USE OF STOCHASTIC ANALYSIS FOR *FMVSS210* SIMULATION READINESS FOR CORRELATION TO HARDWARE TESTING

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Abstract

The FMVSS210 regulation establishes requirements for seat belt assembly anchorage. The Federal government mandate requires use of Pelvic and Torso Body Blocks for testing belt anchor strengths for lap and shoulder belts respectively. The belt anchorages are to be designed to withstand loads of 13.34 kN if both lap and shoulder belts are used and 22.24 kN if only lap belts are used. The analytical simulation of the hardware test is done using LS-DYNA. Hardware testing is of quasi-static nature while the simulation uses the dynamic code. However the analysis could be made to approach the quasi-static test by adjusting some input parameters in the simulation. In addition, some input parameters need adjustment for making the model more robust and to make it correlate with the hardware test.

This study involves the use of Optimal Symmetric Latin Hypercube Design to explore the design space, and to develop a fast surface response model. This response model can be viewed as a surrogate model to the actual LS-DYNA simulation. This response model is used to rank the input parameters by its percent contribution towards the variation of the output responses. After determining the fit of the response model, it is used to perform the stochastic simulation. The confidence interval for test correlation prediction can then be estimated. This technique can further be used for design sensitivity studies and for improving the vehicle structure with respect to FMVSS210 regulation.

Introduction

Federal Safety Standard Number 210 for seat belt assembly anchorages requires quasi-static tests to be performed using Lap and Torso blocks (Figure 1) representing Pelvic and Torso areas in contact with seat belts. Seats with both shoulder and lap belts used are to be designed to constrain Pelvic and Torso Body Blocks at a ramp load of 13.34kN applied in 30 Secs and held for 10 Secs. Seats with lap belts only are to be designed to sustain a force of 22.24kN. For simulation of these events using LS-DYNA, the ramp time used is anywhere from 70 msec to 250 msec. The quasi-static test simulation using dynamic code requires the adjustment of number of input parameters in the simulation. The most important of these parameters is the ramping interval and a key to closeness to a quasi-static behavior is to observe how the load node follows the load pulse. This is done by normalizing the load node displacement to the applied load at the point where the ramp ends and load hold begins. Similar data from the test helps to identify up to what level this follow up is expected. However the most important correlation parameter to observe is the direct comparison of the Applied Load as a function of the Load Node Displacement.

When comparing the Load Node Displacement following the load, two observations are critical. First, the shape of the two curves during the ramp period and second, how quickly the node responds to the hold period load with reference to holding the displacement. The dynamic response of the load node during the ramp period (Figure 2) sometimes needs to be damped using *DAMPING_GLOBAL". Figure 3 shows how the various factors used in damping affect the nodal displacement response during the ramp period. Sometimes it is even necessary to use a time dependent damping to use this feature only during the initial ramp period. Overdamping may even affect the displacement coming to a constant value during the hold period. The use of longer ramping interval will definitely make this dynamic event approach a quasi-static event.

Finite element model for FMVSS210 simulation consists of the following major sub-components:

1. Body in White (BIW)
2. Upper Torso and Lap Body Blocks
3. Seat and supporting structure
4. Steel Cable Beam for load application
5. Belts around Body Blocks
    - As seatbelt elements everywhere except at the block contact surface.
    - Shell elements on blocks.

The shoulder belts are connected to locked retractors at the top and to the vehicle floor at the bottom. The lap belts are connected to the vehicle floor at both ends. The floor connections are modeled using beam elements defined by "*MAT_FORCE_LIMITED" using only the density, Young's Modulus and Poisson's Ratio. This resulted in a uniform displacement on the floor. 6 contact interfaces are modeled as "*CONTACT_SURFACE_TO_SURFACE" for belt shell elements contacting 6 individual blocks. A friction coefficient of 0.9 is used between blocks and belts. Rest off the contacts between vehicle components are initially modeled as "*CONTACT_AUTOMATIC_SINGLE_SURFACE" using the exclude option of LS-DYNA to exclude the 6 contacting parts mentioned above. A friction coefficient of 0.3 is used for the later contact interface. Looking at the kinematics of the LS-DYNA run, if some parts still seem to be penetrating, their contact interface is separately modeled using "*SURFACE_TO_SURFACE" or "*NODE_TO_SURFACE" contact. This resulted in additional 12 contacts in the model.

