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Comparison of predictive techniques for spacecraft shock environment

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Abstract. Shock loads are very high amplitude and short duration transient loads. They are produced in space structures by pyrotechnic devices placed in the launchers initiating the stage or fairing separations. While the spacecraft structure is not susceptible to this range of frequencies, electrical units could be seriously damaged during the launch phase. Shock tests are performed on the electrical units to verify if they withstand the transient loads, thus their compliance to the requirements. To understand how the input force evolves from the launcher-spacecraft interface to the equipment of interest, a model of the dynamical behaviour of the spacecraft at high frequencies has to be developed. An initial approach constitutes the implementation of a mathematical model through the use of Statistical Energy Analysis (SEA). The results of a 4 degrees of freedom model using SEA will be shown. The model can be further developed by the integration of data-driven techniques. In this work a description of two different approaches is presented, that include model-based and data-driven methods. Finally, a cross-cutting potential solution is briefly introduced; it will combine experimental data with a mathematical model as to convey them in the training database of an Artificial Neural Network algorithm. The hybrid solution will possibly turn out as a reliable and efficient way to break down time and costs of the shock test campaign.

Introduction

During launch, the spacecraft experiences full-frequency dynamic loads, which go from 10 up to 10k Hz. The full-frequency band bring about great discrepancy of structure responses at different frequencies. This phenomenon is more evident at high frequencies, where shock occurs. The structure no longer shows a deterministic behaviour, and a statistical approach is needed. A way to boost the spacecraft development process could be to identify a technique that predict the structure response of any spacecraft when it is subjected to shock loads for the entire frequency range that the spacecraft encounters during launch. The integration of the technique in the design phase of the spacecraft structure could facilitate, shorten, or even avoid, the mechanical shock test.

The case study is a multi-Launcher satellite, meaning that it is designed to be compatible with more than one launcher. A satellite test campaign is usually customised for every launch because the requirements are given by the Launcher Authority, which differ from case to case. Having a multi-Launcher satellite means that it is qualified on an envelope of multiple launchers' requirements and there is no need to retest it for every mission.

The multi-launcher Satellite is composed by:

- Bus Module (BM), that supports mechanically the overall Payload Module.
- Payload Module (PM). The structure is mated onto the BM and includes the specific supporting structure required to link (thermo-)mechanically the Payload System to Platform Module.

The study case is the Structural Model (SM) of the Multi-Launcher satellite. The SM is designed to be mechanically representative of the spacecraft and it is used to perform qualification tests. A drawing of the SM is shown in Fig. 1. The SM is composed by two parts:

- Structural part
- Dummy masses, that simulate the mechanical properties of the equipment and the harness.

The peculiarity of this item is its recurrent platform, meaning that the platform can be adapted to multiple launchers and payloads.

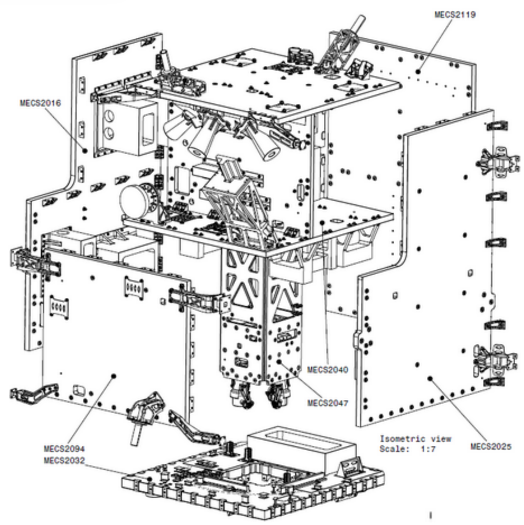

Fig. 1 – Structural Model of the spacecraft

The spacecraft undergoes the shock input represented in Fig. 2, resulting from an envelope of multiple launchers.

