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COMPLEX CRITERIA FOR NAVIGATION EQUIPMENT TEST TABLE OPTIMAL DESIGN PROBLEM

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Abstract*—A multidisciplinary optimization is used for the navigation equipment test table design. The six discipline level optimizations are driven by a top system level optimization which minimizes the manufacturing cost while at the same time coordinating the exchange of information and the interaction among the discipline level optimizations.*

Index terms—Multiobjective optimization; hierarchical systems; simulation table; genetic algorithm; neural network; coordination problem.

I. INTRODUCTION

The increasing complexity of engineering systems has sparked increasing interest in multidisciplinary optimization. Navigation equipment test table as means of providing technical testing navigation equipment in conditions close to the real flight. Navigation equipment test table must ensure tests on the parameters close to real, namely the angularpositions, overload, angular velocity and acceleration of all control channels. Moreover it must ensure required reliability and credibility performance.

Six discipline level performances – dynamic platform, gears, electric drives, electric drive control subsystem, data acquisition subsystem, power supply subsystem – are optimized simultaneously (Fig. 1).

The results from this design approach provides the results to a single design which improves the discipline level objective functions while at the same time producing the highest possible improvement at the system level.

Multidisciplinary design optimization can be described as a methodology for the design of systems, where the interaction between several disciplines must be considered, and where the designer is free to significantly affect the system performance in more than one discipline. To ensure all navigation equipment test table performances on the technical design stage it is necessary to solve the task of developing assembly units, functional task, the task of software development, the task of selecting a set of technical means, etc.

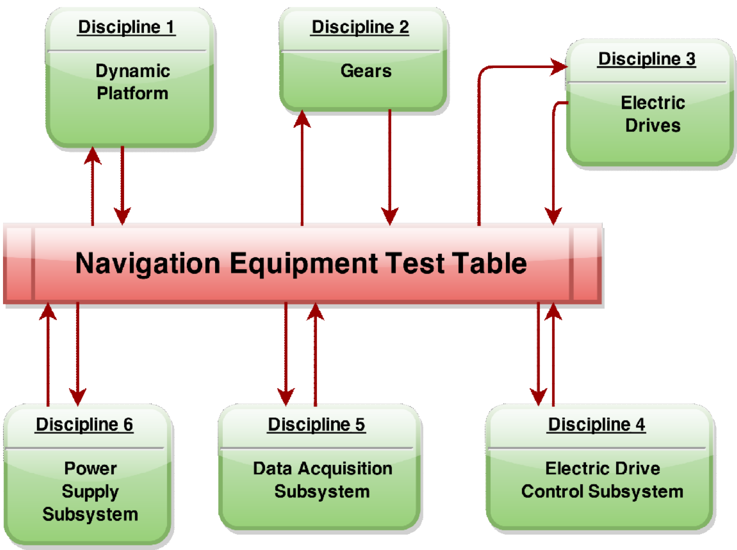

Fig. 1. Schematic of navigation equipment test table design multidisciplinary optimization process

The interdisciplinary coupling inherent in navigation equipment test table design tends to present additional challenges beyond those encountered in a single-discipline optimization. It increases computational burden, and it also increases complexity and creates organizational challenges for implementing the necessary coupling in software systems. To address complexity of the navigation equipment test table design task hierarchical decomposition approach is used.

A hierarchic system is defined as one in which a subsystem exchanges data directly with the system only but not with any other subsystem. Such data exchange occurs in analysis of structures by substructuring. A concept to exploit this in structural optimization was formulated in Schmit and Ramanathan [1] and generalized in Sobieszczanski-Sobieski [2] and [3]. It was then shown in the latter how the hierarchic decomposition derives from the Bellman's optimality criterion of the dynamic programming. The concept was also contributed to by Kirsch, [e.g., Kirsch, 4]. It was demonstrated in several applications, including multidisciplinary ones, e.g., Wrenn and Dovi [5] and Beltracchi [6].

Sobieski [2] proposed an approach described most appropriately as a linear decomposition strategy. Here, the coupling between subproblems was represented at the coordination problem level; this was achieved by using a linear extrapolation of the subproblem optimal design with changes in the coordination problem design variables. The approach, although effective for the class of problems considered, was not without its drawbacks. Perhaps the most significant problem that could exist with the approach in more realistic problems is the accuracy with which the subproblem optimal design is represented at the coordination problem level. This representation requires the sensitivity of the optimal design in each subproblem to prescribed problem parameters, where the latter are the coordination problem design variables. Methods to obtain this sensitivity are restrictive in that the sensitivity is valid for a limited change in the problem parameters; this translates into tighter move limits in the coordination optimization problem.