A ramp load pulse is applied at the end of the loading cable using 70 msec ramp and 50 msec holding period. The loading cable is at 7 ° to the horizontal and the load is applied in a local coordinate system along the cable with cable constrained in all other directions except along the cable length. Weld-Spots are modeled with appropriate input for Normal and Shear failure forces. The load node resultant displacements are obtained from the LS-DYNA run using the NODOUT file. Figure 4 shows Lode Node Displacement plot normalized to Load Pulse by equating values at the start of the hold period.

A March Towards Stochastic Analysis

Based on the kinematics in the simulation and nodal behavior the following 4 input variables along with their possible values are identified as the key variables, in arriving at a *robust model*.

1. Ramp Time *(60-200 msec followed by 50 msec of Hold Period)*
2. Global damping coefficient *(0.2-0.8)*
3. Friction between belts and blocks *(0.5-0.9)*
4. Friction between the rest of the components *(0.1-0.9)*

The thickness of some of the critical parts in the model can be used as the 5th input variable but unlike the other 4 it should be considered as a *design* parameter.

Following variables were used as *performance variables*:

1. Maximum Plastic Strain
2.The average nodal displacement during the hold period

From the maximum and minimum possible values of each of these input variables 30 random combinations were generated (Table 1). These values were then put in LS-DYNA runs to get 30 outputs. During the load hold period all 30 runs showed a very slight increase in the load node resultant displacement as compared to the plateau of the load pulse which means that there is negligible dynamic response left from the system. The following extra checks made on all these runs confirmed the quasi-static and robust nature of all the runs.

1. Maximum Global K.E. was between 0.01 to 0.533% of the Global Internal Energy in all 30 runs.

2. The penetrations between parts need to be avoided in the LS-DYNA simulations. A negative *Sliding Interface Energy* indicates that the parts are penetrating inspite of the use of contact interfaces set up in the model. These situations have to be corrected. In our starting model for this work there were no initial penetrations. None of the 30 runs showed any part penetrations during the run.

Stochastic Analysis and Model Correlation

Stochastic simulation gives us a new insight into the nature of the physical phenomenon involved. Even with the best computing power available today, a typical LS-DYNA simulation for FMVSS 210 takes about 8-10 hours of CPU time. A stochastic Monte Carlo simulation in our case, consisting of even a few hundred runs, is impractical from the point of view of time and computer cost. To get around this constraint a Kriging surface is developed (1) which can be viewed as a surrogate mathematical model of the actual LS-DYNA simulation. This response surface method can capture the non-linearity of the event without guessing its functional form. To develop the Kriging surface an Optimal Symmetric Latin Hypercube experiment was designed with 30 experiments. A Latin Hypercube has a property that the projections on any axis of a set of n points (in our case 30) in d dimensions (in our case 5) form a uniform n-grid. Moreover a symmetric Latin Hypercube has the property that, if point (x1, x2, x3...xd) is in the design then the point (1-x1, 1-x2...1-xd) is also in the design. In an Optimal Latin Hypercube the points are spread uniformly over the n-dimensional projections.

Using the results of these 30 runs a Kriging Surface is developed for the two performance variables namely Maximum Plastic Strain and the Average of the nodal displacement at the start and end of the hold period (hereafter called DISP). To judge the goodness of fit of the Kriging model, we made predictions at 5 new points (Table 1) using the Kriging model. The 5 points were selected by generating 1000 points randomly within the range of input variables. The Euclidean distance of the 1000 points to all of the existing 30 points is calculated. The 1000 points are ranked in terms of the smallest distance from itself to any of the existing 30 points. The first point and the last point are selected as representing the nearest and farthest point from the sampled 30 points. The other 3 points are selected at intermediate distances. The comparison of LS-DYNA runs for these 5 points with the predictions from the Kriging (Figure 6) tests the goodness of the fit. The later can now be used to predict the percentage contribution of the different input variables in predicting the values of the performance variables. This is done using a procedure called the functional ANOVA [1][2][3].