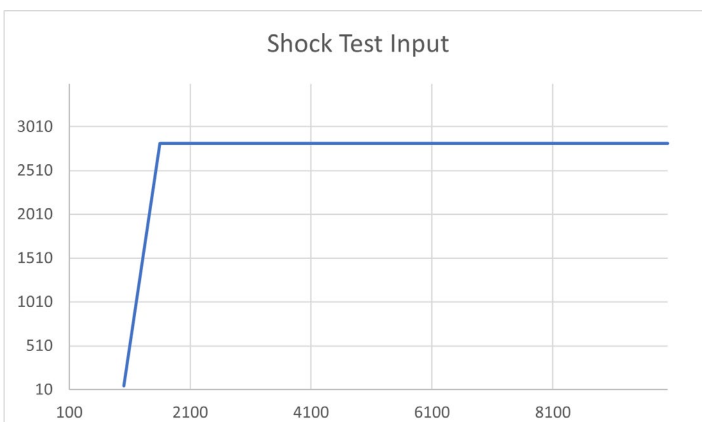

Fig. 2 - Shock input

To compute the response of the spacecraft to any shock load, it is necessary to identify the model that describes the real system behaviour and captures only the essential features of interest, leaving out everything else. If the essential dynamic of the system is known, it is possible to take a white box approach to create a model, using first principles and physics or multi-body technique. In this case, the use of a simplified description of a system is called model-based design. On the opposite side of the spectrum, there is the black box method that is mainly used to make prediction of the behaviour of a system when the dynamics are unknown, but a certain amount of data is available. However, there is a cross between the two approaches. Some rough knowledge of the

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system can help in the decision of the right structure. This is called a grey box method because it is possible to use approximate knowledge of the physics of the system, through the use of numerical investigation techniques, to set up the initial problem and then using data to learn the remaining portion of the model structure or parameters set.

This work explores the white and black approaches that can be implemented for the study case. Finally, a hybrid solution that combines SEA and Artificial Neural Network (ANN) will be introduced. The overall problem is summed up in Fig. 3.

