Proceedings of the 7th International Conference on Mechanics and Materials in Design
Albufeira/Portugal 11-15 June 2017. Editors J.F. Silva Gomes and S.A. Meguid.
Publ. INEGI/FEUP (2017)

PAPER REF: 6574

OPTIMIZATION OF THE AUXILIARY-BEAM SYSTEM IN RAILWAY BRIDGE VIBRATION MITIGATION USING FEM SIMULATION AND GENETIC ALGORITHMS

J.G. Baldonedo[1], A. Segade[1(*)], J.A. López-Campos[1], E. Casarejos[1], J.R. Fernández[2], J.A. Vilán[1], J. Collazo-Rodríguez[1], M. López-Lago[1]

[1]Department of Mechanical Engineering, University of Vigo, Vigo, Spain
[2]Department of Applied Mathematics I, University of Vigo, Vigo, Spain
[(*)]*Email:* asegade@uvigo.es

ABSTRACT

This work studies the mitigation of vertical vibrations in railway bridges by using a so called 'auxiliary beam' system and a finite element method for evaluation. The bridge was modelled as a unidimensional and simply supported beam, in order to run simulations as fast as possible, while keeping the main characteristics of the bridge and producing the key parameters. The studied parameters were the damping coefficient and the moment of inertia of the auxiliary beam. We defined a non-dimensional combination of the parameters in order to generalize the results to any generic case. In our work we combined ANSYS® and MATLAB software to implement a genetic algorithm that optimized the damping characteristics of the system. Finally, a detailed comparison of the original undamped bridge and the bridge with the damping system was carried out.

Keywords: optimization, railway bridge, auxiliary-beam system, damping, moving loads, resonance phenomena, FEM, genetic algorithms.

INTRODUCTION

With the expansion of high-speed railway lines, the railway bridges must tolerate high train speeds while preserving all the safety specifications. The moving trains produce periodical forces due to the constant distance existing between the axles. The repetitive forces induce a vibrational response (Yang, 1996) in the bridge, and that affects directly the allowable speed limit. To safely increase the speed limit of the bridges, different vibration mitigation systems had been implemented.

The Tuned Mass Damper (TMD) system is probably the most studied method for vibration mitigation in both bridges and buildings (Lin, 2005). The alternative 'auxiliary beam' system (Museros, 2006), other times known as 'double beam' system, consists of an added beam installed under the bridge deck, and connected to it by viscous dampers, see Fig. 1. The auxiliary beam would absorb most of the energy generated by the moving loads on the bridge-plus-train assembly, and reducing both the vertical acceleration and the displacement of the bridge itself. The advantage of the auxiliary beam (AB) system over the TMD system is that the AB system works in a wide range of frequencies, while the TDM is tuned to a single frequency value, typically the lowest natural frequency of the bridge. The frequency range difference may be the design key for the design selection. Actually the trains modify the bridge natural frequencies, and the change differs for different trains. For the design of the

AB systems, it is important to define the characteristics and the distribution of the dampers, and obtain an optimized performance.

The goal of this work was to study an AB system defined to allow for the maximum speed of a particular train. The safety constrains were given for the particular safety regulations. We used the Spanish IAPF regulation (Ministerio de Fomento, 2010), which restricts both the maximum displacement in the middle of the bridge span, and its maximum acceleration.

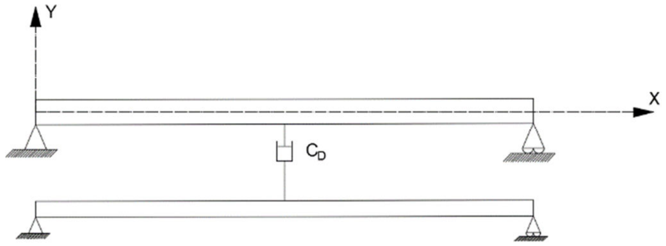


Fig. 1 - Auxiliary-Beam system: A simply supported beam (upper beam) is supplemented by an auxiliary beam connected by viscous dampers.

The mathematical method for the optimization will be a genetic algorithm. This case study with two parameters and a single fitness function could be studied by other methods as gradient conjugate or Newton, but genetic algorithms open other fields as the use of a non-derivable fitness function or multiobjetive studies.

In the next lines, we are going to describe the physical and FEM model of the bridge, the genetic algorithm including its initialization, fitness evaluation and evolution, and finally the obtained results.