Neglecting second order interactions the following conclusions can be made from the Kriging model.

The Average of Displacements at the Start and End of the Hold Period

The friction between the blocks and the belts affect this variable the most at 38%. The nodal damping coefficient used in the analysis is the 2nd most important variable with a contribution of 27%. The ramp time of the load pulse contributed to 21%. The remaining contributors, not including numerical noise in the simulation, amounted to 10%. The noise contribution that amounts to expected variation in analysis was 5%. The confidence interval in the prediction of the performance variable can therefore be said to be 5%.

The Maximum Plastic Strain

The nodal damping coefficient used in the simulation had a 51% contribution to this variable. The ramptime accounted for 32% and the noise contribution was 13%. The rest of the contributors amounted to only 4%.

The Kriging Surface is used to do a Monte-Carlo Simulation of 3000 possible combinations of input variables assuming they are distributed uniformly within the ranges identified. This results in the Anthill plots of the output responses as shown in Figure 5. These plots can now be used to understand global dependencies, to do correlation with the hardware tests and for expected noise (4). To do the model validation, the mean and the standard deviations of the predicted performance variables, plastic strain and DISP are established. If the test results fall within an acceptable confidence interval we can say that the model is representative of the physical test, and from then on the LS-DYNA model can be used to guide the future design. If the test results do not fall within an acceptable confidence interval, the above analysis tells us which input variables need to be changed for each of the two performance variables. For example, Figure 5 show that for better prediction of plastic strain Global Nodal Damping Coefficient needs to be changed and for that of DISP the friction between the blocks and the belts needs to be changed.

Conclusions

The Stochastic software used has therefore a capability of predicting the values of the performance variables expected from the hardware test with average value and the standard deviation. The prerequisite happens to be a systematic study starting from a robust LS-DYNA model of the test event, followed by a generation of a random combination of input variables for only a fraction of the possible combinations, then running these models and following the process elaborated above. The in-advance prediction of results for the hardware test based on the above analysis could help a long way in, attaining a level of correlation of analysis to testing, to a point where at an early stage in vehicle design cycle an analysis model could be perfected to lead the further design iterations through analysis only rather than through costly hardware testing. In our study thickness of some critical parts was the only design variable. Additional input variables were needed to make the model a truly quasi-static representation of the test.

