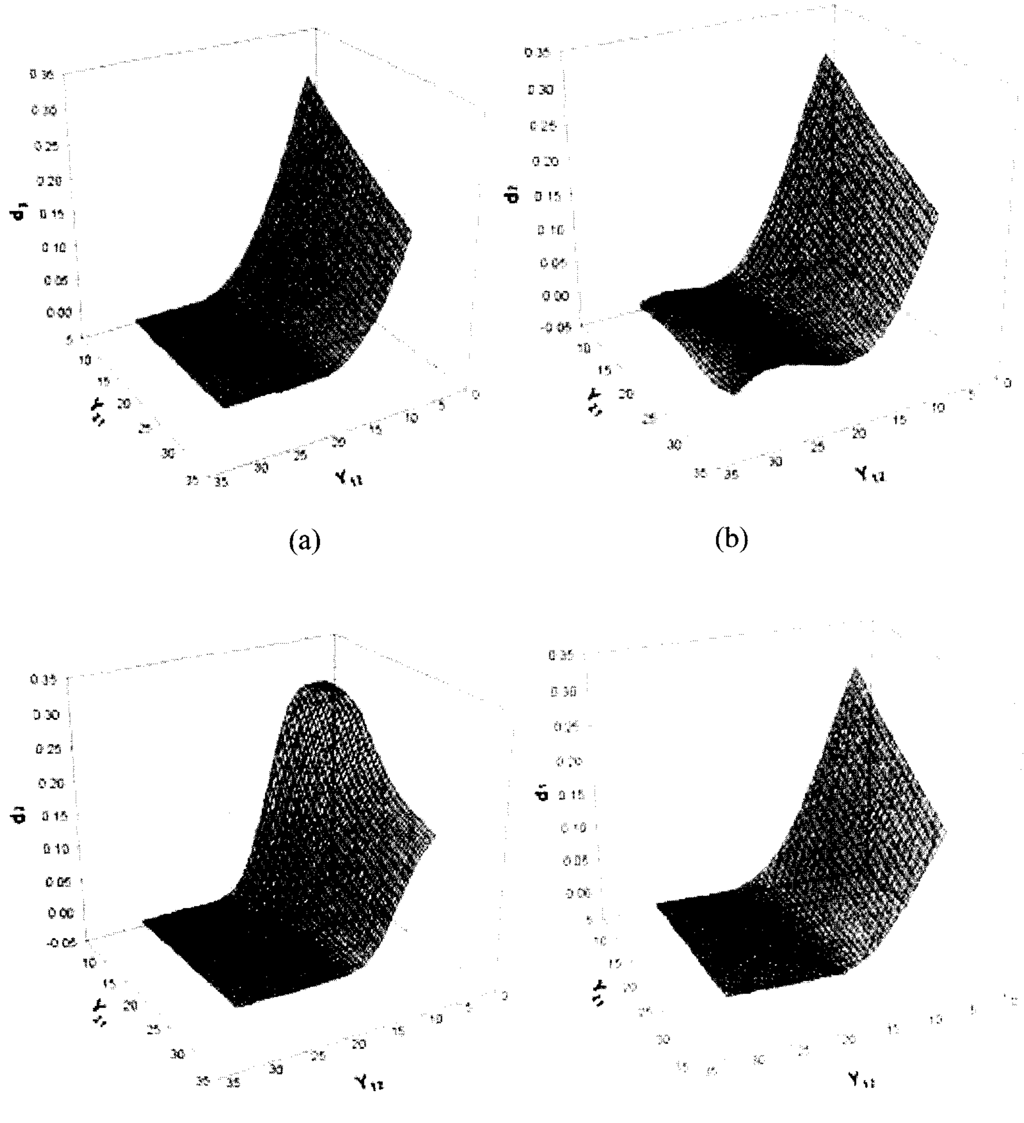


Figure 7: Contour line of discrepancy function 1

The 3-D shape of kriging looks like considerably different from the exact model, that is, over-fitting arises in the central part of feasible region where $d_1 = 0$, however the case using kriging succeeded in finding exact solution. It is because extra points near the exact solution have a strong effect on exactly modeling that region and eventually leads to optimum.



(a) (b) (c) (d)

Figure 8: 3-D shapes of (a) exact model, (b) kriging, (c) neural network and (d) classification+kriging.