PHYSICAL MODEL

The AB system we studied consisted of a simply supported bridge and a set of auxiliary beams connected by viscous dampers. The bridge deck was modelled as a regular homogenous concrete slab, 5 m width and 1.2 m thick. The resulting section inertia moment was 0.720 m^4. The slab was supported at the ends (cf. Fig.1), and the pillars were not considered in the study.

The auxiliary system was made as a set of steel beams with HEM profile located beneath the bridge deck. The number of auxiliary beams considered was ten, which is the maximum number that can be fitted efficiently in a retrofitting method (Lavado, 2013). The size of the beams was one of the parameters to obtain. The beams could be of different sizes for a better performance, within a range of 56 to 486 mm. The beams were connected to the pillars as firmly as possible. We note that the simply supported case we studied corresponds also to the most adverse situation.

The connection between any auxiliary beam element and the bridge was made with viscous dampers located in the middle of the span of the bridge, where the maximum vertical accelerations and displacements appear. The characteristic parameter of the damper was the second parameter to obtain. The load limit of the dampers was set to 5000 kN.

In our model the variables to operate with were the inertia of the beams and the damping coefficient. To obtain a generic description we defined non-dimensional factors. The moments of inertia of the beams (I_z) were normalized to that of the bridge deck. The damping coefficient (C) was normalized to the structural damping of the bridge. We defined both parameters as:

$$\theta = \frac{C_{Bridge}}{C_D};\ C_{Bridge} = \beta \cdot k \approx 2.1 \cdot 10^5$$

$$\gamma = \frac{I_z^{Beam}}{I_z^{Bridge}}$$

β is a coefficient of the stiffness matrix, used to obtain the damping of the bridge. It is obtained from the structural damping coefficient (2%) given by the IAPF, and the frequency of the first mode of vibration, as well as the moment of inertia and the stiffness (EI). k is the flexural stiffness of the bridge.

FEM MODEL

Running a genetic algorithm typically requires many simulations to search for the optimized results. Therefore, the model used must be as simple as possible to ensure a reasonable computing time, while maintaining the quality of the results.

Both the bridge and the auxiliary beams were defined within ANSYS® as uniaxial beam type elements (beam4). Regarding the damper, it is modelled as a spring damper element with uniaxial tension-compression properties (combin14).

The whole system consisted in a two dimensional model: rotations allowed along the x and y axes, and restricted displacement on the z axis. The supports constrained the rotations in the x and y axis, and the vertical displacements.

The number of elements of the grid was determined using a mesh sensitivity analysis, concluding that eleven elements were enough to obtain consistent results for this type of studies.

The time step was defined as 0.05 divided by the maximum natural frequency of the bridge below 30Hz, a value which is recommended by the IAPF rules we were using.

The train was modelled as a set of moving loads, based on the EUROSTAR 373/1 train type. The velocity considered was 330 km/h, at which the bridge reaches the maximum vertical acceleration in the middle of the bridge span.

GENETIC ALGORITHM

Genetic algorithms are valuable tools to optimize parameters in the case of complex problems, which could hardly be obtained analytically (Fonseca, 1995). The technique is inspired in how evolution takes place in nature, selecting the individuals that are more fitted to the environment and discarding the non-fitted ones. The most fitted individuals procreate, having offspring they have to compete with in the next generation. Sometimes an individual can suffer a mutation. It can either be positive to its ability to fit in the environment and the genes will be maintained, or negative, leading to its disappearance.

In this particular case, the individuals (case possibilities) will have only two genes: the normalized inertia (γ) and the normalized damping coefficient (θ). Their performance will determine how much the particular values are preferred. The performance was evaluated by two other parameters: the maximum acceleration in the middle of the bridge span, and the total mass of the beams used in a damping system. The range of variation of the genes (the parametric domain) was established within the ranges mentioned in previous sections.

After a certain number of generations, the individuals have evolved. The most fitted individuals were evaluated individually to obtain the final results.

INITIAL POPULATION

For the first iteration of the algorithm there are no predecessors to evaluate and generate offspring. Therefore, some initial population must be given to the algorithm for initialization purposes. In order to obtain a well-distributed initial population while maintaining it random, we used the Latin Square method (McKay, 1979). This method generates a semi random population in such a way that two individuals will not share any common gen value. A graphic explanation of this method is shown in Fig. 2. The partitions of the gen domains define the number of spaces (N), and determines de number of individuals obtained by this method.