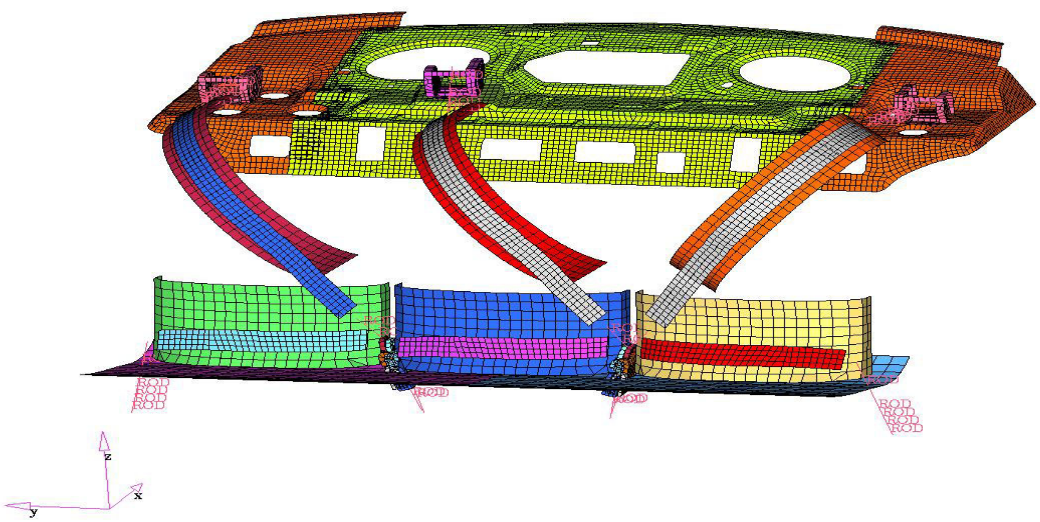


Figure 1: Model details showing Pelvic and Torso Body Blocks

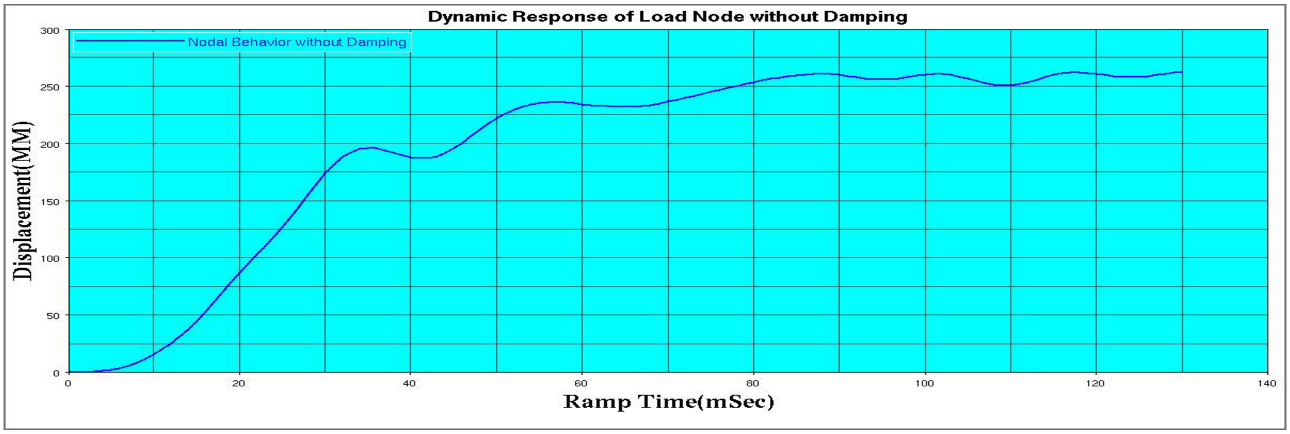


Figure 2: Dynamic Response of Load Node with no added damping

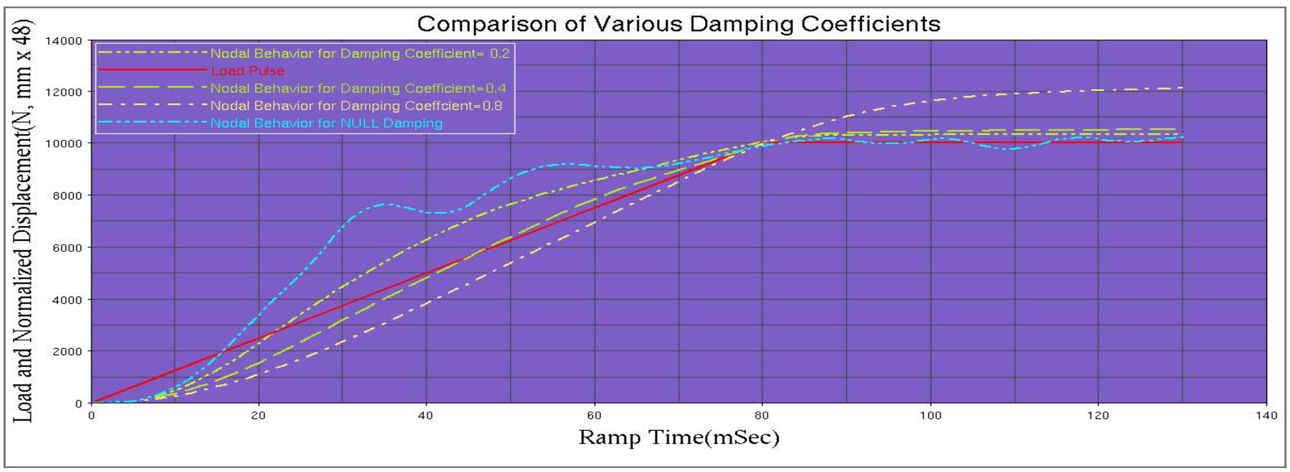