On the other hand, although the shape of neural network seems to be very similar with the exact model in the feasible region, the result of neural network is remarkably different from the exact optimum. This is because there exists so decisive error in the feasible region as to have a critical influence on whether feasible or not. The value of d_1 of exact model has the order of about $10^{-20\sim30}$, however the neural network has the order of about $10^{-2\sim-4}$

which is about an allowable tolerance of the compatibility constraint given by the system level optimization. The combination of classification and kriging provides not only the almost same shape but also value exactly equal to zero in the feasible region. This fact demonstrates the usefulness of classification, especially for the exact approximation of feasible region.

Table 1: Results of mathematical problem

Approximations	No. of Sample Pts	Optimal Point of System-level problem	Objective
Exact Optimum(SQP)	51 (fcn call)	$\{17.732, 25.296\}$	37.677
Kriging	13	$\{17.843, 25.451\}$	37.756
Neural Network	14	$\{19.706, 25.451\}$	41.481
Classification + Kriging	15	$\{17.745, 25.451\}$	37.559

4 Engine selection and propeller design problem

Propeller design and engine selection cannot be considered apart from each other because there exists interdependent relation between the two. This section shows the suitability of collaborative optimization for solving such a relationship by comparing with traditional approach and standard optimization, and demonstrates the usefulness of AASO strategy using the combination of classification and kriging.

4.1 Traditional approach

This problem is to simultaneously select an engine type and determine propeller characteristic variables based on the estimation of ship resistance. This problem can be decomposed into three disciplines; a propulsion performance prediction discipline, a propeller design discipline and an engine selection discipline. Three approaches are applied to this problem; traditional design process, standard optimization and collaborative optimization.

There exists interdependency between them. Figure 9 shows a conventional design sequence including the exchange of parameters between them. First, assume propeller diameter and propeller efficiency using appropriate empirical formulas, and estimate ship resistance for various ship speed (v) along with thrust deduction coefficient (t) and wake fraction (w) using a suitable statistical e.g. Holtrop & Mennen method (Holtrop and Mennen 1982, Holtrop 1984). These estimated values are passed to the propeller design discipline and this discipline finds optimal propeller characteristic values which can attain maximum propeller efficiency (η_o) subject to two equality constraints – torque constraint and thrust constraint – and one inequality constraint – cavitation constraint. Here, propeller rotation speed (rpm) at propeller design point should be preliminarily assumed for its optimization. If the obtained propeller efficiency is considerably different from the given value, it should be returned to the propulsion performance prediction discipline and the related resistance and self-propulsion factors should be computed again.

Next, NCR power and rpm values are given to the engine selection discipline and a diesel engine type and the number of cylinders are selected among 160 types of two stroke MC/MC-C engines of Man B&W company (http://www.manbw.dk/, Engine Selection Guide) considering some restrictions at the engine selection discipline.

If the given rpm value is not appropriate for selecting satisfactory engine type, other values are suggested by the engine selection discipline and they are returned to the propeller design discipline. If the rpm leads to much different propeller efficiency from the previously computed value, the process should restart with the propulsion performance prediction discipline again.

Such an iteration process is required for a solution to satisfy all constraints of three disciplines. Since there is not a higher level discipline to control from a systematic perspective, the process does not guarantee an optimal solution. For an efficient design process for a complex system, it would be better to have a system-centered decision-making team in cooperation with other disciplines. The system-level optimization of CO is expected to play such a role.

