Abstract
This paper presents an inverse procedure for the determination of external loads, given the dynamic responses of the loaded structure and its corresponding finite element model. The influence of the stress-stiffening effect on the dynamic characteristics of structural systems is used to establish a relation between the dynamical responses and the applied external loading. An optimization problem is formulated in which the objective function represents the difference between the measured modal characteristics of the loaded structure and their FE counterparts. The loading parameters, assumed as being unknown, are considered as the design variables. The identification procedure is illustrated by means of numerical simulations. In which the identification problem is solved by using the heuristic named LifeCycle model together with the Lagrange-Newton SQP (Sequential Quadratic Programming) method.

1 Introduction

In various applications related to structural engineering, it is very important to determine the external loading under real service conditions, aiming at evaluating the level of security of the structure, to verify the design configurations that were adopted at the design stage, or for redesigning structural elements for new operating conditions. However, the determination of external loading is not simple from the experimental point of view because, in general, transducers can not be easily introduced in the structure during its mounting. Consequently, in most real-life structures, experimental determination of external loading is not feasible.

By taking into account the influence exerted by the external loading on the dynamical response of the system through the effect of stress-stiffening, it is possible to obtain information about the loading distribution, through an inverse problem approach. Depending on the size of the structure, such a procedure presents a number of practical advantages:

- simple measurement and processing of dynamical responses by using a limited amount of sensors and signal conditioners;
- simple access to the measurement points along the structure (the dynamical responses represent global characteristics of the structure);
- availability of experimental techniques for excitation and data acquisition, as currently used in classical experimental modal analysis.

On the other hand, some difficulties that are intrinsic to inverse problems may arise, such as:

- it is required an accurate mathematical model of the structure (the results of the identification procedure rely upon the mathematical model used);
- in general, identification problems are ill conditioned from the mathematical point of view (this means that the procedure is sensitive to noise that can contaminate experimental data);
the experimental data are incomplete either in the spatial sense (responses are available only in a limited number of positions along the structure), as in the spectral sense (responses are obtained in a given frequency band). Consequently, the uniqueness of the solution can not be assured.

In structural systems for which operation, integrity and security rely on the dynamical characteristics, the effect of external loading on the dynamical behavior of the system is to be carefully analyzed. The study of the dynamical behavior of mechanical systems can be done through numerical modeling techniques or by means of experimental modal analysis. Each technique exhibits its own hypotheses, limitations, advantages and disadvantages as shown in [3]. In this sense, parameter identification by model updating involves various steps and the main objective is to improve the model, in such a way that numerical results mimic those obtained from experimental testing.

Many modeling techniques are available, however the Finite Element Method – FEM is recognized as being the most flexible tool for structural analysis and for that reason has become very popular in the engineering community, as described in [1]. It is worth mentioning that, in parallel with the development of the finite element method, modal analysis techniques have been improved significantly in the past twenty years and are considered as being fairly reliable in determining the dynamical characteristics of mechanical systems. Parameter identification methods and model updating techniques result from the necessity of constructing more reliable mathematical models, considering that finite element models and experimental models are only approximations of real structure behavior, as illustrated in [4].

There exist various techniques to solve inverse problems by using optimization methods, involving either classical as well as heuristic approaches. In this case, optimizing an objective function, which is related to the dynamic behavior of the system, performs identification. It is expected that the optimal parameter values correspond to the real ones. Once the parameters are identified, the mathematical model becomes an effective tool to analyze and predict the dynamics of the structure under different operating conditions.

It is well known that the solution of inverse problems by using optimization methods is a difficult task due to the existence of local minima in the design space. This aspect has motivated the authors of this paper to explore an inverse problem approach for the determination of external loading in structures, based on a new heuristic named LifeCycle model that was introduced in reference [13]. In the present paper this heuristics is coupled with a classical approach to refine the local search. The Lagrange-Newton sequential quadratic programming technique is used [5].

In order to improve the identification algorithm, other heuristic methods can be implemented. In such a way, one of the heuristics used in LifeCycle model, the Particle Swarm Optimization, was implemented to solve the same kind of problem in a companion paper [14].