Figure 3: Effect of damping on the nodal displacement

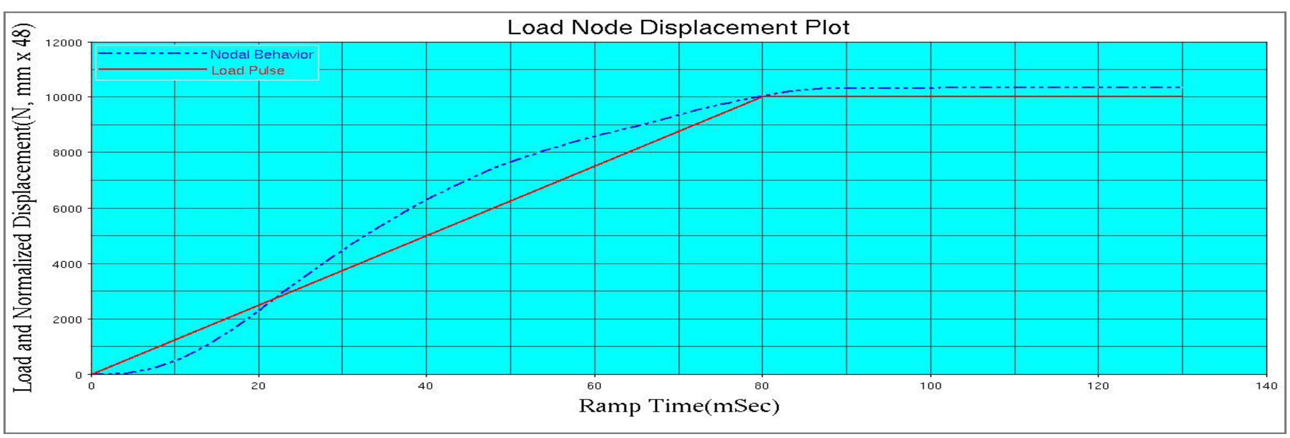


Figure 4: Load and Normalized Node displacement plot

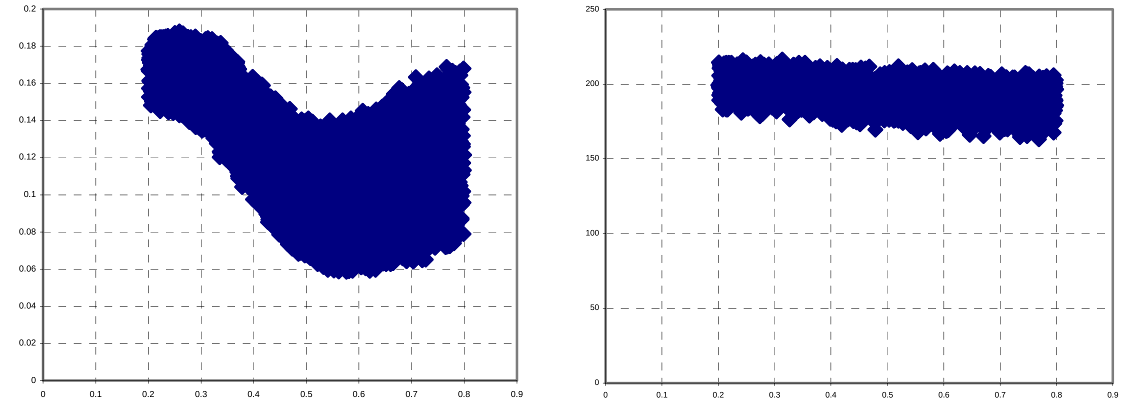
Table 1 : Random Combinations used for Latin Hypercube