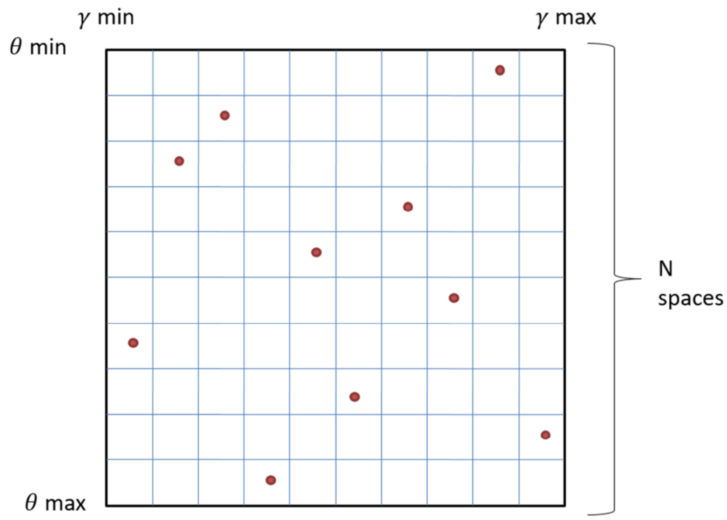
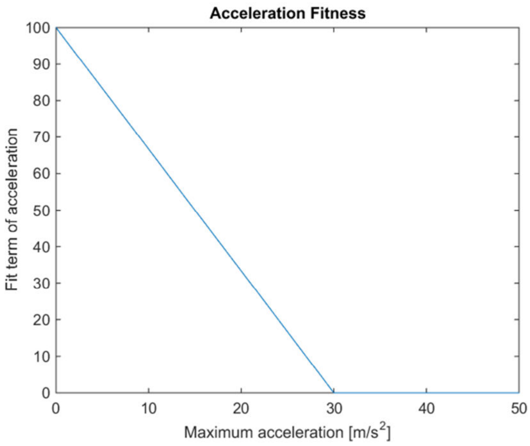


Fig. 2 - Latin Square method (McKay, 1979). The two gens (γ and θ) are within their parametric domain. The partition of each domain and the combinations of the two gens with the not-sharing condition, define the maximum number of available individuals.

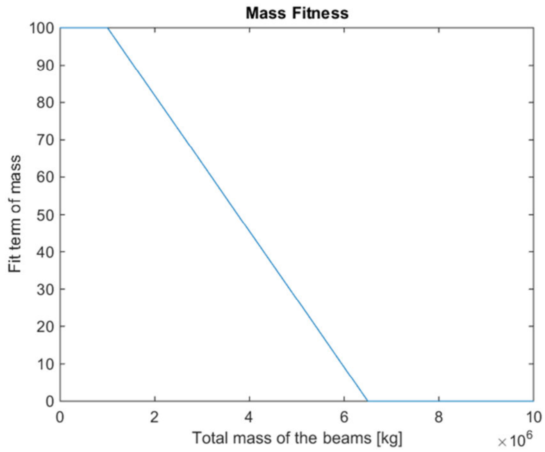
FITNESS EVALUATION

The performance (fitness) of the individuals was evaluated in terms of the maximum acceleration reached in the middle of the span of the bridge, and the total mass of the beams obtained in any particular solution. These two parameters had to be minimized. Therefore if the acceleration or the mass values increased, the performance value had to decrease. The function that assigned the fit of an individual (particular solution) based in the input parameters is the key point in the development of the algorithm. There is no general rule to generate this performance function. Only the know-how and the trial-and-error can provide with suitable solutions (Fonseca, 1995).

We used a performance evaluation so that the two parameters were calculated independently. The limit values for acceleration were in the range from 0 m/s^2 to 30 m/s^2 (structural failure), corresponding linearly to 100 and 0 performance values respectively, see Fig.3a. For the mass parameter we assigned a linear function between 10.000 and 65.000 kg, being constant for lower and bigger values, see Fig.3b. The total performance value was evaluated as the combination of the two independent performances, with a weight of 0.95 for acceleration and 0.05 for mass. The weighting coefficients were selected by trial-and-error. We obtained that for higher values of the mass weight the algorithm was only selecting more reduced masses for any acceleration values. With this weighting, a proper balance of the two parameters was achieved. Finally, the fitness function provides with values in the range within 100 for no acceleration and mass below 10.000 Kg, down to 0 for maximum acceleration and mass over 65.000 kg



(a)



(b)

Fig. 3 - a (left) Fitness function for acceleration. Fig. 3b (right) Fitness function for total mass.

SELECTION OPERATOR, CROSSOVER AND MUTATION

For the progress of the algorithm and to choose the best fitted individuals for obtaining their offspring, a selection must be done. We e used a simple Stochastic Universal Sampling (SUS) technique (Baker, 1987). The SUS method divides the total fitness space in a number of sections with lengths according to the fitness value, see Fig. 4. A straight random sampling provides better options to solutions with better performances. Note that each segment contains a collection of the genes corresponding to the original partitions of γ and θ.

