

# Design Optimization utilizing Dynamic Substructuring and Artificial Intelligence Techniques

D. Akçay Perdahcioğlu, M.H.M. Ellenbroek, P.J.M. van der Hoogt, A. de Boer

University of Twente, Department of Engineering Technology. P.O. Box 217, 7500AE Enschede The Netherlands, d.akcay@utwente.nl

## Abstract

In mechanical and structural systems, resonance may cause large strains and stresses which can lead to the failure of the system. Since it is often not possible to change the frequency content of the external load excitation, the phenomenon can only be avoided by updating the design of the structure. In this paper, a design optimization strategy based on the integration of the Component Mode Synthesis (CMS) method with numerical optimization techniques is presented. For reasons of numerical efficiency, a Finite Element (FE) model is represented by a surrogate model which is a function of the design parameters. The surrogate model is obtained in four steps: First, the reduced FE models of the components are derived using the CMS method. Then the components are assembled to obtain the entire structural response. Afterwards the dynamic behavior is determined for a number of design parameter settings. Finally, the surrogate model representing the dynamic behavior is obtained. In this research, the surrogate model is determined using the Backpropagation Neural Networks which is then optimized using the Genetic Algorithms and Sequential Quadratic Programming method. The application of the introduced techniques is demonstrated on a simple test problem.

## 1 Introduction

Modal analysis is utilized for testing structures in order to obtain an understanding of their dynamic and vibration characteristics. One of the common vibration problems identified by modal analysis is the harmonic excitation at one of the resonance frequencies of a structure by an external force. This may cause large strains and stresses in a structure. These facts may lead to failure by fatigue. In most of the situations it is not possible to control the frequency content of the external load excitation. Therefore, resonance conditions can only be avoided by changing or modifying the design in order to keep the resonance frequencies away from the excitation frequency. The solution strategies lie under the concept of *design optimization* which involves firstly the *modeling* of the problem and then *optimizing* it. Modeling consists of: problem analysis, selection of the design variables, construction of the analysis model of the problem (e.g. FE model), formulation of the objective function and decision of the constraints. Optimization consists of: selection of any suitably chosen optimization algorithm and optimizing the objective function under the defined constraints using this algorithm.

With modern numerical methods such as the Finite Element (FE) Method, it is possible to perform a comprehensive modal analysis and investigate the effects of various parameters (e.g. thickness) on the eigenfrequencies of the structure. On the other hand, especially for very complex and large structures (e.g. space shuttle), this can not be carried out easily because of the lack of computer storage and long computation time. Therefore, *Component Mode Synthesis* (CMS) technique has been utilized since 1960s for the modal analysis of complex structures. The idea behind this technique is: dividing the structure into a number of substructures, obtaining the reduced order FE models of each substructure and assemble them in order to obtain a reduced order FE model of the complete structure. With CMS, design changes in the single substructure affect only the system matrices of that substructure; thus, additional computations are necessary only for that component. This property constitutes one of the crucial basis of our design optimization strategy. Especially in very complex and large structures where the only intention is to modify a single component, CMS reduces the computation time significantly. In this research, the CMS technique based on Craig-Bampton method is utilized. However utilizing a CMS based model directly in the numerical optimization scheme is still very time consuming. Therefore, simpler approximation of the CMS based model (model of the model) is constructed which is called the *surrogate model* and employed in the optimization stage. The surrogate model is obtained as follows: First, the reduced FE models of the components are derived using the CMS method. Then the component that is going to be modified is assembled with the rest of the components for a number of design parameter settings and the structures overall dynamic response is obtained for each

case. Finally, the surrogate model representing the relation between the parameter-response set is obtained. In this research, the surrogate model is determined using the Backpropagation Neural Networks (NNs) and utilized in the optimization scheme. The optimization scheme is based on the combination of two strategies, the Genetic Algorithms (GAs) and the Sequential Quadratic Programming (SQP). The GA is used for estimating the possible location of the global optimum and afterwards SQP is employed for finding the exact optimum.

This paper is built up as follows: In Section 2, the CMS technique based on Craig-Bampton method is mentioned briefly. In Section 3 and 4, essential elements of the design optimization concept, namely NN surrogate models and optimization topics are pointed out. Next, the design optimization strategy is introduced. Then, the introduced strategy is demonstrated on a simple test problem and finally in Section 7 conclusions are given.