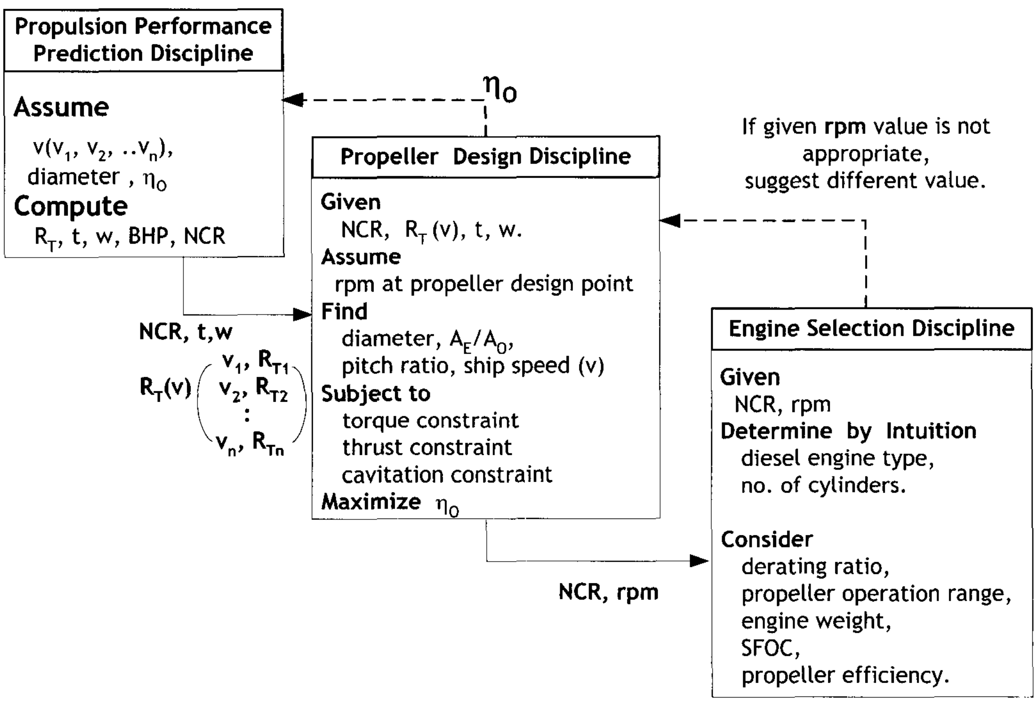


Figure 9: Traditional design process

4.2 Formulation of engine selection and propeller design problem into CO framework.

This problem can be integrated into one optimizer as depicted in Figure 10. Fortunately, there is no coupling between the analyses of three disciplines; therefore, a system analysis to solve a suite of coupled analyses can be avoided. However, the design variable of engine type burdens the integrated optimizer with considerable computational expense. Selecting the best one among the 160 engine types together with determining other continuous variables is not easy to be formulated as an optimization problem. Therefore, the engine type is determined in such a way that an optimization to determine only continuous design variable is executed for all of the 160 types of engine and the best is selected among the 160 optimums. As the number of the continuous design variable increases, the computational cost increases rapidly.

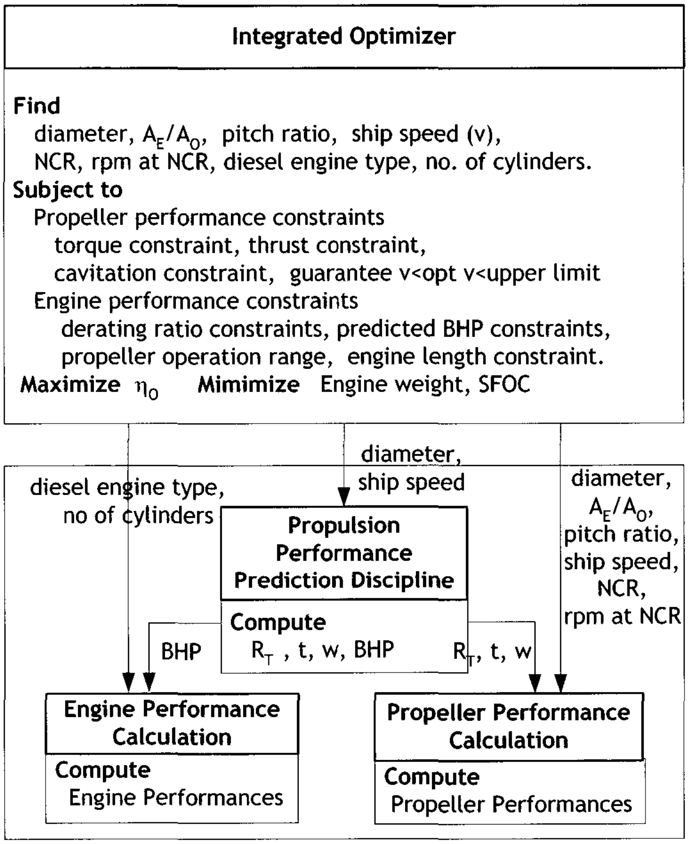


Figure 10: Formulation of Standard optimization

Figure 11 shows the formulation of CO problem and the use of approximation in place of the propeller optimization results. The discrepancy function of the propeller discipline is modeled as a function of system-level target variables (*NCR**, *rpm** *at NCR*, and *BHP**) by the combined classification + kriging. The optimal propeller efficiency value, η_0, is modeled by only kriging. Three objective functions are employed at the system-level optimization; maximize propeller efficiency (η_0), minimize engine weight, and minimize Specific Fuel Oil Consumption (*SFOC*). They are equally weighted and summed into a single objective function after normalized. To decompose design variables as in CO is quite advantageous from a computational point of view compared with the standard optimization because the selection of engine is separated completely from the determination of continuous variables.