2 Dynamic modeling of two dimensional structures including the stress-stiffening effect

In this section it is briefly reviewed the finite element modeling of two-dimensional beam-like structures, according to the theory of Euler-Bernoulli, including the effect of the axial load, as illustrated in Figure 1.
Where:

- \( u_i^L \) and \( u_i^R \) are the longitudinal nodal displacements,
- \( v_i^L \) and \( v_i^R \) are the transversal nodal displacements,
- \( \theta_i^L \) and \( \theta_i^R \) are the nodal cross section rotations,
- \( l_i \) is the length of the element,
- \( E_i \) is the modulus of elasticity of the material,
- \( A_i \) is the area of the cross section,
- \( I_i \) is the area moment of inertia,
- \( p_i \) is the distributed longitudinal load and
- \( N_i \) is the concentrated axial load applied to the nodes of the element.

The indexes \( L \) and \( R \) indicate, respectively, the displacements and rotations at the left hand and right hand nodes of the element.

Using a linear interpolation function to represent the longitudinal displacement and a cubical function for the transversal displacement, the following expressions for the element stiffness and mass matrices are obtained [2]:

\[
K_i = \begin{bmatrix}
\frac{E_i A_i}{l_i} & 0 & 0 & -\frac{E_i A_i}{l_i} & 0 & 0 \\
\frac{12E_i I_i}{l_i^3} + \frac{6N_i}{5} l_i & \frac{6E_i I_i}{l_i^2} + \frac{1}{10} N_i & 0 & -\frac{12E_i I_i}{l_i^3} - \frac{6N_i}{5} l_i & \frac{6E_i I_i}{l_i^2} + \frac{1}{10} N_i \\
4E_i I_i + \frac{2}{15} N_i l_i & 0 & -\frac{6E_i I_i}{l_i^2} - \frac{1}{10} N_i & 2E_i I_i - \frac{1}{30} N_i l_i & 0 \\
\frac{E_i A_i}{l_i} & 0 & 0 & \frac{12E_i I_i}{l_i^3} + \frac{6N_i}{5} l_i & -\frac{6E_i I_i}{l_i^2} - \frac{1}{10} N_i \\
\frac{4E_i I_i}{l_i^2} + \frac{2}{15} N_i l_i & 0 & -\frac{6E_i I_i}{l_i^2} - \frac{1}{10} N_i & \frac{4E_i I_i}{l_i} + \frac{2}{15} N_i l_i
\end{bmatrix}
\]  

(1)

\[
M_i = \frac{m_i}{420} \begin{bmatrix}
140 & 0 & 0 & 70 & 0 & 0 \\
156 & 22I_i & 0 & 54 & -13l_i & 0 \\
4l_i^2 & 0 & 13l_i & -3l_i^2 & 0 & 0 \\
70 & 0 & 0 & \frac{156}{420} & -22l_i & 0 \\
\end{bmatrix}
\]  

(2)

where \( m_i = \rho_i A_i l_i \) and \( \rho_i \) represents the density of the material.

The influence of the axial load can be observed in the stiffness matrix at the elements corresponding to the bending stiffness, representing, therefore, the effect of stress-stiffening.

The global equations of motion are represented in the matrix form by (3):

\[
M \ddot{X}(t) + K(p) X(t) = Q(t)
\]  

(3)
where \( \mathbf{p} \) is the vector of the axial loads applied to the beam elements that integrate the finite element model of the structure.

From the equations of motion, the following eigenvalue problem can be derived:

\[
\left[ \mathbf{K}(\mathbf{p}) - \lambda \mathbf{M} \right] \mathbf{X} = \mathbf{0}
\]  \( \text{(4)} \)

Where \( \lambda = \Omega^2 \) is the eigenvalue (natural frequency) and \( \mathbf{X} \) is the eigenvector (mode shape).

The matrix form of the frequency response functions (FRFs) is calculated as:

\[
\mathbf{H}(\Omega) = \left[ \mathbf{K}(\mathbf{p}) - \Omega^2 \mathbf{M} \right]^{-1}
\]  \( \text{(5)} \)

The equations above show that the dynamic responses depend on the applied axial loads in the elements of the structure, which depend directly on the external load applied to the structure. Before performing the dynamic analysis of the structure, a static analysis must be carried out to determine the axial loads for each element.

### 3 Inverse problem description

The identification procedure to determine the external loads consists in solving a constrained optimization problem, whose cost function represents the difference between the measured and model-predicted natural frequencies and/or the vibration mode shapes of the loaded structure. The magnitude, position and direction of the external loads (assumed as unknown) play the role of design variables.

This way, one intends to obtain the loads to be applied in the model that optimally reproduces the experimental responses of the loaded structure.