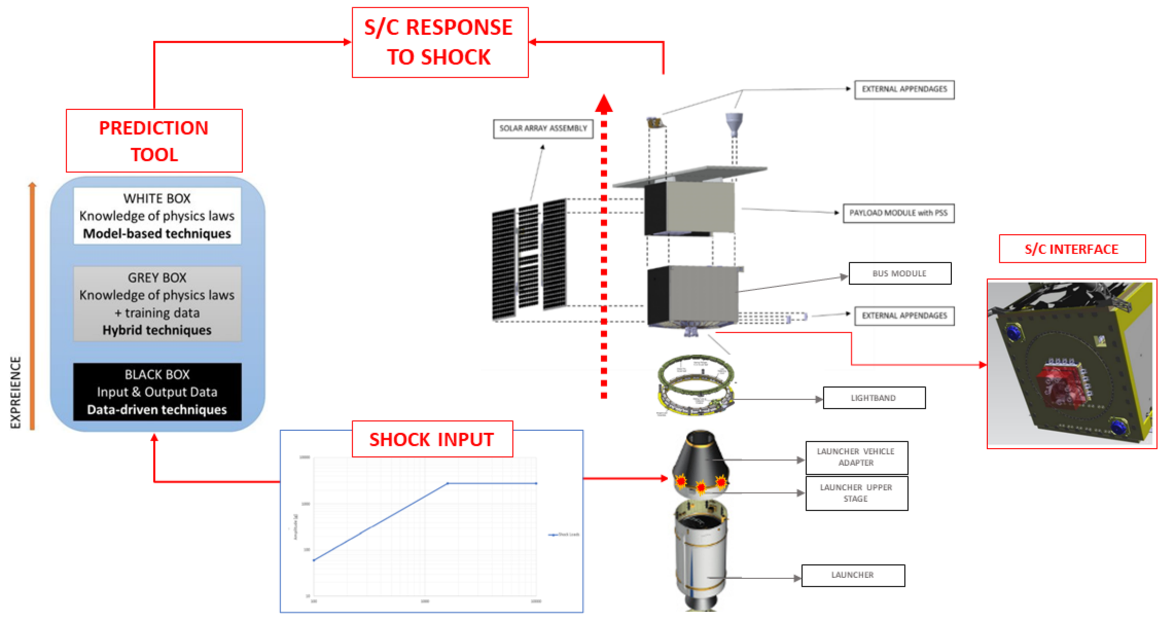

Fig. 3 - Illustration of the problem

State of the art

The major issue of shock prediction is due to its wide frequency range. The main difference is encountered between low and high frequency. At low frequency identical structures produce the same response, and it is possible to use a deterministic approach. For low frequency range, Finite Element Method (FEM) is one of the most mature and accepted numerical tool. On the other hand, at high frequencies, the modes have very small effective mass and there is high modal density and modal overlap. Thus, a minor difference between two identical structures could results in totally different response and the structure does not longer show a deterministic and predictable behaviour. FEM starts to be too sensitive to details and less accurate since the mesh must decrease in size resulting in to match the smallest characteristic deformations that occur a such frequencies [1], resulting in high computation costs [2]. A statistical approach needs to be applied. The most common technique is the Statistical Energy Analysis (SEA): the main idea in SEA is that a complex structure (e.g., a spacecraft) is described as a network of subsystems where the stored and exchanged energies are analysed [3].When dealing with mid frequency there is no universally accepted method as the structure does show neither a deterministic nor a chaotic behaviour. Accordingly, [4] proposed an improved methodology based on the Hybrid Finite Element-Statistical Energy Analysis (FE-SEA) method. Since SEA is able to deal with high frequency problems, combining FEM and SEA it is possible to cover the entire frequency range with rationality and sufficient accuracy of the prediction results. The hybrid method can predict the middle and high frequency shock response more effectively and reasonably, and the computational efficiency is greatly improved, compared with the traditional FEM. [5] proposed the Virtual Mode Synthesis Simulation (VMSS) method, where the dynamical system is numerically convoluted with a measurement or simulated excitation force to obtain the dynamic response in the time domain. This numerical method resulted to be suitable to solve the problem of transient and high frequency environment prediction. [6] combined SEA in conjunction with VMSS to predict the dynamic response of a low altitude earth observation satellite during launch vehicle separation. In industry, The *Unified Approach And Practical Implementation Of Attenuation Rules For Typical Spacecraft Shock Generated Environments* [7] is a common technique that uses experimental data and allows to determine the acceleration at the mounting points of most critical components. This method traces the path of the shock load that propagates from its source (i.e., the spacecraft interface), where the acceleration is known, to the locations of the critical units. The attenuation factor is computed for each section of the path. It depends mainly on distance, angle, type of structure (e.g., honeycomb, skin-frame, monocoque, etc.) and presence of joints. These data have been collected mainly during experimental activities performed over the years in the European Space Agency (ESA).

The last several years have seen the academic field increasingly focused on data analysis subjects [8]. The effort arose from the fact that physics-based models have a relatively high computational demand, and are unsuitable for probabilistic, risk-based analyses. Quite the opposite, the data-driven methodology is simple in principle and easy to implement. Hence, a new data-driven approach makes use of Artificial Intelligence (AI) in building models that would replace the model-based techniques describing physical systems. The main advantage is that data-driven techniques work well with black box approaches, when the physical behaviour is unknown. Nevertheless, this activity is close in its objectives to traditional approaches to modelling and follows the traditionally accepted modelling steps.