Artificial neural network based approximations can be used to mitigate some of the aforementioned problems. In particular, the multilayered feed-forward network can be used to map the coordination problem design variables into subproblem optimal solutions. This eliminates the need to construct restrictive linear approximations of the subproblem optimal solutions in terms of the coordination problem design variables. In hierarchical optimization, it is typical to distribute the design variables and design requirements into loosely coupled subgroups. Such a grouping is typically facilitated by classifying the design requirements into either a global or local category.

II. COMPLEX CRITERIA STATEMENT

Consider the navigation equipment test table design problem formulated in terms of a design variable vector **X [H, P, N, G, Q, L, E, R]**, where

H is the size of the mounting for the equipment under test;

P is the mass of the test equipment;

N is the maximum overload;

G is the limits of the angular positions;

Q is the motion trajectory deviation limits;

L is the digital resolution of test results;

E is the accuracy of the acquisition of the test results digital information;

R is the reliability.

Also, let the design constraints $g_j(\mathbf{X})$ belong to the global constraint set **G**. The vector **X** and constraint set G are said to define system level problem.

Assume further that problem was decomposed into six discipline subproblems d_1, d_2, d_3, d_4, d_5, d_6. The design variables and constraints for each of these disciplines are denoted by X_{d1}, X_{d2}, X_{d3}, X_{d4}, X_{d5}, X_{d6}, and g_{d1}, g_{d2}, g_{d3}, g_{d4}, g_{d5} and g_{d6}, respectively (Table 1).

TABLE 1

DESIGN VARIABLE DEFINITIONS

Variable	Definition
	X_{d1} is the dynamic platform
M	Test equipment load capacity
m	Mass of platform
D	Dimensions of platform
	X_{d2} is the gears
r	Dependability
d	Types of sizes
a	The degree of accuracy
s	The gear ratio
T	Output torque
B	Mechanical backlash
	X_{d3} is the electric drives
b	The mechanical stiffness of the drive
h	Weight and dimensions
l	Reliability
S	Response performance of the drive
	X_{d4} is the electric drive control subsystem
u	Performance of control equipment
j	Smoothness of the drive motion control
g	Control accuracy
	X_{d5} is the data acquisition subsystem
A	Accuracy
n	Sampling frequency
i	Noise immunity
	X_{d6} is the power supply subsystem
K	Efficiency
o	Fault tolerance

The objective function $F(X)$ for each of the discipline is the same, and is the system level objective function defined in terms of accuracy, reliability and cost.

$$F = (F_1(x), ..., F_i(x), ..., F_l(x)), (i = 1, ..., l)$$

$$\min F(X)$$

$$\text{subject to } G = \{g_j(X), j = 1 ... N\} \leq 0,$$

where N is the number of constraints.

After problem decomposition, the design optimization problem is represented by the following six disciplines subproblems.

$$\min F(X_{d1}), \text{ subject to } g_{d1}(X_{d1}) \leq 0,$$

$$X_{d2}, X_{d3}, X_{d4}, X_{d5}, X_{d6} = \text{const}$$

$$\min F(X_{d2}), \text{ subject to } g_{d2}(X_{d2}) \leq 0,$$

$$X_{d1}, X_{d3}, X_{d4}, X_{d5}, X_{d6} = \text{const}$$

$$\min F(X_{d3}), \text{ subject to } g_{d3}(X_{d3}) \leq 0,$$

$$X_{d1}, X_{d2}, X_{d4}, X_{d5}, X_{d6} = \text{const}$$

$$\min F(X_{d4}), \text{ subject to } g_{d4}(X_{d4}) \leq 0,$$

$$X_{d1}, X_{d2}, X_{d3}, X_{d5}, X_{d6} = \text{const}$$

$$\min F(X_{d5}), \text{ subject to } g_{d5}(X_{d5}) \leq 0,$$

$$X_{d1}, X_{d2}, X_{d3}, X_{d4}, X_{d6} = \text{const}$$

$$\min F(X_{d6}), \text{ subject to } g_{d6}(X_{d6}) \leq 0,$$

$$X_{d1}, X_{d2}, X_{d3}, X_{d4}, X_{d5} = \text{const}$$

The methods of computing the sensitivity of subproblem optimal solutions are not well developed, and for the above linear approximation to be valid, very restrictive move limits on the global variables have to be imposed at the coordination problem level. Instead, a back-propagation network can be used to develop the nonlinear relationship between the subproblem optimal solution and the global design variables.

The back-propagation algorithm is an error-correcting learning procedure that generalizes the delta rule to multi-layer feedforward neural networks with hidden units between the input and output units. In order to train a back-propagation neural network, it is necessary to have a set of input patterns and corresponding desired output, and an error function that measures the cost of differences between network output and the desired values. This is the basic steps to implement a back-propagation neural network.