The detail definition of CO problem is described as follows. The formulation are based on (Carlton 1994) and (Harvald 1983).

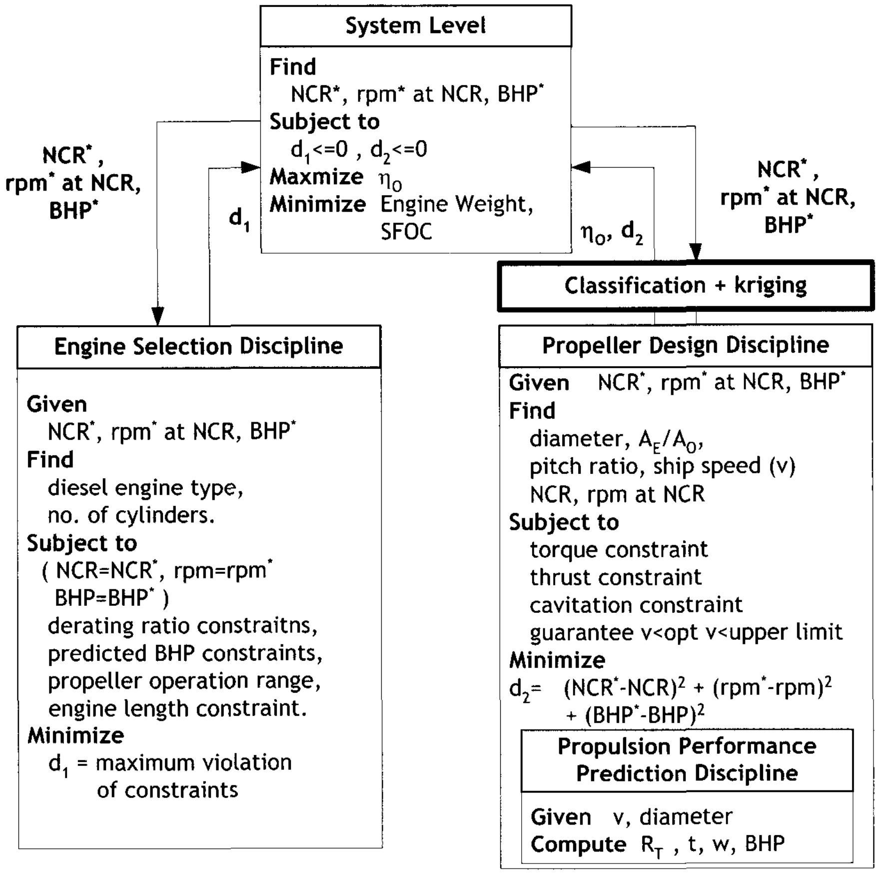


Figure 11: Formulation of CO problem

System Level

Find

$$NCR^*,\quad rpm^*(at\,NCR),\quad BHP^*$$

subject to

$$d_1 \le 0,\ d_2 \le 0$$

minimize,

$$W_1(1-\eta_0) + W_2\,Engine\ Weight + W_3\,SFOC\,,\qquad W_1 = W_2 = W_3 = 0.333$$

Engine Selection Discipline

given

NCR^*, $rpm^*(at\,NCR)$, BHP^*, *sea margin (15%), engine margin (10%)*

find

engine type, no. of cylinder

(select among 160 combinations of MAN B&W diesel engines and cylinders)

subject to

low limit(1.1) < derating ratio of BHP (NMCR/MCR) < upper limit (1.2)

low limit(1.1) < derating ratio of rpm (rpm of L1 /rpm at MCR) < upper limit (1.2)

$0.9 \times$ *predicted BHP < BHP <* $1.1 \times$ *predicted BHP*

NCR point and 80% of NCR point should be within engine load diagram (see Figure 11).