Data-driven modelling comprehends a wide range of techniques, which include Machine learning (ML) and Artificial Neural Network (ANN). ANN turns out to be a powerful means because is able to store large amounts of experimental information to solve poorly defined problems that have eluded solutions by conventional computing techniques. This technology takes inspiration from a simplified biological neural network: an artificial neuron receives a signal then processes it through mathematical functions and sends it to the connected neurons, which are typically aggregated in layers. The output of each layer is the weighted sum of the outputs from the previous one. During the learning or training process, the weighting factors are modified so that the calculated output match the actual output, trying to minimise the error. An ANN is thus a dynamic system. This feature would result in a highly robust system where, changing the information stored in one element will have little effect on the final output. [9] proposed an ANN model for complex contacting bodies that, compared with the conventional model-based methods, is simple in principle and easy to implement. The method demonstrates great advantages of ANN when the internal mechanisms are unknown or too complicated to be explored so far. Contrary to conventional model-based techniques, neural networks can learn from example and generalize solutions to new representations of a problem, can adapt to small changes in a problem, are tolerant to errors in the input data, can process information rapidly, and are modular between computing systems. Neural networks cannot, however, guarantee success in finding an acceptable solution, and a limited ability to rationalise the solutions provided[10]. Moreover, ANN has been applied successfully to solve many difficult and diverse problems by training them with the feedforward and back-propagation algorithm. [11] presented a method for solving both ordinary differential equations (ODE's) and partial differential equations (PDE's) that relies on the function approximation capabilities of feedforward neural networks and results in the construction of a solution written in a differentiable, closed analytic form. The method could be extended in the abovementioned study case, for example to solve eigenvalue problems for differential operators.

[12] investigated the use of black-box ODE solvers as a model component, allowing explicit control of the trade-off between computation speed and accuracy.

Statistical Energy Analysis

In the first part of the work a traditional model-based method has been investigated. Statistical Energy Analysis (SEA) is a well-known method notably used for acoustics problems in the sixties. Later, it has been introduced in shock prediction to overcome FEM limitations at high frequencies. SEA describes behavior of complex systems by a set of energy-balanced equations between the various domains (subsystems) of the analyzed system. SEA assumes both perfect diffusion and weak coupling of subsystem vibrations. It makes use of wave propagation theory rather than modal approach, in order to decrease the computational cost at high frequencies. Coefficients of energy exchange driving the equations are predicted classically from analytical wave theory by decomposing modes into uncorrelated waves (diffusion of energy).

A single subsystem is considered as a separated part of the structure to be analysed. Any excitation acting on the subsystem can be characterised by the resulting power input P_i into the subsystem. If power is injected, the subsystem stores vibrational energy W_i. In practice, there will be also a power loss P_{ii} due to dissipation. This power loss may be related to the stored energy by the Damping Loss Factor (DLF) η_i by

$$P_i = \omega * \eta_i * W_i \quad . \tag{1}$$

If we consider a coupled subsystem, they share vibrational energy, in addition to the previous formula. So, the first subsystem will have two types of dissipation, one towards the external and one flowing to the other subsystem. The same phenomena occur in the reverse direction, so the Exchanged Power P_{ij} is the same for directly coupled subsystems.

$$P_{ij} = P_{ji} = \omega * \eta_{ij} * W_i \quad , \tag{2}$$

with η_{ij} known as the Coupling Loss Factor (CLF), indicating how well the subsystems are connected with each other. The global energy balance of the whole system can be written as

$$P_i = \omega * \eta_{ij} * E_i + \sum_{j=\neq}^{n} \omega * \eta_{ij} * E_i - \eta_{ji} * E_j \quad , \tag{3}$$

where ω represents the angular center frequency and Ei and Ej are the frequency energy levels of the subsystems. It can also be written in compact matrix form:

$$P = \omega[\eta]E, \tag{4}$$

where [η] is known as Damping Loss Matrix. Finally, we have the reciprocity relation:

$$n_i * \eta_{ij} = n_j * \eta_{ji} \quad , \tag{5}$$

with n_i and n_j being the modal densities. Eq. 4 and Eq. 5 constitute the basic SEA equations.

As soon as matrix [η] is known, it can be used repeatedly to predict the response of the subsystems for any given vector of injected powers at a negligible computational cost. It constitutes a reduced model, which describes the global system in terms of the energy content of its subsystems. This is what renders it well suited for high frequency simulations, where local indicator results are inefficient.

As an example, the method is applied on a 4 Degrees-of-Freedom (DoFs) system. The system is composed of two aluminium beams connected on their extremities with an angle of 90°. The system presents four subsystems, each one related to a different exchange of energy in terms of longitudinal and flexural waves, as shown in Fig. 4. It has been chosen to neglect the energy transmission of longitudinal waves between the two beams.