For that purpose, the cost function used in this work is defined as:

\[
J(\mathbf{p}) = \sum_{i=1}^{m} \left\{ W_m \left| \frac{\Omega_i^{(m)}(\mathbf{p}) - \Omega_i^{(e)}}{\Omega_i^{(e)}} \right| + W_e \left| \frac{\mathbf{V}_i^{(m)}(\mathbf{p}) - \mathbf{V}_i^{(e)}}{\mathbf{V}_i^{(e)}} \right| + W_M \left[ 1 - MAC\left[ \mathbf{V}_i^{(m)}(\mathbf{p}), \mathbf{V}_i^{(e)} \right] \right] \right\}
\]  \( \text{(6)} \)

with the side constraints:

\[
\mathbf{p}^L \leq \mathbf{p} \leq \mathbf{p}^U
\]  \( \text{(7)} \)

where:

- \( MAC\left[ \mathbf{V}_i^{(m)}(\mathbf{p}), \mathbf{V}_i^{(e)} \right] = \left[ \frac{\mathbf{V}_i^{(m)}(\mathbf{p})^T \mathbf{V}_i^{(e)} \mathbf{V}_i^{(e)} \mathbf{V}_i^{(e)}}{\mathbf{V}_i^{(m)}(\mathbf{p})^T \mathbf{V}_i^{(e)} \mathbf{V}_i^{(e)}} \right]^2 \) is the so-called Modal Assurance Criterion;
- \( m \) is the number of eigen-solutions used;
- \( \mathbf{p} \) is the vector of external load parameters (to be identified);
• $\omega_i^{(m)}(p)$ and $V_i^{(m)}(p)$ are natural frequencies and vibration mode shapes calculated from the finite element model, respectively;

• $\omega_i^{(e)}(p)$ and $V_i^{(e)}(p)$ are experimental natural frequencies and vibration mode shapes of the loaded-structure, respectively;

• $W_o$, $W_v$ and $W_M$ are weighting factors.

The side constraints are introduced to limit the values of the design variables within a feasible design sub-space (design space), avoiding the possibility of buckling or structural collapse due to extreme external load levels.

In the applications considered in this work, the cost function was constructed by using the first six modal parameters and limiting the value of the total load identified between zero and the first buckling load of the structure. Obviously, when the position and the directions of the load are to be identified, the design space becomes discrete and its dimension depends on the maximum number of nodes of the finite element model and the number of degrees of freedom for each node, respectively. The following applications illustrate different load configurations (magnitude, position and direction) that are characterized by increasing the number of load parameters to be identified, aiming at evaluating the influence of the number of unknown parameters in the performance of the identification procedure, as in [8]. Also, it is intended to present examples showing structures with different levels of complexity.

In this paper the optimization procedure uses modal parameters obtained through numerical simulation as “experimental values” in the objective function. Since this methodology is devoted to further experimental developments, it is important to take into account errors that arise in experimental modal analysis. Consequently, modal data are corrupted by random perturbations and the results are compared to those obtained for the case without noise.

The numerical solution of the optimization problem is accomplished by using the pseudo-random heuristic LyfeCycle model together with the traditional gradient-based Sequential Quadratic Programming – SQP optimization method.

4 Optimization strategy

The natural optimization methods are known to be effective in complex problems where classical techniques fail due to local minima. However, optimization tools like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have their performance dependent on the problem features. The goal of this new method, named LifeCycle model, is to overcome this limitation through a self-adaptive heuristic, in which each individual can decide the best scheme to improve the optimization work.

In this paper, the answer obtained from LifeCycle model is used as an initial estimation to the SQP technique. This hybrid approach refines the solution given by the LifeCycle optimizer.

4.1 The LifeCycle model

4.1.1 Artificial life background

LifeCycle model is an optimization method based on artificial life (ALife) principles. The term ALife is used to describe the study of systems that have some essential features of life. ALife can be divided in two important topics:

• how computational techniques can help in biologic phenomenon studies.

• how biologic principles can help to solve computational problems.
In this context, the LifeCycle model is a computational tool inspired in the biologic concept of life cycle. From a biology viewpoint, the term is used here to define the passage through the phases during the life of an individual. Some phases, as sexual maturity, are one-time events, others, as the mating seasons, are re-occurring. Although it does not happen in every case, the transitions between life cycle phases are started by environmental factors or by the necessity to fit to a new condition [13]. The transition process promotes the maturity of an individual and contributes to the adaptation and evolution of its species.