MCR(=DMCR)= NCR/(1-engine margin)

$$rpm\ at\ MCR = \left(\frac{MCR}{NCR}\right)^{1/3} rpm\, at\, NCR$$

$$predicted\ BHP = \frac{NCR}{(1 + sea\ margin)}$$

$$NCR = NCR^*, \quad rpm = rpm^*(at\, NCR), \quad BHP = BHP^*$$

minimize

maximum violation of constraints

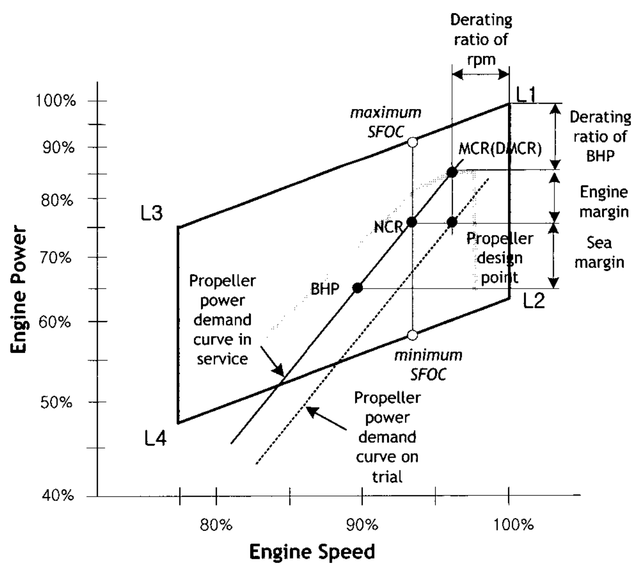


Figure 12: Engine layout and load diagrams and propeller operation range

Propeller Design Discipline

given

$NCR^*, \quad rpm^*(at\, NCR), \quad BHP^*$

Find

$NCR, \quad rpm(at\, NCR)$, *diameter(D), pitch ratio(P/D),* A_E / A_o, *ship speed(v)* subject to

Torque constraint, $\frac{DHP \times \eta_R}{2\pi n} = \rho n^2 D^5 K_Q$

$DHP \times \eta_R = BHP \times \eta_T \times \eta_R = NCR/(1 + sea\ m\arg in) \times \eta_T \times \eta_R$

Thrust constraint, $\frac{R_T(1 + sea\, margin)}{1-t} = \rho n^2 D^4 K_T$,

K_t, K_Q*: calculated based on Wageningen B-series regression model*

Cavitation constraint, $A_E / A_O \geq K + \frac{(1.3 + 0.3Z)T}{(D^2(p_o + \rho gh - p_v))}$ *(Keller's criterion)*

$n = rpm\, at\, MCR = (\frac{MCR}{NCR})^{1/3} rpm(at\, NCR)$

minimize $d_2 = (NCR - NCR^*)^2 + (rpm - rpm^*)^2 + (BHP - BHP^*)^2$

Propulsion performance prediction Discipline

Given

ship speed (v), diameter, L, B, D, T, C_B

Compute

R_T, t, w, *BHP with Holtrop-Mennen method.*

The calculated torque and trust capacity should match with the estimated ship resistance and DHP level. There are two different approaches to treat this condition. The first is to determine diameter and rpm directly from the given ship resistance and DHP. The second is to treat this condition as constraints as this paper.

Usually the thrust and the torque value can be estimated, either by empirical formulas based on regression analysis for the systematic model tests of standard propeller series such as B-series and MAU series, or by computational estimation based on numerical analysis using a tool such as lifting surface codes, surface panel codes, and CFD codes. This paper employed the first approach.

The propeller power absorption characteristics would be influenced by a number of factors such as propeller geometrical features, sea conditions, hull conditions and displacement. Due to those effects the propeller demand power at delivery of a ship would differ from that in the service life of a ship and throughout the docking cycle. With regard to such difference in ship performance, the designer generally use a derated engine power by introducing the so-called 'sea margin' and 'engine margin' in order to ensure that the ship has sufficient power available in service. In practice, the intersection between the engine characteristics curve at the derated condition and the initial propeller demand power curve becomes the condition for propeller design. The design condition corresponds to 'Propeller design point' indicated in Figure12. The values of the design variables (BHP, derating ratios of BHP and RPM) are bounded by the lower and upper limits in the form of their ratios for specifying a simplified range.