1. Present a training pattern and propagate it through the network to obtain the desired outputs.
2. Compare the network outputs with the desired target values and then calculate the error.
3. Calculate the derivatives of the error with respect to the weights.
4. Adjust the weights to minimize the error.
5. Repeat the above procedure until the error is acceptably small or the limit of iteration is reached.

Such an approach circumvents the need to construct the linear approximation required at the global level.

The genetic algorithm (GA) strategy can be implemented for each of the disciplines. The genetic evolution process can be carried out in parallel. The principal difficulty in this approach is that the constraint sets identified for a particular discipline, are not completely independent of the design variables that may have been assigned to another discipline. Such coupling must be accommodated in the parallel optimization scheme, and was facilitated through the use of a neutral network based approximation [7], [8]. An important property of this network is a pattern completion capability - if an incomplete input pattern is presented to the network, the network estimates the most likely make-up of the missing components.

Barai and Pandey [12] proposed a conclusion that issues will affect the design performance of a neural network. Selecting an optimal neural network architecture depends on the application domain. The successful application of neural networks to a specific problem depends mainly on two factors, representation and learning. Choosing a topology and training parameters are very much context-dependent and usually arrived at by trial-and-error.

1. Choosing Input/Output nodes. Every training example will decide the number of input nodes, and the corresponding desired output parameter gives the number of nodes in the output layer.
2. Training Patterns. It is very important to present a good training set in network learning and the decision is very critical. If a small percentage of the resulting generalization may be poor, while in the opposite case it is likely that higher oscillation would make it impossible to reach a state of global minima.
3. Normalization of the Training Set. The input patterns must be normalized before being given to the network. This gives an advantage over the size of the network.
4. Number of Hidden Layers in the Network. Two to three layers are sufficient for most problems. However, the optimal number of layers will dependent on different applications. It is suggested that multilayer networks with linear neurons are equivalent to two-layer networks. Hence, the various weight matrices can be combined into a single matrix, which serves the same purpose as a multilayer network with linear neurons.

5. Number of Neurons in the Hidden Layers. How many hidden neurons should be used in a layer is arbitrary, and has been usually decided by trail-and-error. It is good enough to use the average of the number of input and output neurons. Another possibility is to make the hidden layer of the same size as either the input or the output layer. The fewer hidden neurons the fewer connections, and hence less training capacity. Generally the hidden layer should not be the smallest layer in the network, nor should it be the largest.

6. Choosing Training Parameters. The training parameters are arrived at by investigating the application domain. Though these parameters have generally been frozen in several investigations, it would be desirable to carry out a further study of these parameters in order to see their influence in the context of the application.

7. Choosing the Activation Function. There are several types of activation functions, linear, linear threshold, step, sigmoid, and Gaussian activation functions. With the exception of the linear activation functions, all these functions introduce a nonlinear in the network dynamics by bounding the output values within fixed ranges. The sigmoid function (S-shaped semi-linear or squashing function) has been recommended in most of the back-propagation applications. In a sigmoid function the output is a continuous, monotonic function of the input. The function itself and its derivatives are continuous everywhere.

8. Choosing the Average System Error. The acceptable average system error depends upon the amount of accuracy required for training and testing the network. The acceptable error plays an important role in determining the number of training cycles, and finally it has an impact on the training time. The best way to choose the average system error is to start with a large value of the average system error and watch the performance of the network. Then, depending upon the accuracy required from the network, reduce the value of average system error. The initial large value of average system error also helps in determining the possibility of the network's convergence for a small value of the average system error.

Proposed coordination strategy is based on QSD (Quasiseparable Decomposition) approach [9] where each discipline is assigned a manufacturing cost (*cd, cr, cm, ck, cd, cp*) for a local objective and the discipline problems maximize the margin in their local constraints and the cost objective (Fig. 2). System subproblem minimizes a shared objective and the manufacturing cost of each discipline subject to shared design constraints and positivity of the margin in each discipline.