From the optimization viewpoint, the capability of changing to a different stage by searching a way to improve the own fitness to the environment can be used to inspire a new optimization method. In this sense, the fitness provides a criterion used by each individual to shift its life stage. Different from what happens in genetic algorithms, where the natural evolution inspires the optimization method as a whole, in the LifeCycle model the transitions between the stages inspire just a part of the method. The transitions are used to deal with the mechanism of self-adaptation to the optimization problem. To close the definition, the LifeCycle stages must be defined. In the present work, two heuristics are used as stages, namely the GA and the PSO. Others versions of the LifeCycle model can be proposed by considering other heuristics and a mix of them as shown in [13]. This means that the optimization approach does not follow a rigid scheme as proposed in [10], in which various techniques are used sequentially in a cascade-type of structure.

4.1.2 Basic LifeCycle model algorithm

The outline of a basic LifeCycle algorithm is as follows:

1. Initialize the algorithm parameters for the PSO and GA.
2. Evaluate the fitness for all particles (PSO) and individuals (GA).
   - If there is no recent improvement, switch the LifeCycle stage (change from GA to PSO or vice-versa).
3. For all PSO particles, run the PSO algorithm.
4. For all GA individuals, run the GA algorithm.
5. Go to step 2 and iterate until a stop criterion is achieved.

In the above LifeCycle model the algorithm is initialized with a set of particles of a PSO swarm, which can turn into GA individuals, and then, according to their performance, back to particles again and so on. A LifeCycle individual switches its stage when there is no fitness improvement for more than a previously defined number of iterations. In this work, this will be a parameter that can be adjusted according to the problem.

4.1.3 Parameters of LifeCycle model

Since the algorithm is composed by various heuristics, it is necessary to set the parameters of every heuristic used in the LifeCycle Model. Nevertheless, there is a parameter inherent to the LifeCycle model, namely the number of iterations that represents a stage of the LifeCycle. The authors, to improve the algorithm performance, have introduced this parameter, differently from what is usually done by simply fixing this number as in [13]. We call this number as stage interval. At the end of each stage interval, the less well-succeeded individuals must change their stage in order to improve their fitness.

4.1.4 The stop criteria

In this work no convergence criterion is used. Simply, the number of iterations was defined previously and the algorithm iterates until this number is achieved. However, relative errors calculated for successive iterations can be used to stop the algorithm.
4.1.5 The PSO heuristic

PSO is an optimization algorithm based in the swarm theory. The electrical engineer Russell Eberhart and the social psychologist James Kennedy introduced the basic PSO algorithm, in 1995 as shown in [9]. They were inspired in the “flocking behavior” models developed by the biologist Frank Heppner, as illustrated in [12].

Heppner’s birds’ model counterbalances the desire to stay in the flock with the desire to roost. Initially, the birds are searching for a roosting area. If a bird searches alone, the success probability is small, but in a flocking work, the birds can cooperate with each other and this behavior will facilitate the global search.

Using simple rules, a bird in its flight is influenced by its own movement, its knowledge about the flight area and the flock performance. In this way, if a bird finds the roosting area, this would result in some birds moving towards the roost. From the socio-cognitive viewpoint this means that mind and intelligence are social features, as demonstrated in [12].

Following this principle, each individual learns (and contributes) primarily to the success of his neighbors. This fact requires the balance between exploration (the capacity of individual search) and exploitation (the capacity of learning from the neighbors).

Search for a roost is an analogous procedure to optimization, and the flying search area has the same meaning as the design or search space in optimization. In the PSO algorithm the social behavior of birds is modeled by using position and velocity vectors together with parameters like self-trust, swarm trust and inertia of the particle [11]. The outline of a basic PSO is as follows:

1. Define the PSO parameters (inertia, self trust, swarm trust, etc.).
2. Create an initial swarm, randomly distributed throughout the design space (other distributions can be performed).
3. Update the velocity vector of each particle.
4. Update the position vector of each particle.
5. Go to step 3 and iterate until the stop criterion is achieved.

Unlike the Genetic Algorithms, the PSO algorithm is inherently a continuous optimization tool, however, by using straightforward approaches (by rounding) it is possible to deal with discrete/integer design variables.