## 2 Component Mode Synthesis

In dealing with dynamic analysis of complex structures with many degrees of freedom (d.o.f.), CMS has proved to be an efficient method. It is widely used because of its economic and executive properties. CMS involves breaking up a large structure into several substructures, obtaining reduced order models of each component and assembling these models in order to obtain the reduced structure model. All substructure calculations are independent from each other, therefore design changes in one component has no effect on the system matrices of the other components.

CMS involves the following steps: Division of the structure into its components, decision of the utilized component modes and the coupling of the component mode models. The classification in CMS techniques are based on the selected dynamic and static component modes and the utilized methods for enforcing compatibility of substructures.

In this study only the accuracy of the lower modes of the assembled structure is sufficient, thus the CMS strategy based on Craig-Bampton technique is preferred [5]. In this strategy two types of component modes are employed which are *fixed interface normal modes* and *constraint modes*. The former modes are calculated by restraining all d.o.f. at the interface and solving the usual undamped vibration problem. Only truncated set of these modes are calculated and utilized in the component models. The latter modes are calculated by statically imposing a unit displacement to the interface d.o.f. one by one while keeping the displacement of other interface d.o.f. zero and the interior d.o.f. of the substructure force free. The compatibility of the neighboring substructures are ensured by taking the interface node displacements equal.

## 3 Neural Network Surrogate Models

In most engineering problems, the numerical analyzes are based on Finite Element (FE) simulations. Investigation of very complex structures using these simulations is very time consuming. Therefore, instead of employing these simulations in applications (e.g. design optimization of products), a surrogate model can be used to represent the FE model which is a function of the design parameters, of interest.

There are several methods for surrogate modeling. The Response Surface Methodology (RSM) and Kriging are the most common ones [2, 14]. In these techniques the user needs to make some assumptions on the shape of the response which may cause difficulties if the underlying behavior is unknown. Employing Neural Networks is also an option for surrogate modeling [11]. There is no need to make any assumption for the shape of the response because this is automatically done by the utilized transfer functions in the NN structure. The sigmoid functions and the linear transfer functions are usually used in the hidden layer and the output layer, respectively, as transfer functions. The nonlinearity of the NN caused by the number of the hidden layer neurons are prevented by the *regularization* technique. In this sense, NNs are very practical tools especially when there is no information on the complexity of the problem.

A two layer NN structure is illustrated in figure 1. As it is deduced from [13], a two layer NN having a nonlinear transfer function with sufficient number of neurons in the hidden layer and a linear transfer function in the output layer can be trained to approximate any function. This ability to approximate functions to any desired degree of accuracy makes NNs an attractive tool for surrogate modeling.

A mathematical description of a two layer NN can be given as

$$\begin{aligned}
 \hat{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{b} \\
 \tilde{\mathbf{x}} &= f(\hat{\mathbf{x}}) \\
 \mathbf{y} &= \mathbf{B}\tilde{\mathbf{x}} + \mathbf{c},
 \end{aligned} \tag{1}$$

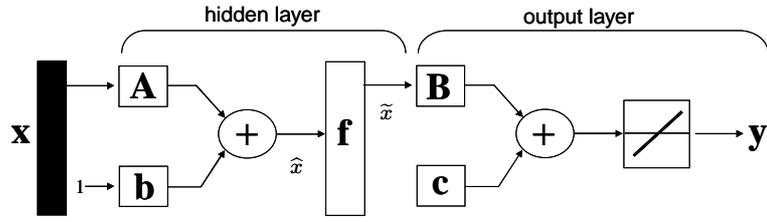


Figure 1: A two layer NN structure.

where  $\mathbf{x} \in \mathbb{R}^{N_i \times 1}$ ,  $\mathbf{y} \in \mathbb{R}^{N_h^2 \times 1}$  represent the input-target vectors (training set),  $\tilde{\mathbf{x}} \in \mathbb{R}^{N_h^1 \times 1}$  stands for the hidden layer outputs (at the same time an input for the output layer) and  $N_i, N_h^1, N_h^2$  denote the number of input vector elements, hidden layer neurons and output vector elements, respectively. The function  $f$  used in the hidden layer stands for the set of nonlinear (sigmoid) transfer functions and allows the network to learn nonlinear and linear relationships between the input-target pairs. The linear output layer lets the network produce values outside the range of sigmoid functions. The number of the neurons utilized in the hidden layer has an effect on the complexity of the network and allows NNs to figure out complicated underlying behaviors.  $\mathbf{A} \in \mathbb{R}^{N_h^1 \times N_i}$ ,  $\mathbf{B} \in \mathbb{R}^{N_h^2 \times N_h^1}$ ,  $\mathbf{b} \in \mathbb{R}^{N_h^1 \times 1}$  and  $\mathbf{c} \in \mathbb{R}^{N_h^2 \times 1}$  denotes the network parameters. The weights  $\mathbf{A}$ ,  $\mathbf{B}$  have an effect on the slope of the network output and the bias terms  $\mathbf{b}$ ,  $\mathbf{c}$  shift the entire network output on the coordinate axis [11]. Therefore, NNs are very flexible tools for curve fitting.