Two different approaches for solving CO problem without approximation and two approaches for CO problem with approximation are taken. Five trials for each approach are attempted. Table 2 summarizes the results. The approach of the standard optimization is to determine all design variables at a time by an overall single optimizer without decomposition. It is carried out many times and the repeatedly obtained result is contained in Table 2. The result can be regarded as the practically actual optimum. The approach proposed in this paper, named AASO in CO, gives design points very close to the actual optimal point. Four of the five trials succeed while the other one gives a slightly different optimum value. The approach named "one approximation" which does not include the process to update approximation models gives a result very different from the optimum.

Table 2: The results of engine selection and propeller design.

		Exp No.	Design Variables {NCR, rpm, BHP}	Objective	I_1 (<0.5%)	d_2 (<0)	Engine Type	No. of fcn calls	Elapsed time (s)
CO without Approxi -mation	SQP *Random Starting point,*	1	{31,915, 71.433, 29,679}	0.6904	0.496%	-1.31 e-2	9L90MC-C	20	998
		2	{27,228, 72.776, 26,305}	0.6823	0.370%	-6.70 e-5	8L90MC-C	37	754
		3	{31,858, 70.004, 29,481}	0.6894	0.420%	-1.47 e-2	9L90MC-C	9	451
		4	{31,497, 65.817, 29,055}	0.6823	0.500%	-1.58 e-4	8S90MC-C	42	2240
		5	{31,814, 72.850, 29,812}	0.6909	0.500%	-1.00 e-6	9L90MC-C	39	2177
	SA *Random Starting point,*	1	{27,496, 63.628, 26,494}	0.6517	0.410%	-1.13 e-3	11S80MC	1,207	21,830
		2	**{23,870, 61.446, 23,000}**	**0.6443**	**0.356%**	**-7.32 e-4**	**8S80MC-C**	**1,207**	**18,251**
		3	{31,464, 65.814, 27,274}	0.6604	0.390%	-6.02 e-5	8S90MC-C	1,207	20,969
		4	**{23,849, 61.512, 23,000}**	**0.6443**	**0.338%**	**-1.80 e-3**	**8S80MC-C**	**1,207**	**20,005**
		5	{35,000, 75.000, 30,036}	0.6841	0.036%	5.37 e-3	6K98MC	1,207	19,981
CO with Approxi -mation	AASO in CO	**1**	**{25,381, 62.367, 24,503}**	**0.6468**	**0.338%**	**-6.12 e-4**	**8S80MC-C**	**26**	**1,093**
		2	{26,050, 63.973, 25,174}	0.6506	0.339 %	-1.37 e-9	11S80MC	14	557
		3	**{24,361, 66.349, 23,481}**	**0.6484**	**0.359%**	**-1.24 e-8**	**8S80MC-C**	**14**	**558**
		4	**{25,393, 62.346, 24,490}**	**0.6468**	**0.348%**	**-3.36 e-3**	**8S80MC-C**	**15**	**627**
		5	**{23,808, 61.198, 23,002}**	**0.6444**	**0.315 %**	**-1.51 e-5**	**8S80MC-C**	**39**	**1,900**
	One Approxi-mation	-	{29,370, 67.537, 27,974}	0.6656	0.225%	3.38 e-2	8L90MC-C	27	1,021
Standard Optimization		-	{NCR, rpm, A_E/A_O, diameter, pitch ratio, speed} = {**23,644, 61.936**, 0.518, 14.065, 1.032, 13.724} , ※BHP = **23,030**, Objective = **0.6441**				**8S80MC-C**	-	3,683

For an approach to execute CO without using approximation, two optimization techniques are employed; Sequential Quadratic Programming (SQP) and Simulated Annealing (SA). In the former case, none of the five trials succeeds in converging to the actual optimal point, while two trials succeed in the latter case. However, the latter case requires too many discipline-level optimizations (function calls) and therefore spends too much computational time. These cases give incorrect results in spite of directly using the discipline-level optimization results instead of approximation.