4.1.6 The GA heuristic

GA is an optimization algorithm based on Darwin’s theory of survival and evolution of species, as explained in [6] and [7]. The algorithm starts from a population of random individuals, viewed as candidate solutions to the problem. During the evolutionary process, each individual of the population is evaluated, reflecting its adaptation capability to the environment. Some of the individuals of the population are preserved while others are discarded; this process mimics the natural selection in the Darwinism. The remained group of individuals is paired in order to generate new individuals to replace the worst ones in the population, which are discarded in the selection process. Finally, some of them can be submitted to mutation, and as a consequence, the chromosomes of these individuals are altered. The entire process is repeated until a satisfactory solution is found.

The outline of a basic GA is as follows:

1. Define the GA parameters (number of individuals, selection method, crossover method, mutation rate, etc.).
2. Create an initial population, randomly distributed throughout the design space (other distributions can be performed).
3. Evaluate the objective function and take it as a fitness measure of each individual.
4. Select mates to the crossover; this mimics the natural selection.
5. Reproduce and replace the worst individuals in the population by the offspring.
6. Mutate, to avoid premature convergence (other parts of the design space are explored).
7. Go to step 3 and repeat until the stop criterion is achieved.

Although the initial proposed GA algorithm was dedicated to discrete variables, nowadays, improvements are available to deal with discrete and continuous variables, see [6] and [7] for more details.

4.2 Sequential quadratic programming (SQP)

The linear search algorithm used in this paper is based on the Lagrange-Newton Sequential Quadratic Method (SQP) and is devoted to the minimization of a function of several variables $f(x)$, subjected to linear/non-linear equality and inequality constraints ($Ax \leq B$, $A_{eq}x = B_{eq}$, $Cx \leq 0$, $C_{eq}x = 0$) and side constraints ($l_b \leq x \leq l_u$). To obtain the optimal solution it is required an initial estimation of the optimization parameters [5]. Obviously, in the case of the present contribution, the results obtained from SPQ depend on the initial estimation of the external forces and the number of variables to be identified.

5 Identification results

5.1 Simple structure

Figure 2 shows a finite element model of a simple frame structure used in the identification process, for which the first buckling load is $20123 \,[\text{N}]$. It is submitted to four different load configurations. The identification problem consists in determining the loading parameters.

Finite element model
24 elements
66 degrees of freedom

$E = 2.1 \times 10^{11} \, [\text{Pa}]$
$B = 1.50 \, [\text{m}]$
$H = 1.00 \, [\text{m}]$
$b = 0.04 \, [\text{m}]$
$h = 0.015 \, [\text{m}]$
$\rho = 7800 \, [\text{Kg/m}^3]$
$\nu = 0.30$

$F_1 = 8049.00 \, [\text{N}]$ $F_2 = 7545.94 \, [\text{N}]$ $F_3 = 10061.25 \, [\text{N}]$

Figure 2: Simple structure FEM model

The following scenarios are studied: 1 - identification of the magnitude of $F_1$; 2 - identification of the magnitude and position of $F_1$; 3 - identification of the magnitude, position and direction of $F_1$; 4 -
identification of the magnitude and position of forces $F_2$ and $F_3$. Table 1 presents the natural frequencies with and without the external load for all studied scenarios.

Table 2 presents the identification results to various loading configurations (scenarios) for the simple structure. In real applications, the identification method has to be robust enough to deal with experimental errors. Consequently, the method is also applied to a situation in which “experimental” data are corrupted with 10% of random error, as can be observed in Table 2. The results show that the optimization approach used in the force identification procedure was efficient for all scenarios analyzed.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Natural Frequencies [Hz]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.42 15.07 22.74 28.30 51.85 59.64</td>
</tr>
<tr>
<td>2</td>
<td>3.49 13.20 21.69 28.56 49.89 58.05</td>
</tr>
<tr>
<td>3</td>
<td>1.66 10.59 20.34 28.71 47.30 56.22</td>
</tr>
</tbody>
</table>

Table 1: Natural frequencies of the simple structure

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Without corrupted data</th>
<th>With corrupted data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LifeCycle</td>
<td>Hybrid</td>
</tr>
<tr>
<td>1 $F_1$ [N]</td>
<td>8049.00</td>
<td>8053.03</td>
</tr>
<tr>
<td>2 $F_1$ [N]</td>
<td>8049.00</td>
<td>8278.40</td>
</tr>
<tr>
<td>$P_1$</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>3 $F_1$ [N]</td>
<td>8049.00</td>
<td>8044.98</td>
</tr>
<tr>
<td>$P_1$</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>$D_1$</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>4 $F_2$ [N]</td>
<td>7545.94</td>
<td>6547.86</td>
</tr>
<tr>
<td>$P_2$</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>$F_3$ [N]</td>
<td>10061.26</td>
<td>11023.11</td>
</tr>
<tr>
<td>$P_3$</td>
<td>11</td>
<td>11</td>
</tr>
</tbody>
</table>