The working principle of NNs is the same as the Least Squares Method (LSM). NNs are provided with a set of input-target pairs  $\{\mathbf{p}_1, \mathbf{t}_1\}, \{\mathbf{p}_2, \mathbf{t}_2\}, \dots, \{\mathbf{p}_Q, \mathbf{t}_Q\}$  where  $\mathbf{p}_q$  is an input to the network and  $\mathbf{t}_q$  is the corresponding target (input can be thickness and width, target can be one of the natural frequencies). The input pairs are applied to the network, the obtained network outputs are compared to the target value and the network parameters (weights and bias terms) are adjusted in order to minimize the mean square error

$$\min_{\mathbf{A}, \mathbf{B}, \mathbf{b}, \mathbf{c}} F_m = \sum_{q=1}^Q (\mathbf{t}_q - \mathbf{y}_q)^T (\mathbf{t}_q - \mathbf{y}_q) \quad (2)$$

where  $Q$  is the total number of input-target pairs and  $\mathbf{y}$  is a function of network parameters. Equation (2) defines an unconstrained optimization problem and can be solved using any appropriate iterative algorithm [16]. Most of the traditional numerical algorithms need the knowledge of the gradient. Thus, for the solution of equation (2), the partial derivatives of  $F_m$  with respect to the network parameters are required. Since  $F_m$  is an implicit function of the hidden layer parameters, the chain rule of calculus is used to calculate the derivatives which proceeds from the output layer through the hidden layer. The Backpropagation NNs takes its name from this property.

As mentioned early in this section, NNs complexity are determined by the number of neurons utilized in the hidden layer. The increasing number of neurons leads to highly nonlinear NN structures which may cause *overfitting*. Overfitting occurs when the error on the training set of the network is driven to a very small value and a new input-target pair is introduced, the network becomes too poor to generalize the new situation. When there is no information about the complexity of the underlying behavior, the efficient number of hidden layer neurons can not be estimated beforehand. In order to prevent finding this number from trial and error, there are several developed techniques. In this study *regularization* is utilized which ensures that the function computed by the network is no more curved than necessary. This is achieved by modifying the error function  $F_m$  (see equation (2)) with a penalty term  $F_p$  where the general function becomes

$$F = \alpha F_m + \beta F_p. \quad (3)$$

One possible form of the penalty term comes from the observation that an overfitted function with regions of large curvature have large network parameters. Choosing the penalty term as *the sum of squares of the network parameters* is one option that is used in this study. Another challenge in equation (3) is the decision of the objective function parameters  $\alpha$  and  $\beta$ . Their relative size determines the training process. If  $\alpha \ll \beta$ , the training algorithm will minimize the errors. If  $\alpha \gg \beta$ , the training algorithm will reduce the size of the network parameters to produce a smoother network response. The *Bayesian regularization* [15] is used for the calculation of these parameters and the modified function (equation (3)) is solved by the Levenberg-Marquardt method. The algorithm defined in [9] is utilized for this purpose.

## 4 Optimization with GAs and SQP

The Genetic Algorithm (GA) is a method for solving parameter optimization problems in the global sense by imitating the principles of natural evolution. The GA generates a population of points in each iteration and the best point of the population approaches an optimal solution which increases the possibility of finding the global optimum. During its process, the GA does not require any derivative information of the objective function.

There are many ways to handle constraints in GAs [3]. The algorithm utilized in this study solves bound and linear constraint optimization problems by generating *feasible* children, either by making random changes to a single parent (mutation) or by combining the vector entries of a pair of parents (crossover). For the nonlinear constraints, the Composite Lagrangian Barrier-Augmented Lagrangian (CLB-AL) algorithm of Conn et al. [4, 8], provides a framework for the GAs' nonlinear constraint solver. A subproblem is formulated by combining the objective function with the nonlinear constraint functions. The GA minimizes a sequence of the subproblem. At the end of each minimization, depending on the feasibility of the solution, subproblem parameters are updated in the outer iteration. This results in a new subproblem formulation and minimization. These steps are repeated until the stopping criteria is met. The stopping criterion is the same one as used for the GA without nonlinear constraints.