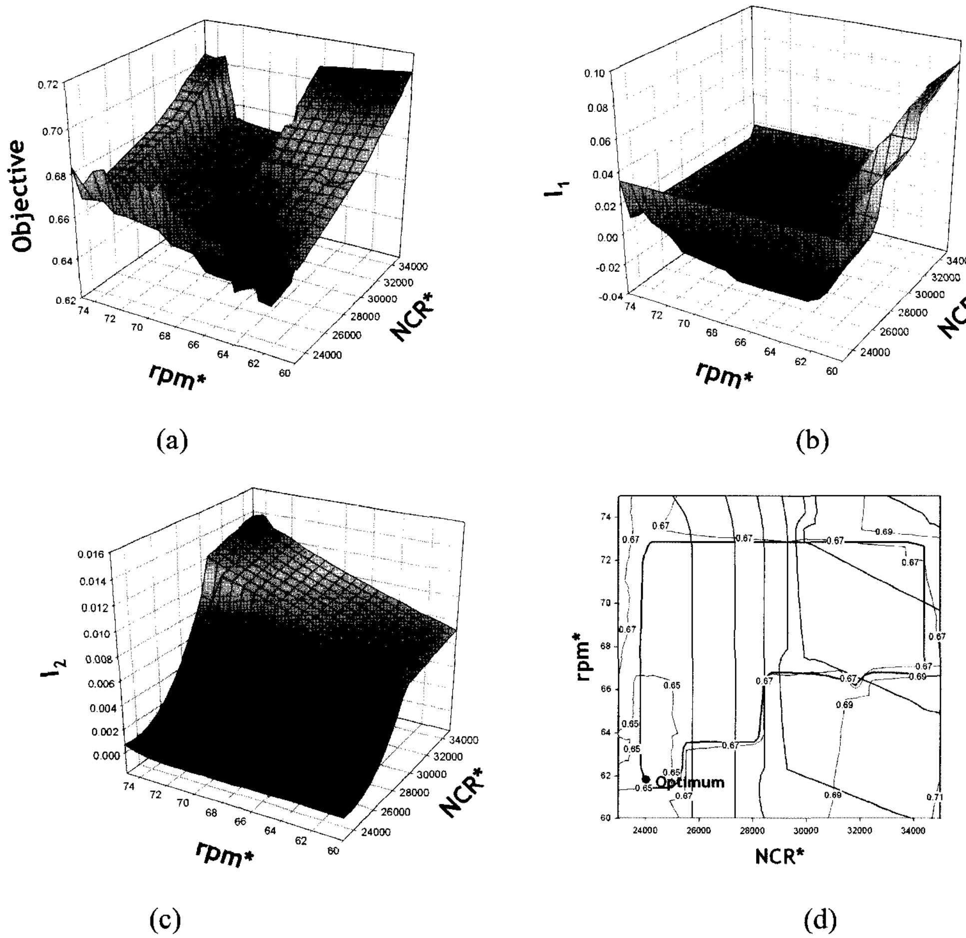


Figure 13: 3D plots through a series of actual evaluations (a) objective function, (b) discrepancy function 1, (c) discrepancy function 2, (d) propeller efficiency contours.

The failure originates from the non-smoothness of the system-level objective function, especially, the propeller efficiency. This can be observed in Figures 13 and 14 which present the results obtained through a series of actual discipline-level optimizations with varying NCR* and rpm* for BHP*. The exact optimal point can be identified in Figure 13 (d). The objective function is characteristic of discontinuity and non-smoothness. The discontinuity is mostly caused by the objective functions of engine weight and SFOC which are functions of the discrete variable, engine type, of the engine selection discipline as shown in Figure 14 (b) and (c). The non-smoothness is due to the objective function of propeller efficiency, as shown in Figure 14 (a). Since the propeller efficiency is determined by an optimization including two equality constraints at the propeller design discipline optimization, some noise in its response cannot be avoided. Such characteristics make it difficult to use the gradient-based method at the system-level optimization.