Table 2: Identification results – simple structure

The behavior of the LifeCycle model along the iterations can be observed in Figure 3 for the scenario 4, without noise. Figure 3-a shows the transitions due to its self-adaptation skills and Figure 3-b shows which heuristics is conducting the optimization process along the iterations.
In the case illustrated in Figure 3 the stage interval is equal to 5 iterations; this means that transitions between PSO and GA happen at each group of 5 iterations. Since LifeCycle starts with PSO particles (in this case), in the first 5 iterations there are no GA individuals in the population. During the optimization process it can be observed that the LifeCycle individuals switch their stage (transition) to improve the objective function value.

5.2 Complex structure

Also, the authors intended to evaluate the efficiency of the identification algorithm when applied to a more complex finite element model. For this aim, a mechanical structure for which the first buckling load is 4669060 [N] is presented in Figure 4. In this case, the magnitude of a single force was determined (its position and direction were known \textit{a priori}). Table 3 presents the natural frequencies with and without the external load for the complex structure.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Natural Frequencies [Hz]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Without load</td>
<td>29.51</td>
</tr>
<tr>
<td>1 ( F_1 \text{[N]} )</td>
<td>23.50</td>
</tr>
</tbody>
</table>

Table 3: Natural frequencies of the complex structure
Finite element model
81 elements
204 degrees of freedom

\[ E = 2.1 \times 10^{11} \text{ [Pa]} \]
\[ A = 6.16 \times 10^{-4} \text{ [m}^2\text{]} \]
\[ I = 7.40 \times 10^{-7} \text{ [m}^4\text{]} \]
\[ \rho = 7800 \text{ [Kg/m}^3\text{]} \]
\[ \nu = 0.30 \]

\[ F_1 = 2334530.00 \text{ [N]} \]

Finite element model
81 elements
204 degrees of freedom

Table 4 presents the identification results for the complex structure. As in the previous case, “experimental” data were corrupted with 10% of random error for comparison purposes. Again, the results demonstrate the efficiency of the identification procedure.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Without corrupted data</th>
<th>With corrupted data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LifeCycle</td>
<td>Hybrid</td>
</tr>
<tr>
<td>1</td>
<td>Exact</td>
<td>Optimum</td>
</tr>
<tr>
<td></td>
<td>( F_1 \text{ [N]} )</td>
<td>2334530.00</td>
</tr>
</tbody>
</table>

Table 4: Identification results – complex structure

As it was illustrated for the simple structure (Figure 3), Figure 5 shows how the self-adaptation has performed in the complex structure case. The transitions between PSO and GA and the objective function value through the iterations can be seen.
In both cases presented (simple and complex mechanical structures), the results obtained by using LifeCycle model were used as an initial configuration for a second optimization run. This way the SQP method was used in this final step, thus forming a hybrid optimization approach. The most significant result of this approach is that the continuous design variables (force magnitudes) could be improved with respect to the previous step as obtained at the end of the LifeCycle run.

6 Conclusions

This paper presented an identification procedure to determine external forces applied to mechanical structures. The identification strategy is based on hybrid optimization methods as performed by LifeCycle model and SPQ techniques. The influence of experimental errors was taken into account to test the robustness of the procedure. Various identification scenarios were investigated, in such a way that the efficiency of the identification procedure was checked from a simple case in which a single force magnitude was determined to a configuration in which two force magnitudes and positions were obtained. In the cases for which the force positions were to be determined, the optimizer was able to deal with discrete design variables together with continuous ones. In most cases, the second optimization run using SPQ was very important to improve the results obtained from LifeCycle model, since LifeCycle alone is not able to reach the global optimum. However, when corrupted data are used, SQP does not improve the results obtained from LifeCycle for all cases studied. This can be explained by the fact that SQP requires the computation of gradients of the cost function (partial derivatives). The corrupted data may locally increase the noise effect in calculating such derivatives, thus compromising the resulting optimal value obtained as demonstrated in [15]. Random data errors smaller than 3% do not influence the identification procedure. The results obtained are encouraging in the sense that real experimental data can be used in the near future to test the methodology developed under real-world conditions.

Acknowledgements

The authors are thankful to the Brazilian Research Agencies CNPq and CAPES for the financial support of this research work.
References