The strength of the GA is handling general classes of optimization problems that are not well suited for gradient based optimization algorithms. The GA can process optimization problems which have discontinuous, nondifferentiable, stochastic or highly nonlinear objective functions. Additionally, it is more likely to get a solution in the vicinity of the global optimum. All these nice features come with a cost: the GA requires more function evaluations than the gradient based algorithms. Furthermore, GAs only estimate the exact optimum, whereas gradient based methods find it exactly. For specific optimization problems, with a good initial guess close to the global optimum, a gradient based method will probably be much faster and more accurate than GAs. Since in this study the interested problems are very well suited to the concept of gradient based methods and considering the mentioned problem, the GA approach is supported by the gradient based technique called *Sequential Quadratic Programming* (SQP).

In SQP, the nonlinear programming problem is attempted to solve with a sequence of quadratic programming (QP) subproblems. At each major iteration, an approximation is made of the QP parameters which is then used to generate a QP subproblem. Its solution is used to form a search direction and the next iteration point. The QP parameters are updated based on this information and this iteration continues until convergence to an optimum is attained. The construction of the QP subproblems are the same for all SQP strategies; they only differ by the selection of the QP solver and the utilized merit function whose value defines a balance between the current objective and constraint violations. In this study, *the null space active set method of Gill et. al.* [6] is used and the merit function is selected as in [12]. The obtained optimum solution of SQP is initial point dependent, like in all gradient based techniques. Based on the selected initial point, it is possible to be trapped in one of the local optimum point.

Since it is not possible to find an initial estimate for many highly nonlinear problems leading to the global solution, in the strategy first GA is used and then it is followed by SQP in order to increase the chance of finding the exact global optimum.

## 5 Design Optimization Strategy

The design optimization starts with the modeling of the problem and then optimizing it. The followed strategy is illustrated in figure 2.

In the modeling stage, first the *problem analysis* is done, which involves understanding what is happening in the structure and investigating the effect of several structural parameters on the system's response. Based on the obtained knowledge, the design parameters are selected, the optimization problem is determined, the substructures are selected and the FE based component models of each substructure are constructed.

Complex FE based models are not desired to be utilized directly in the optimization scheme because of their long computation times. Therefore they are replaced by surrogate models which are functions of the selected design parameters. In order to find these surrogates, sampling on the design set has to be done. In statistics another name given to samples is *experiments*. The quality of the surrogate models changes with the number and the distribution of the experiments. Since all our experiments are based on computer calculations and the results are deterministic, generation of computer experiments are studied under the concept of *design of computer experiments (DOCE)*. Latin hypercube sampling is utilized in the research for this purpose, where the experimental design points are guaranteed to be spread over the entire design space [7]. The effective number of the experiments that has to be

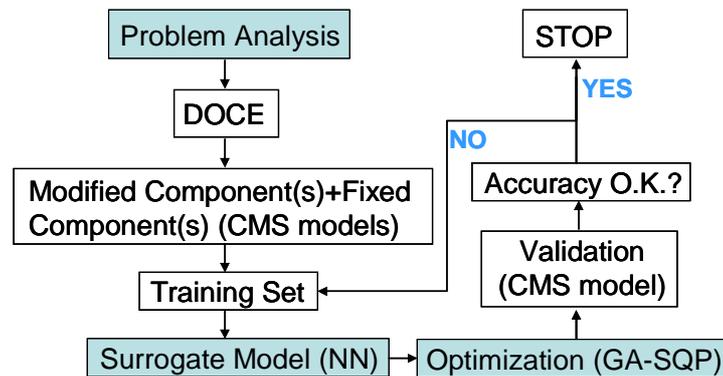


Figure 2: Design optimization strategy.

utilized in the surrogate modeling still remains to be an issue. The effective number depends on the nonlinearity of the behavior of interest. Since it is usually not possible to predict this behavior, the effective number of samples can not be estimated beforehand. This drawback can be prevented by selecting a large amount of sampling points in the design space. On the other hand, considering the fact that one FE analysis might take several hours, we are not that flexible to increase that amount. Thus, for the initial training set this number is chosen as in [17], being 10 times the number of design parameters.

In [18] design optimization of complex structures involving many design parameters which are distributed overall the structure are approached using the *CMS technique* in combination with NNs and GAs. In this study, the aim is to perform a design optimization of complex structures, where design parameters are located only in a particular component of the structure and the full structure modal response is required. The CMS method benefited the strategy in the following way: First the component models of the structure are obtained based on the knowledge of the initial design. Since all the design parameters are located in particular components of the structure, the reduced mass and reduced stiffness matrices of the unmodified components are saved for later use. The modified components' reduced mass and reduced stiffness matrices are calculated for each element of the DOCE set, coupled with the saved matrices and the full system response is obtained for each DOCE set element. This approach prevents the calculation of the full FE model for each design change and reduces the computation time significantly.