Iteration #	Ramp_Time	Damping_Coefficient	Friction_1	Friction_2	Thickness
1	70	0.2	0.5	0.1	0.8
2	190	0.8	0.9	0.9	0.8
3	80	0.5	0.8	0.4	1.5
4	180	0.5	0.6	0.6	0.8
5	160	0.3	0.7	0.1	1.2
6	120	0.8	0.8	0.7	1.3
7	140	0.2	0.6	0.3	1.0
8	100	0.7	0.7	0.9	1.1
9	130	0.7	0.9	0.4	0.9
10	130	0.5	0.5	0.7	1.5
11	170	0.4	0.9	0.7	1.1
12	90	0.6	0.5	0.3	1.2
13	200	0.2	0.6	0.4	1.3
14	70	0.8	0.9	0.6	1.0
15	70	0.6	0.6	0.7	1.4
16	190	0.4	0.9	0.3	0.9
17	140	0.6	0.8	0.8	0.8
18	120	0.5	0.6	0.1	1.5
19	150	0.5	0.7	0.5	1.3
20	150	0.7	0.5	0.8	1.0
21	110	0.3	0.9	0.2	1.3
22	60	0.4	0.7	0.1	1.2
23	200	0.6	0.7	0.1	1.1
24	90	0.7	0.8	0.2	1.2
25	170	0.3	0.6	0.8	1.1
26	80	0.3	0.8	0.5	0.9
27	180	0.7	0.6	0.5	1.4
28	110	0.5	0.7	0.5	1.0
29	100	0.4	0.8	0.8	1.4
30	160	0.7	0.7	0.2	0.9

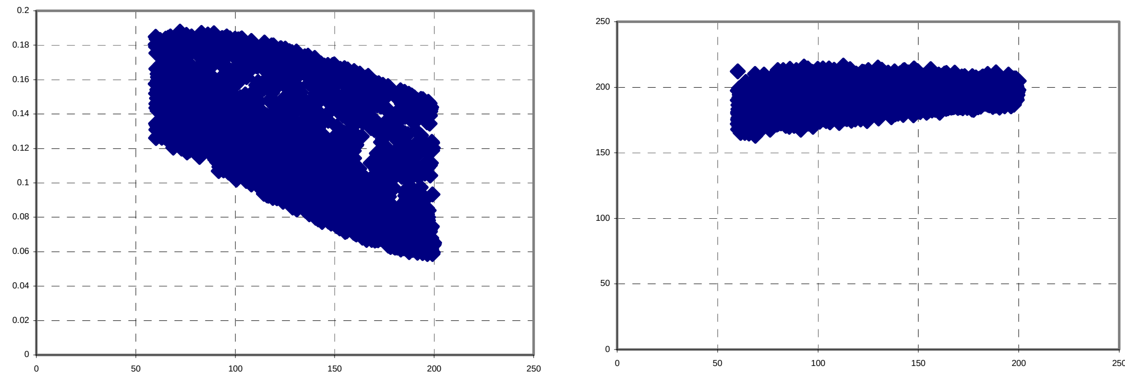
** Friction_1--> Friction Coeffcient between body blocks and seat belts
Friction_2---> Friction Coeffcient between other critical parts defined in the *CONTACTS except those defined for Friction 1

Table 2 : New Prediction points for Kriging Model

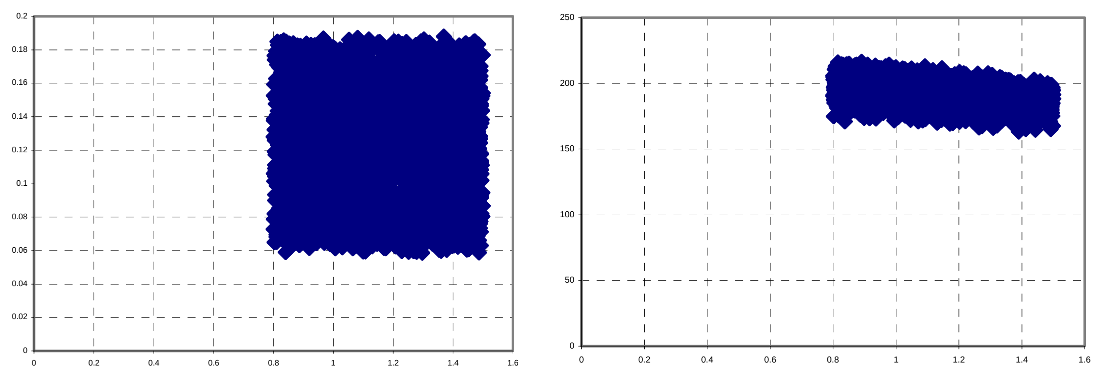
Iteration#	Ramp_Time	Damping_Coefficient	Friction_1	Friction_2	Thickness
1	160	0.6	0.5	0.2	0.8
2	120	0.6	0.7	0.5	1.2
3	90	0.6	0.5	0.5	1.3
4	70	0.3	0.8	0.3	0.8
5	80	0.2	0.5	0.2	0.8