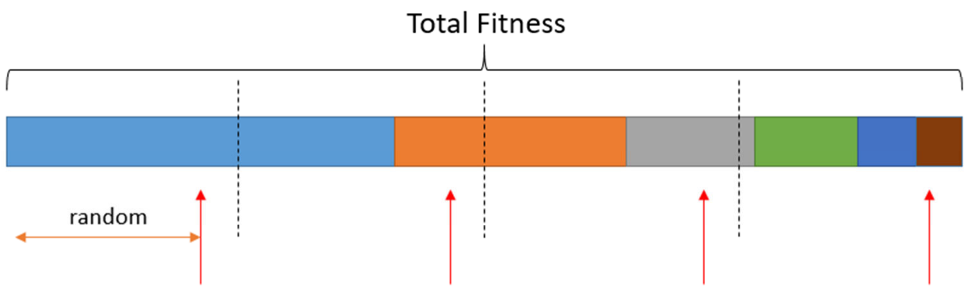


Fig. 4 - Stochastic Universal Sampling implementation.

Once the best fitted individuals are chosen in one step, all possible combinations between pairs of genes were made, and, from each gen couple, a new individual appears for the evaluation of its performance. The rule followed to obtain the genes of this new individual is a random weighted mean between the genes of its progenitors. A numerical example follows, for a pair (γ,θ)

$$Progenitor\ A: (0.01, 4) \qquad Progenitor\ B: (0.02, 6)$$
$$for\ \alpha \equiv random\ number, the\ new\ individual\ C\ is:$$
$$First\ Gen = 0.01 \cdot \alpha + 0.02 \cdot (1 - \alpha) \qquad Second\ Gen = 4 \cdot \alpha + 6 \cdot (1 - \alpha)$$
$$for\ \alpha = 0.3, C \equiv (0.017, 5.4)$$

Some of the new individuals will be closer to one of the progenitor's, others will be an equilibrated mixing, and it is indeed possible to obtain muted gen values, away of the original seeds. This method helps in creating diversity, which allows the algorithm to evaluate regions of the parametric domain that were previously discarded.

RESULTS OF THE GENETIC ALGORITHM

According to our model conditions we obtained parametric domains with values of γ in the range from 0.001 to 0.035 and values of θ in the range from 0.5 to 20. The genetic algorithm applied provided the following results.

In Fig.5 we plot the (γ, θ) region population obtained after 16 generations, being the color scale the performance, ranging from blue (low performance) till red (high performance). As expected the preferred regions show a higher density and performance. That is the function of the offspring selection. Indeed, the whole region is explored, due to the diversity allowed to the descendants.