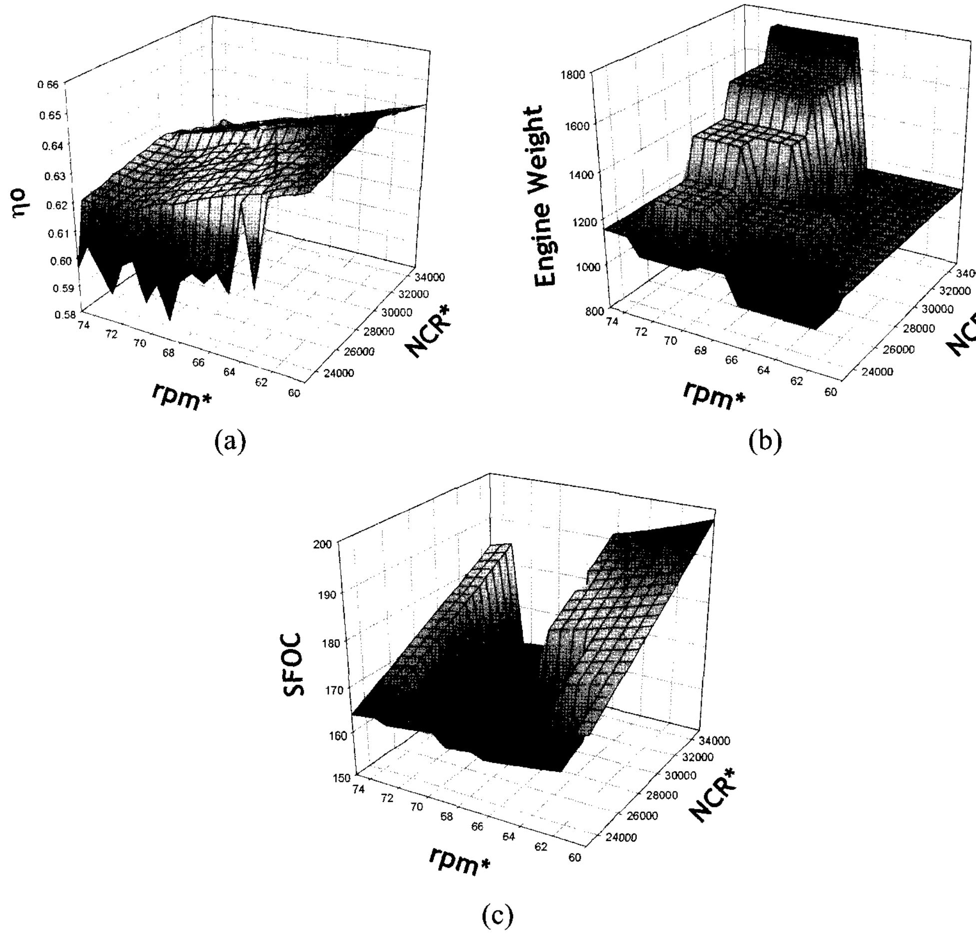


Figure 14: 3D shapes of objective functions through a series of actual evaluations (a) maximize propeller efficiency (η_o), (b) minimize engine weight (c) minimize Specific Fuel Oil Consumption (*SFOC*).

In the other hand, the case of AASO in CO can overcome such problems of the objective function due to the use of both genetic algorithm and approximation. Genetic algorithm can resolve the problem of discontinuity and non-smoothness and the use of approximation in place of the propeller design disciplinary optimization can relieve a computational burden of using genetic algorithm in the system level optimization.

5 Conclusions

This paper presents a method to use approximation methods in collaborative optimization (CO).to overcome the drawbacks of CO in applying to practical engineering design. The approximation substitutes for disciplinary optimization itself differently from the general use in place of a time-consuming analysis. The disciplinary optimal result, called discrepancy function, is approximated as a function of the system level design variables passed to the disciplinary optimization. The obtained function is used during the system level optimization in place of executing the exhaustive disciplinary optimization. This approach can reduce the number of required disciplinary optimizations in CO remarkably.

However, the peculiar form of the target of the approximation makes it difficult to employ conventional approximation methods. This paper introduces a combination of neural network classification and kriging. Since, the neural network classification approximates a decision whether a design is feasible or not instead of response value of a function, it can avoid the difficulty in modeling caused by the particular trend of the profile of the discrepancy function. In addition, a method to update the approximation models using the information obtained from the optimization is applied to enhance the accuracy of the approximation models.

The engine selection and propeller design problems cannot be solved separately because of their strong interdependent relationship. This paper presents an approach to such problems based on multidisciplinary design viewpoint instead of traditional design spiral approach. The problem is formulated as a CO problem and the proposed approximation methods are applied to the propeller disciplinary optimization. Through this problem, the validity of the proposed approximation in collaborative optimization has been demonstrated.

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