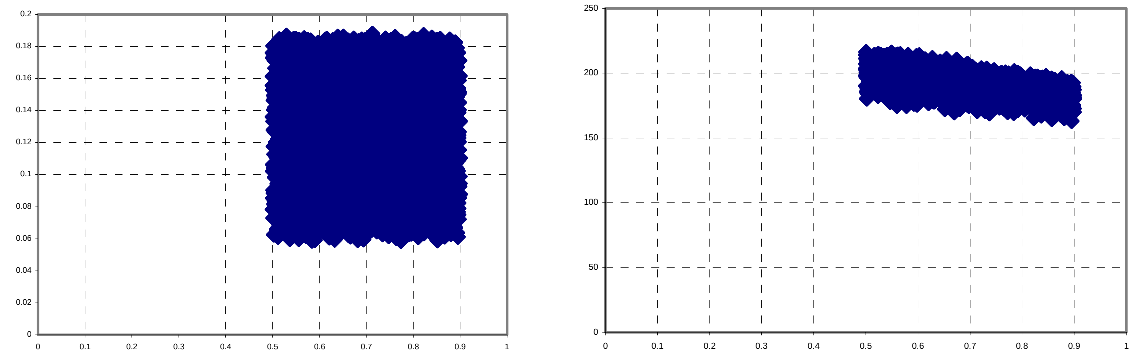
Plastic strain (left) and Average displacement (right) versus Damping Coefficient



Plastic strain (left) and Average displacement (right) versus Ramp Time



Plastic strain (left) and Average displacement (right) versus thickness



Plastic strain (left) and Displacement (right) versus the friction between the blocks and the belts

Figure 5: Anthill plots of the output responses

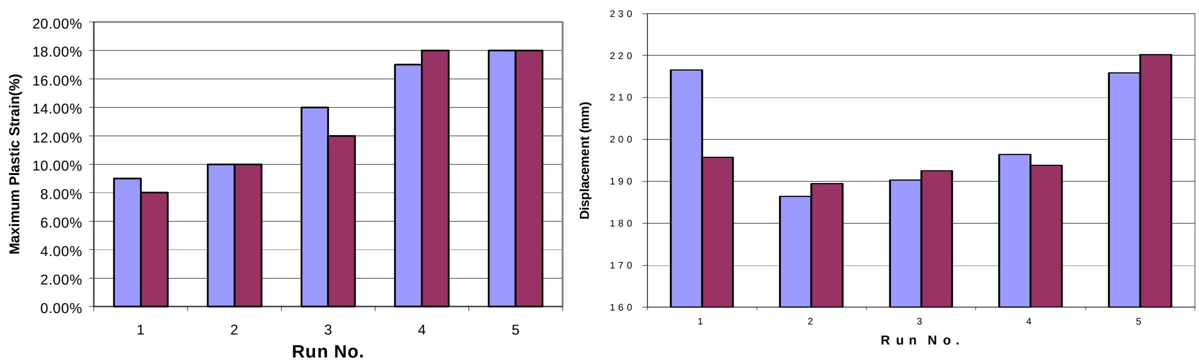


Figure 6: Comparison of LS-DYNA with Kriging predictions - Plastic strain (left) & Average Displacement (right)

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