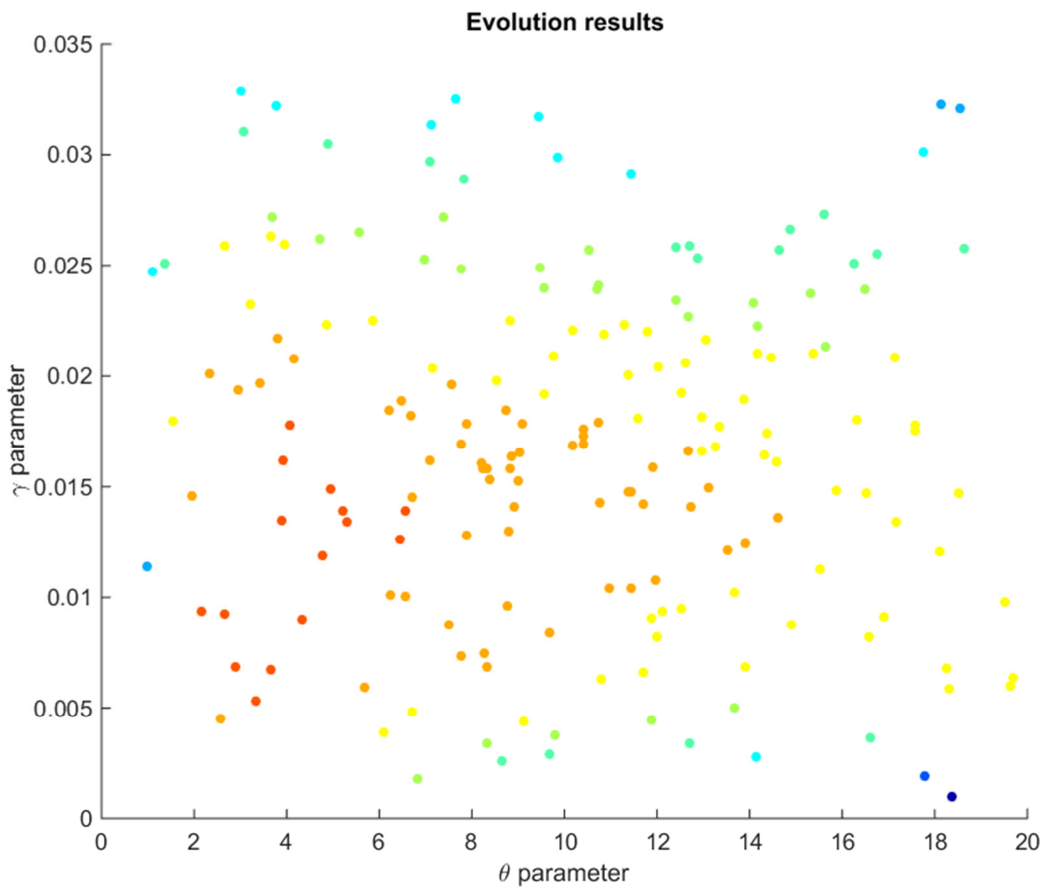


Fig. 5 - Results of the Genetic Algorithm. The (γ, θ) region population was obtained after 16 generations, being the color scale the performance, ranging from blue (low performance) till red (high performance). As expected the preferred regions show a higher density and performance.

After the initial screening, we made a second study focused into limited ranges of values of γ (from 0.001 to 0.02) and θ (from 0.5 to 10). In Fig.6 we show the same plot adapted to the new region, after 16 generations of the algorithm. We obtained most individuals with high performance values. The 3 cases with the highest performances are listed in Table.1.

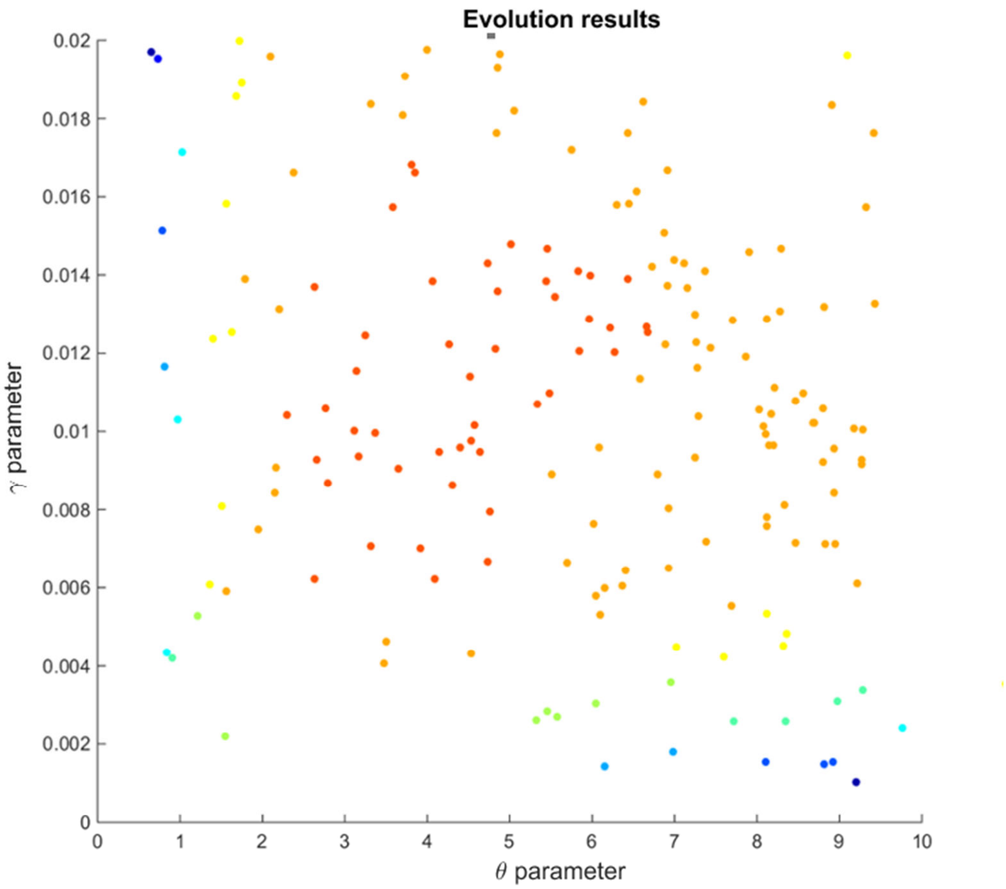


Fig. 6 - Results of the Genetic Algorithm applied to a limited parameter region. After 16 generations most of the individuals show a high performance value.