Once the training set is obtained, the *surrogate model* representing the relationship between the response and the parameters are estimated using Backpropagation NNs. From now on the obtained model can be used either as an objective function or as a constraint function in the constructed optimization problem. This step is the end of the modeling stage.

In the *optimization stage* GAs and SQP is utilized together because of the reasons discussed in section (4) and also illustrated very well in [1].

After the exact optimum point is found in the optimization stage, it is *validated* using the CMS based model. The modified structures' reduced mass and reduced stiffness matrices are calculated based on the obtained optimum parameter set, assembled with the rest of the component matrices and the whole structure response is attained. Then this result is compared with the obtained optimum response. If the error between the results are satisfactorily small enough then the procedure is stopped, otherwise the training set is feeded with the CMS model result for the optimum parameters and the procedure is iterated until the result is satisfactory. Since the surrogate model is estimated based on a limited amount of data, the validation step guarantees that the NN estimation is good enough.

## 6 Demonstration of the Concepts

For the demonstration of the strategy presented in the previous section, the first natural frequency of a plate with ribs (see figure 3) is minimized under the constraint of keeping the total mass constant. The plate is clamped at the boundaries. All the design parameters are located in the second component.

Two test cases are investigated: for the first case 7 design parameters are considered. In the second test case, the number of design parameters are increased to 8.

**Case 1:** The thickness and the width of Rib 1 and Rib 2, the thickness of Plate 1 and Plate2 and the distance

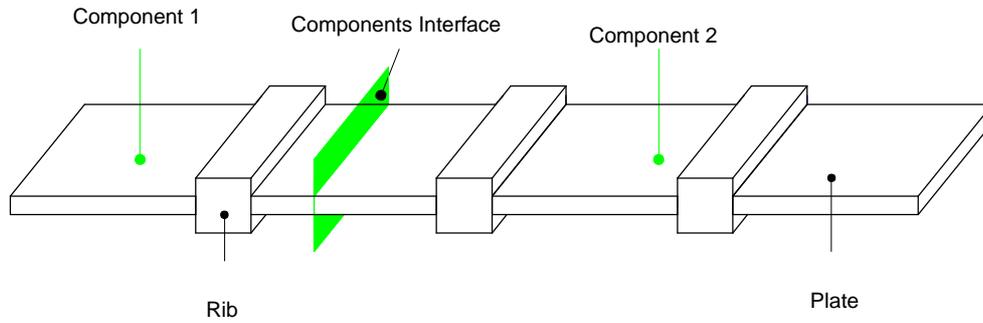


Figure 3: A plate with three ribs.

$c$  between Rib 1 and Rib2 are the design parameters (see figure 4). The CMS based modal analysis is carried out using the FE software ANSYS. The remaining parameters of the plate are the width of the plate, the thickness of the fixed plate, the thickness and width of the fixed rib which are set to 0.3m, 0.005m, 0.05m, 0.05m, respectively. The plate and the ribs are modeled using the Shell63 element which has both bending and membrane capabilities. The element has six degrees of freedom at each node which are the translations and the rotations on the x,y,z coordinates. The material properties are selected as: the Young's modulus is 210 GPa, density is 7800 kg/m<sup>3</sup> for both plates and the ribs. In Component 1, the first 5 and in Component 2, the first 20 dynamic modes are taken into account. The initial design parameters are selected as follows: the thickness and the width of Rib 1 and Rib 2 are 0.05m, the thickness of Plate 1 and Plate2 are 0.005m and the distance  $c$  between Rib 1 and Rib2 is 0.5m. ANSYS is coupled with MATLAB and several functions of MATLABs' NN and GA toolboxes are employed during the optimization process.