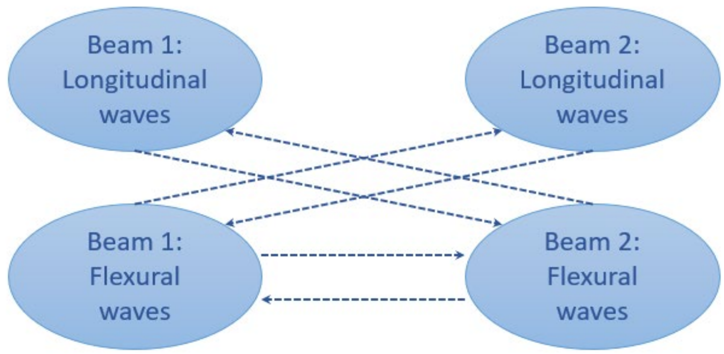

Fig. 4 - SEA subsystems

Basics SEA equations have been computed and the has been determined for each subsystem, as shown in Figure. The major difference between deterministic methods and SEA is that the former uses displacements, velocities and accelerations computed in determined locations and frequencies as parameters. The latter express averaged global variables. The resulting average square velocity, as shown in Fig. 5, has been averaged over points of observation, points of excitation and frequency.

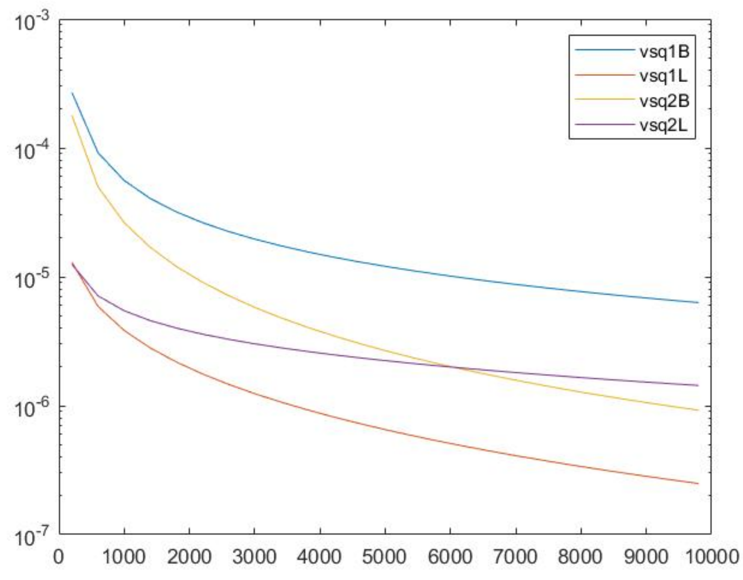

Fig. 5 - Average square velocities for bending and flexural waves of systems 1,2

The following step will be to adapt the SEA model using the previously presented shock input and converting the resulting average square velocity in terms of averaged acceleration. The model can be adapted for CFRP honeycomb sandwich panels, simulating the Structural Model mechanical properties. In this case a 6 DoF system should be modelled, as shear forces will appear. The results will be compared with the experimental method which is currently used in the industry [7]. Both the approaches computer the attenuation path of the shock load from its source to the location of interest.

Afterwards, the model forms the basis to implement an hybrid technique, that will involve a ANN algorithm. It will be trained with shock test data history that has been collected over the years and combined with the SEA model.

Conclusion

To avoid damage of the sensitive units during launch, the spacecraft must be tested thoroughly before it is sent into space. During the various phases of its development the spacecraft and its component parts undergo extensive testing. In the development process of a spacecraft, the shock test phase is time-consuming and expensive. It could be replaced by a mathematical model that predict, with certain assumptions, the structure response to dynamic loads. However, accurate prediction of the shock environment is critical to system and structure design, due to its broad frequency range and high acceleration levels. The combination of model-based and data-driven techniques to predict the structure response to shock loads could result in a reliable and efficient way to break down time and costs of the shock test campaign. This work presented SEA and ANN as potential solutions. A SEA model has been represented as a starting point for further development.

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