Table 1: Parameters of the 3 cases with highest performance obtained

	θ	γ	Max. Acceleration (m/s^2)	Beam Mass (kg)	Total Performance
Individual 1	3,13483	0,0115446	7,93833	49.918	71,2331
Individual 2	2,20038	0,0131284	8,09074	50.602	70,6882
Individual 3	7,29121	0,0103875	8,19198	49.485	70,4692

As can be seen in Table 1, the values of the parameters vary in more than 100% for the mean value of θ, and about 20% for γ.

In Figs. 7, 8 y 9 we plot the vertical acceleration in the middle of the bridge span, the displacement and the reaction loads in the pillars, respectively, given for the three selected solutions, as well as the un-damped solution. All individuals produce an important reduction (up to 50% for acceleration and more for displacement and load) in respect to the un-damped solution.

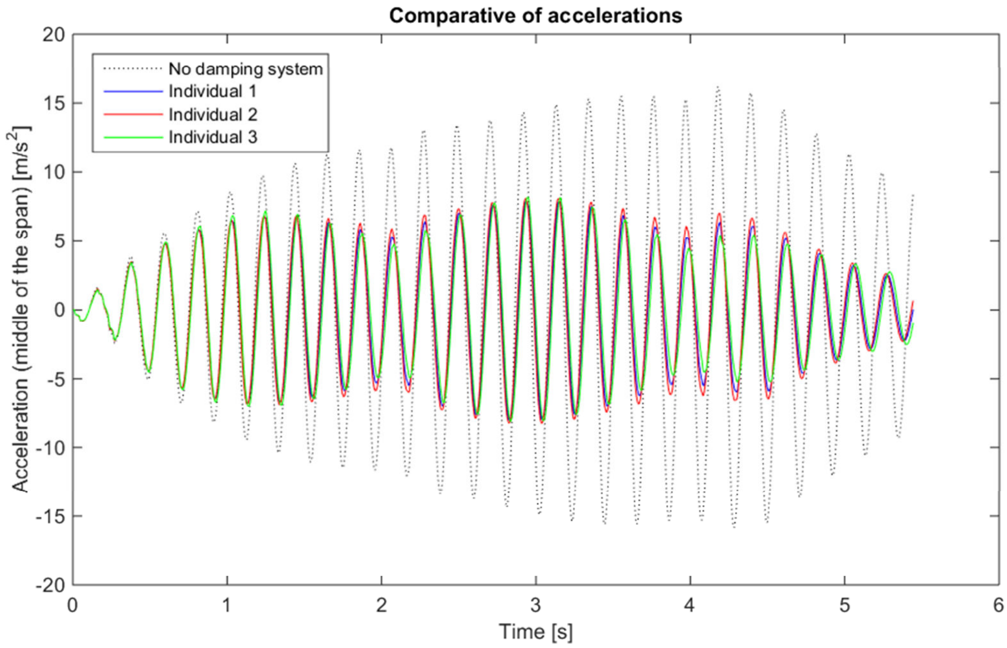


Fig. 7 - Vertical acceleration in the middle of the bridge span given for the three selected solutions, as well as the un-damped solution.