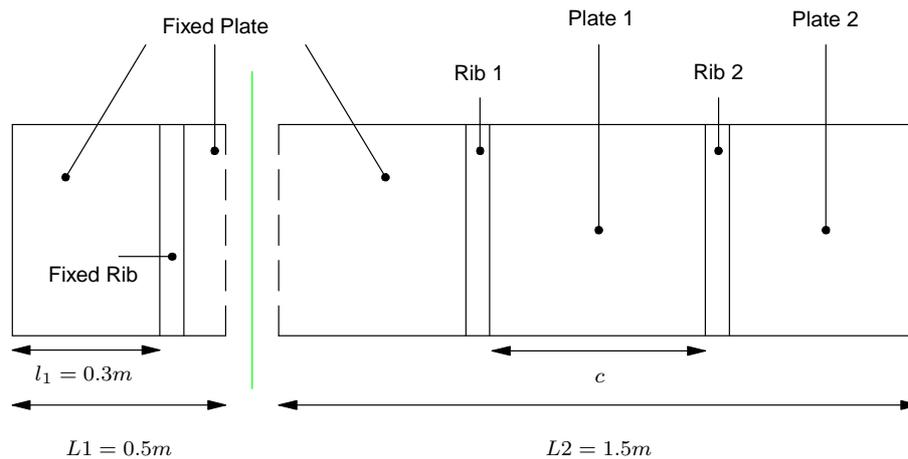


Figure 4: Design parameters and the fixed parameters for Case 1.

The optimization problem is defined as follows

$$\begin{aligned}
& \min f_1 \\
& \text{sbj. to } 0.01 \leq \text{Rib1 thickness} \leq 0.05 \\
& \quad 0.01 \leq \text{Rib2 thickness} \leq 0.05 \\
& \quad 0.01 \leq \text{Rib1 width} \leq 0.05 \\
& \quad 0.01 \leq \text{Rib2 width} \leq 0.05 \\
& \quad 0.001 \leq \text{Plate1 thickness} \leq 0.009 \\
& \quad 0.001 \leq \text{Plate2 thickness} \leq 0.009 \\
& \quad 0.2 \leq c \leq 1.3 \\
& \quad \text{Mass} = 39.1950,
\end{aligned}$$

where  $f_1$  is the surrogate model representing the relationship between the design parameters and the first natural frequency.

Based on the initial design parameters, the first natural frequency of the plate calculated using CMS method is 340.13 Hz. When this value is compared with the full models' result (340.011 Hz.) a minor difference is recognized. This is because the first bending mode is passing over the junction of two components which is illustrated in figure 5.

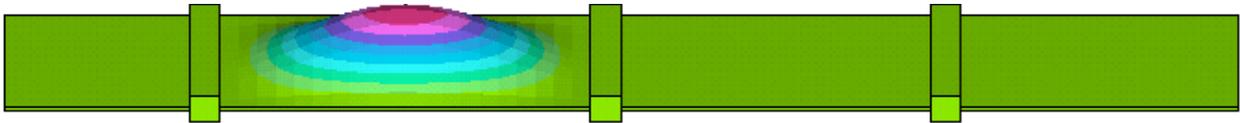


Figure 5: Initial design and the first bending mode.

The optimization process is started with 70 DOCE set. The number of the utilized hidden layer neurons in NN structure is 25. As a consequence, the number of the NN parameters (which is 226) are more than the number of the data points. Utilizing Bayesian Regularization with NN (see section 3) restricts the maximum allowable parameter number in the modeling with the data number in order to prevent overfitting and ill-posedness. Therefore, even if the number of the hidden layer neurons is large, there is no need to use a lot of data points. The only disadvantage coming with employing lot of hidden layer neurons is the increase of computation time.

When the optimization strategy is completed, the number of the elements in the training set was 107. That means, the iteration proceeds 37 times until the result of the strategy compromises with the ANSYS result (until the relative error is smaller than 0.01). The first natural bending frequency is reduced from 340.13 Hz. to 73.9043 Hz. The optimum design parameters are as follows: the thickness of Rib 1 and Rib 2 are 0.05m, the width of Rib1 and Rib2 are 0.0477m, 0.0494m respectively. The thickness of Plate 1 is 0.009m and the thickness of Plate2 is 0.001m and finally the distance  $c$  between Rib 1 and Rib2 is 0.4893m. The ANSYS CMS and the full model lowest frequencies are the same which is 74.1960 Hz. The first bending mode lies in the second component that explains the matching results of the CMS and the full model. The optimum design and the first bending mode of the plate is shown in figure 6.

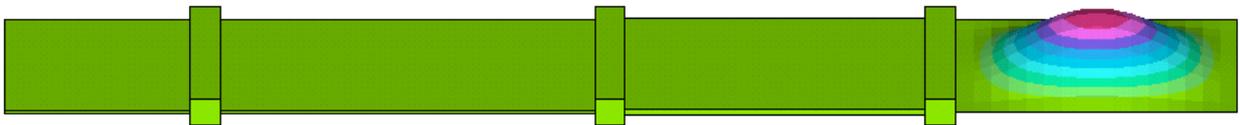


Figure 6: Optimum design and the first bending mode for Case 1.