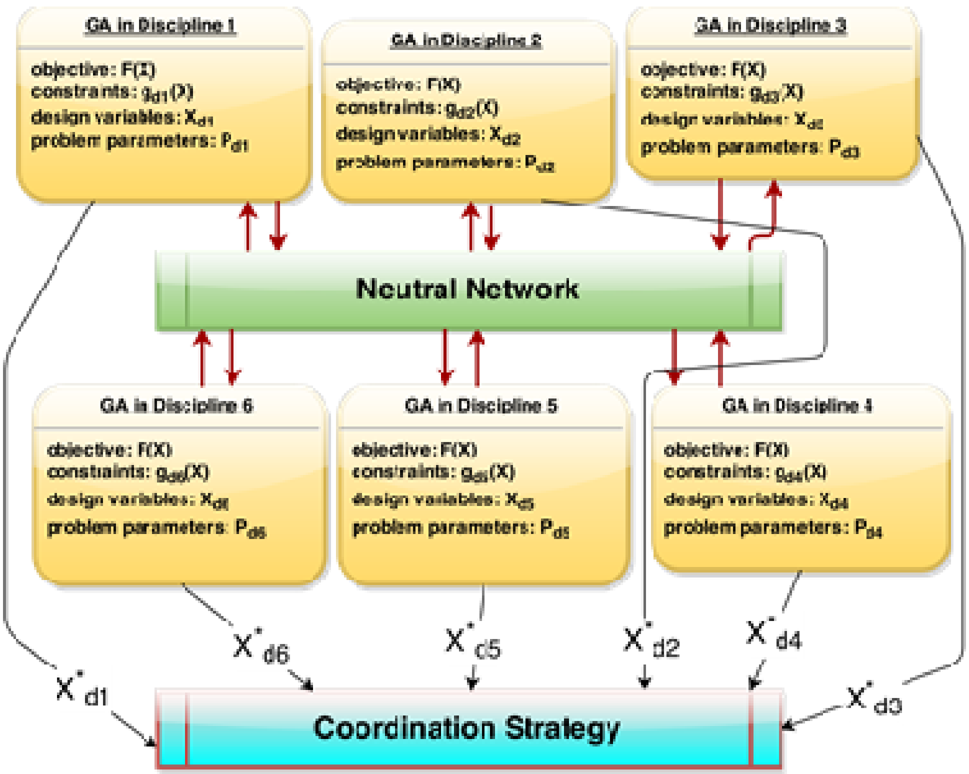

Fig. 2. Multidisciplinary design optimization design process in GA decomposition approach

A number of numerical experiments were conducted to determine the validity of the proposed approach [10]. One of them is the use of neural networks to design helicopter rotor blade [11]. The convergence histories of the system level objective function for two different strategies of the coordination are shown in Fig. 3. These would include current problem parameters, and those available as the new best designs in other disciplines. Select a combination so that the current objective function either improves or, at worst, stays the same.

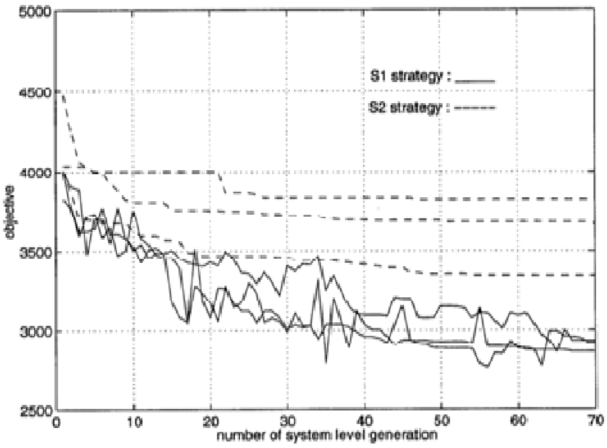

Fig. 3. System level objective function convergence history of GA based neutral networks MSDO approach: *S*1 for each discipline, use as problem parameters the current best design variable values of other subproblems; *S*2 for each discipline, evaluate all possible combinations of problem parameters

Thus, the proper selection of coordination strategy directly affects the overall design results.

CONCLUSIONS

Multidisciplinary design optimization approach for navigation equipment test table design adapting genetic algorithms and neural networks for development of a rational approach by which the multidisciplinary design problem could be partitioned into a number of separate disciplines was described. Once the optimization task was decomposed by six subproblems, the GA based search was implemented in parallel in each of the disciplines. Coordination strategies to account for the interactions between disciplines were the other focus of the present study.

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В. М. Синєглазов, С. О. Долгоруков. Багатокритеріальне оптимальне проектування випробувального стенду навігаційного обладнання
Розроблено методологію багаторівневої багатокритеріальної оптимізації випробувального стенду навігаційного обладнання. Запроповано багаторівневу процедуру вирішення завдання оптимізації, яка складається с шести елементів, що координуються за принципом мінімізації загальної вартості виробництва.
Ключові слова: багатокритеріальна оптимізація; ієрархічні системи; випробувальний стенд; генетичний алгоритм; задача координації.

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В. М. Синеглазов, С. О. Долгоруков. Многокритериальное оптимальное проектирование испытательного стенда навигационного оборудования
Разработана методология многоуровневой многокритериальной оптимизации испытательного стенда навигационного оборудования. Представлена многоуровневая процедура решения задачи оптимизации состоящая из шести елементов координируемых по принципу минимизации общей стоимости производства.
Ключевые слова: многокритериальная оптимизация; иерархические системы; испытательный стенд; генетический алгоритм; задача координации.

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