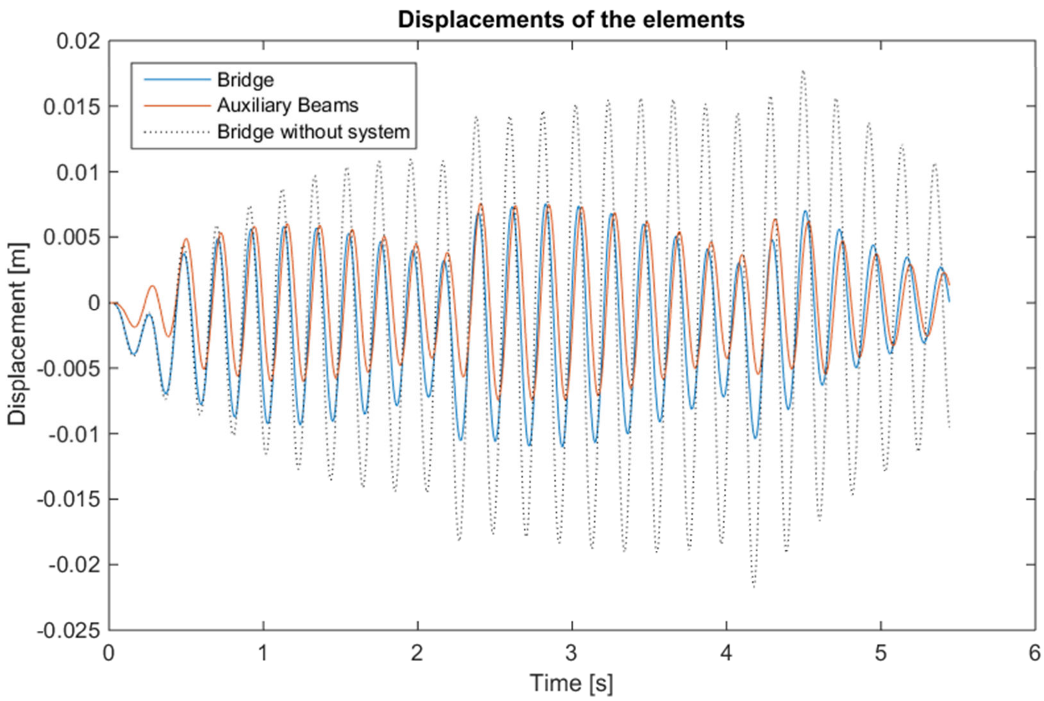


Fig. 8 - Displacement in the middle span of the bridge and the beams for the three solutions and the un-damped case.

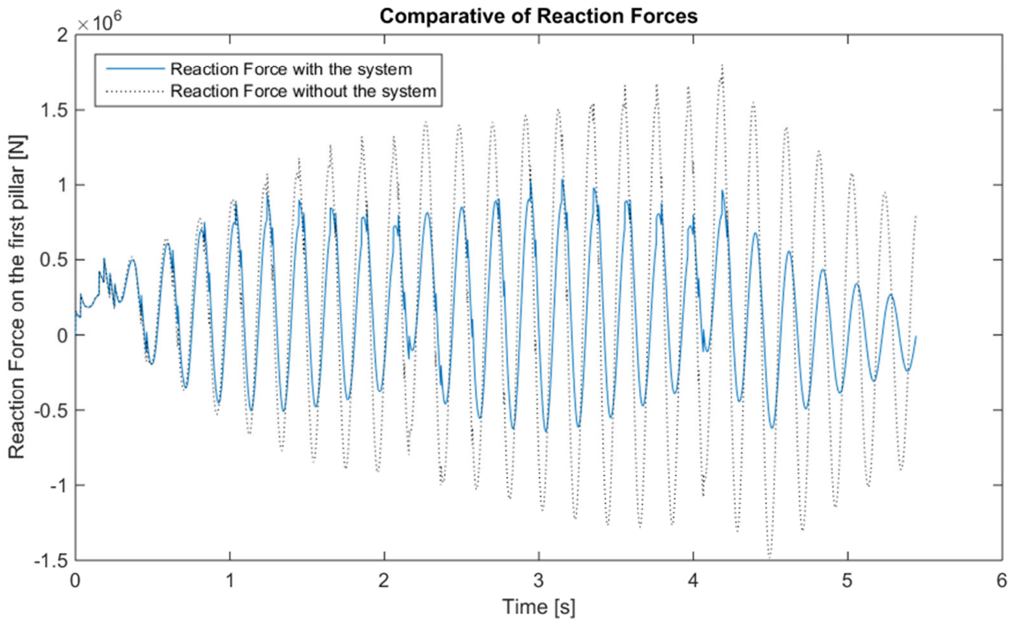


Fig. 9 - Reaction loads in the pillars of the bridge for the three solutions and the un-damped case.

When a range of velocities from 100 to 400 km/h is studied (Fig. 10), the differences between the three candidates become evident. In general, candidates 1 and 2 show a better performance than candidate 3. Particularly, candidate 2 presents a lower acceleration peak than candidate 1, however they have a very similar performance within all the range.