**Case 2:** In addition to the design parameters defined in Case 1, the thickness parameter of Plate 3 is added to the design parameters set (see figure 7). The new optimization problem is as follows

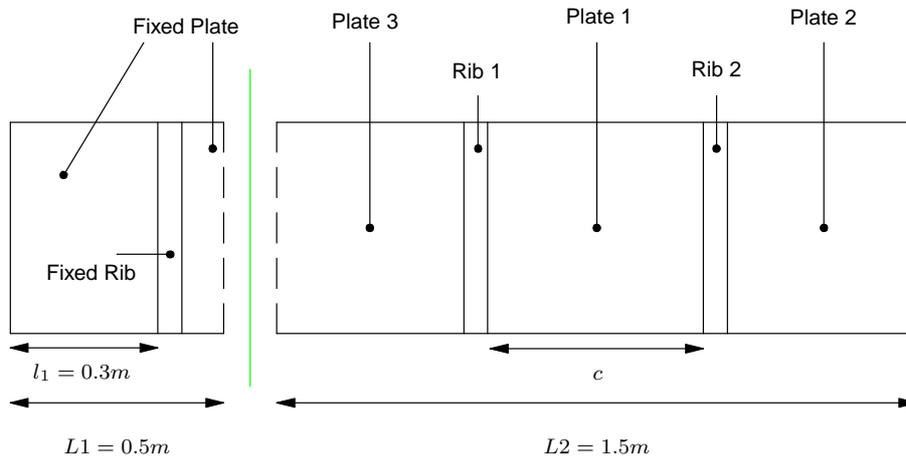


Figure 7: Design parameters and the fixed parameters for Case 2.

$$\begin{aligned} & \min f_1 \\ & \text{sbj. to } 0.01 \leq \text{Rib1 thickness} \leq 0.05 \\ & \quad 0.01 \leq \text{Rib2 thickness} \leq 0.05 \\ & \quad 0.01 \leq \text{Rib1 width} \leq 0.05 \\ & \quad 0.01 \leq \text{Rib2 width} \leq 0.05 \\ & \quad 0.001 \leq \text{Plate1 thickness} \leq 0.009 \\ & \quad 0.001 \leq \text{Plate2 thickness} \leq 0.009 \\ & \quad 0.001 \leq \text{Plate3 thickness} \leq 0.009 \\ & \quad 0.2 \leq c \leq 1.3 \\ & \quad \text{Mass} = 39.1950. \end{aligned}$$

The optimization process is started with 80 DOCE set. The number of utilized hidden layer neurons in NN structure are 25.

The iterations in the strategy proceeded 6 times for this case. Therefore there are 86 elements in the last training set. The first natural bending frequency is reduced from 340.13 Hz. to 68.7679 Hz. The optimum design parameters are as follows: the thickness of Rib 1 and Rib 2 and the width of Rib1 and Rib2 are 0.05m, 0.0392m, 0.05m and 0.0366m, respectively. The thickness of Plate 1 is 0.009m, the thickness of Plate2 is 0.009m, the thickness of Plate3 is 0.001m and finally the distance  $c$  between Rib 1 and Rib2 is 0.2499m. The ANSYS CMS and the full model lowest frequencies are the same which is 68.478 Hz. As in the previous case, the first bending mode lies in the second component. In figure 8, the optimum design and the first bending mode of the plate is illustrated.

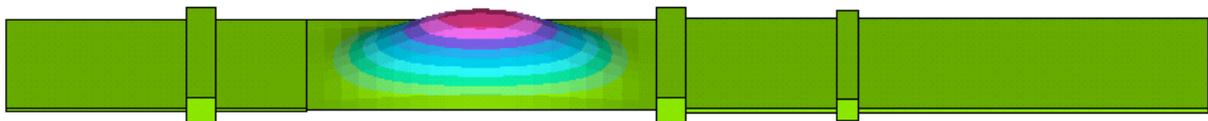


Figure 8: Optimum design and the first bending mode for Case 2.

In the first case; due to the total mass constraint and the fixed Plate 3 thickness, the first natural bending frequency was reduced to 73.9043 Hz. and the first bending mode was lying on Plate 2. When the thickness parameter of Plate 3 is added to the design parameters set, the first natural bending frequency is reduced until 68.7679 Hz. and the location of the first bending mode was detected on Plate3. The CMS results (location of

mode shapes and first eigenfrequencies) agree with the full FE analysis results. The initial design parameters, optimum parameters obtained from Case 1 and Case 2 and the corresponding first natural bending frequencies are summarized in Table 1.