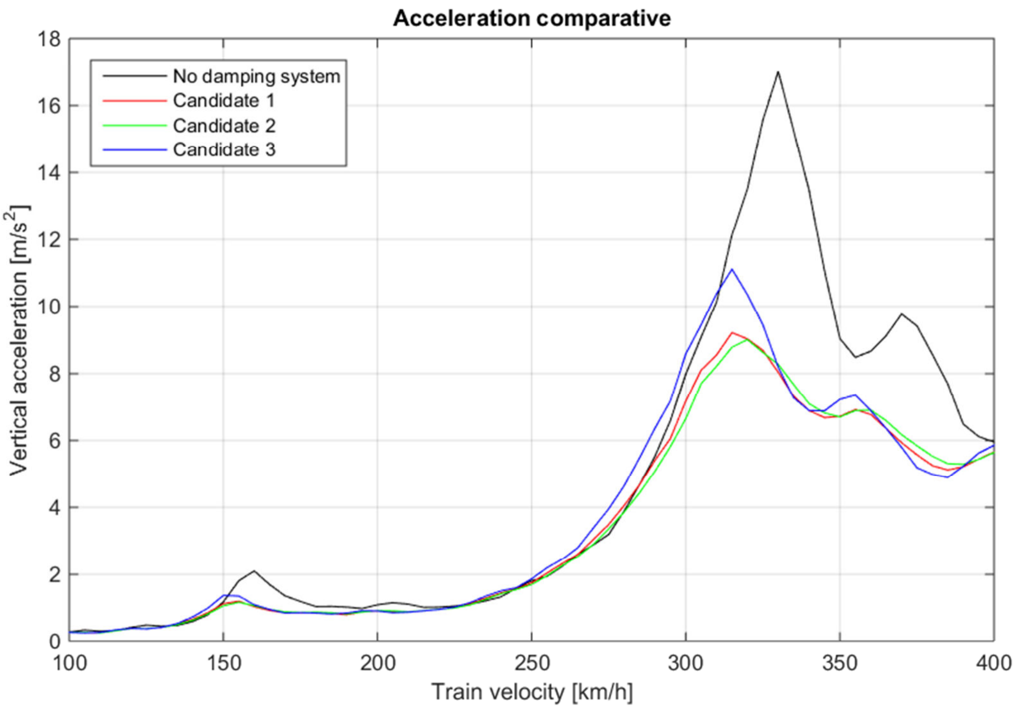


Fig. 10 - Comparative of the vertical accelerations with the three candidates and the undamped bridge in a range of train velocities.

CONCLUSION

In this study, we investigated the design of an auxiliary beam system to help in the behaviour of bridges with high-speed trains passing on. We used a simplified 2D model and ANSYS® to provide the modal analysis, while we implemented a genetic algorithm in MATLAB for the searching of the preferred parameters of the AB system. This study showed the capabilities of implementing adequate particular software tools to undertake complex problems.

We developed a parametric search such that we could define best combinations for the parameters that define an AB system in a generic case. We obtained solutions that differ in the particular values applied to the masses and damping characteristics, and, however, provide the best compensation effects on the bridge. This wide-spectra searching method shows the powerful capabilities of the technique to provide with robust results for complex phenomena.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the funding by Xunta de Galicia, Spain, under the program Grupos de Referencia Competitiva with reference GRC2015/016.

López-Campos gratefully acknowledge the funding by “Universidade de Vigo”, Spain, under the program “Axudas predoutorais” with reference 00VI 131H 641.02

REFERENCES

[1]-Baker JE. Reducing Bias and Inefficiency in the Selection Algorithm. Proceedings of the Second International Conference on Genetic Algorithms and their Application, 1987, p. 14-21.

[2]-Fonseca CM, Fleming PJ. An Overview of Evolutionary Algorithms in Multiobjective Optimization. Evolutionary Computation, 1995, 3, p. 1-16.

[3]-Lavado J, Doménech A, Martínez-Rodrigo MD. Dynamic performance of existing high-speed railway bridges under resonant conditions following a retrofit with fluid viscous dampers supported on clamped auxiliary beams. Engineering Structures, 2013, 59, p. 355-374.

[4]-Lin CC, Wang JF, Chen BL. Train-Induced vibration control of high-speed railway bridges equipped with multiple tuned mass dampers. Journal of Bridge and Engineering, 2005, 10, p. 398-414.

[5]-McKay MD, Beckman RJ, Conover WJ. A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code. American Statistical Association, 1979, 21, p. 239-245.

[6]-Ministerio de Fomento. Instrucción de acciones a considerar en puentes de ferrocarril (IAPF). NIPO: 161-10-229-X, 2010.

[7]-Museros P, Martinez-Rodrigo MD. Vibration control of simply supported beams under moving loads using fluid viscous dampers. Journal of Sound and Vibration, 2007, 300, p. 292-315.

[8]-Yang YB, Yau JD, Hsu LC. Vibration of simple beams due to trains moving at high speeds. Engineering Structures, 1996, 19, p. 936-944.