Table 1: Initial design parameters and the results of the test cases.

	Rib1		Rib2		Plate1	Plate2	Plate3	c	$f_1$	
	thck(m)	width(m)	thck(m)	width(m)	thck(m)	thck(m)	thck(m)		NN(Hz.)	CMS(Hz.)
Initial	0.05	0.05	0.05	0.05	0.005	0.005	0.005	0.5	-	340.13
<b>Case1:</b>	0.05	0.0477	0.05	0.0494	0.009	0.001	-	0.49	73.90	74.20
<b>Case2:</b>	0.05	0.05	0.0392	0.0366	0.009	0.009	0.001	0.25	68.77	68.48

## 7 Conclusion

A design optimization strategy based on the integration of the CMS method with the numerical optimization techniques is introduced. FE based models are replaced by their NN surrogate models in the optimization process in order to reduce the computation time. A simple test problem is used for the demonstration of the concepts.

The proposed strategy was shown to be performing well. Once the training data is gathered, one optimization process takes only few minutes. On the other hand, it is not possible to demonstrate its computational efficiency over simple problems. The utilized CMS technique is meant for the analysis of complex structures which might be costly compared with the full FE analysis for small scale problems.

## References

- [1] Akçay Perdahcioğlu D., van der Hoogt P.J.M. and de Boer A., Design optimization applied in structural dynamics. 1st International Conference on Artificial Intelligence for Industrial Applications, 45-50, 2007.
- [2] Bonte M.H.A., Optimization Strategies for Metal Forming Processes, PhD. Thesis, University of Twente, 2007.
- [3] Coello Coello C.A., Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: A survey of the state of the art. Computer Methods in Applied Mechanics and Engineering, Volume 191, 1245-1287, 2002.
- [4] Conn A.R., Gould N.I.M and Toint P.L., A globally convergent augmented lagrangian algorithm for optimization with general constraints and simple bounds. SIAM J. Numerical Analysis, Volume 28, Number 2, 545-572, 1991.
- [5] Craig Jr. R.R. and Bampton M.C.C., Coupling of substructures for dynamic analyses. AIAA, Volume 6, Number 7, 1313-1319, 1968.
- [6] Gill P.E., Murray W., Saunders M.A. and Wright M.H., Procedures for optimization problems with a mixture of bounds and General Constraints. ACM Transactions on Mathematical Software, Volume 10, Number 3, 282-298, 1984.
- [7] Giunta A.A., Wojtkiewicz Jr. S.F. and Eldred M.S., Overview of modern design of experiments for computational simulations. AIAA, 41st Aerospace Sciences Meeting and Exhibit, Reno, Nevada, Jan. 6-9, 2003.
- [8] Gould N., Conn A.R. and Toint P.L., A globally convergent lagrangian barrier algorithm for optimization with general inequality constraints and simple bounds. Mathematics of Computation, Volume 66, Number 217, 261-288, 1997.
- [9] Foresee F.D. and Hagan M.T., Gauss Newton Approximation to Bayesian Learning. Int. Joint. Conf. Neural Networks, Volume 2, 1930-1935, 1997.
- [10] Hagan M.T. and Mohammad B.M., Training feedforward networks with the Marquardt Algorithm. IEEE Transactions on Neural Networks, Volume 5, Number 6, 989-993, 1994.

- [11] Hagan M.T., Demuth H.B. and Beale M., Neural Network Design. PWS Publishing Company, 1996.
- [12] Han S.P., A globally convergent method for nonlinear programming. Journal of Optimization Theory and Applications, Volume 22, Number 3, 297-309, 1977.
- [13] Hornik K., Multilayer feedforward networks are universal approximators. Neural Networks, Volume 2, 359-366, 1989.
- [14] Jones D.R., Schonlau M. and Welch W.J., Efficient global optimization of expensive black-box functions. Journal of Global Optimization, Volume 13, Number 4, 455-492, 1998.
- [15] Mackay D.J.C., Bayesian interpolation. Neural Computation, Volume 4, 415-447, 1992.
- [16] Nocedal J. and Wright S.J., Numerical Optimization. Springer-Verlag, New York, 1999.
- [17] Schonlau M., Computer Experiments and Global Optimization. PhD. Thesis, University of Waterloo, 1997.
- [18] Wind J., Akçay Perdahcioğlu D. and de Boer A., Distributed Multilevel Optimization for Complex Structures. Structural and Multidisciplinary Optimization Journal (accepted for publication), 2007.