

Robust Design in Occupant Safety Simulation

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ABSTRACT

Explicit FE-simulation has become a standard design tool in passive safety development as it can help to reduce the number of vehicle prototype tests, especially in the early project stages. Due to fewer hardware tests available as sources of validation, the expectations towards predictability of dummy injury occurrence have strongly increased. To produce robust results, virtual passive safety analysis has to take real uncertainties of test condition and their probabilistic effects upon the system's response into account. Findings by simulation therefore should not be regarded anymore as single point statements in a pure deterministic approach. They rather need to be extended into statements upon grades of correlation between individual system parameters taking into account their stochastic nature. This paper illustrates a process for complete robustness analysis in occupant safety simulation. It introduces techniques to document statistical confidence intervals of the correlations determined, and uses statistical "bootstrapping" in populations where only a limited number of samplings can be generated. Finally, by regression analysis within the reduced relevant physical parameter space, a risk assessment upon a potential failure within the specific test requirements is carried out.

Identification of initial design space parameters requires experience and proper preparation when one is conducting statistical analysis on occupant safety. This work explains relevant design space parameters for a typical full vehicle test and classifies them in proper ways since obtaining their sampling often requires additional pre-simulation efforts. In this context a number of in-house tools are highlighted here that helps the designer in obtaining work intensive design parameters such as the distribution of dummy, seat & belt positions. The entire robustness design process uses automated work flows and tools to visualize the statistical data observed since the simulation model complexity and its computational costs are extremely high. Finally, the gained correlations are discussed, interpreted and explained in terms of real life phenomenon that can be observed in testing.

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INTRODUCTION

With laboratory tests in automotive passive safety, authorities aim to assess the safety feature representatively for an infinite number of possible accident occurrences in the real life. The different kinds of crash test definitions had been motivated by an analysis of real traffic accidents data that was collected. This lead to test specification which contributed to a sufficiently high number of accident configurations observed as well as configurations which lead to a consideration since they come along with a typical high risk of severe injury and corresponding medical costs. Furthermore, the type of collision e.g. between cars, trucks or static obstacles, in frontal or lateral, or with the male or

female occupants of various body sizes in its statistical representation and severity found entry in existing regulation.

In this paper, FMVSS214 Oblique Pole 5% specification is chosen as a representative crash test specification for impact of lateral obstacles (here a rigid pole). This load case is part of the legal requirement imposed by the NHTSA in its final rule for the US car market.

In this test, the car is positioned on a movable floor, on which the car travels under a 15° angle with 32 km/h against a rigid pole of 254 mm in diameter as illustrated in [Figure 1](#).

Hereby the car has to be positioned in that way on the movable platform, so that the trajectory of the head's center of gravity is directly pointing onto the oblique pole's center line. This is measured after adjusting the seat in its required

position (full frontal, seat tilting adjustment down, seat height adjustment middle) and placing a crash test dummy Type SID2s BLD on it, again following the tests specification regarding angles of e.g. the dummies neck, torso legs and so on.

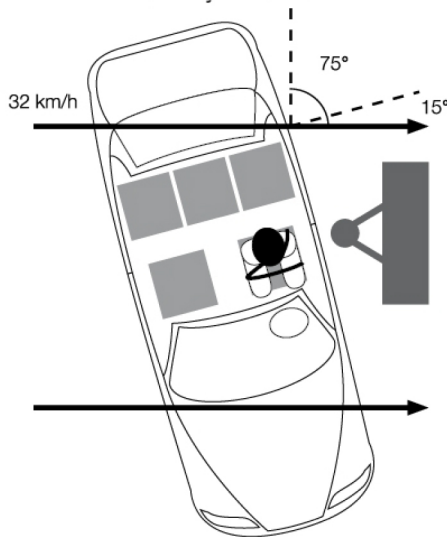


Figure 1. FMVSS214 OP 5%, 2004

The major results that will be recorded by the dummy are loadings on pelvis and torso body regions as well as the head. They all need to be under an imposed legal limit beyond which the test will be considered as “failed”. These values will be further explained in the later section, for now they are only mentioned as:

- Pelvis: Combined Iliac and Acetabulum Force (CIAF)
- Torso: 12th thoracic spine acceleration (T12)
- Head: Head Injury Criterion (HIC36)

Now, also tests under laboratory conditions depend on a certain statistical distribution of parameters. This should be illustrated in one example:

The required position of the pole in the test is exactly defined: Dummy Head C.O.G travels on pole rotation axis. However, to understand the existing sources of uncertainty - even under laboratory condition - one should reflect the chain of measurements that it takes only to determine the nominal pole position:

Adjusting seat position + Dummy positioning = Pole Position

Each of these steps is subjected to statistical uncertainty, e.g. the dummy size or seat adjustment will contribute their portions of uncertainty before finally the measure of the head C.O.G. is taken.

It is therefore clear that we cannot expect a test parameter such as a pole position to be exact but rather do we have to regard them as statistically distributed in a way that remain to be defined. At the same time one can already estimate that a

parameter as the position of the main impacting object will have its effect on the measurements of the dummy. It is understandable that car makers want to ensure that their designs are sufficiently robust, so that the before mentioned, realistic and unavoidable uncertainties within the test parameters, will (under certain probability) not lead to any unwanted consequences by accidentally not meeting the legal requirements. This statistical approach in passive safety automatically leads to a virtual testing by FEA due to the required number of tests that need to be carried out for that.

FEA ROBUSTNESS PROCESS

The techniques and standards to build up crash models and simulate them in FE analysis should only briefly be mentioned here since it is not in the main scope of this work but rather a tool being part of the robustness analysis process for obtaining realistic system responses upon variation of input parameters. In this paper the underlying non-linear crash simulation are performed with the Abaqus/Explicit Solver but would work with any solver typically used in crash simulation.

In this section, we want to emphasis on the entire workflow to practically undertake robustness analyses in an occupant safety FEA Crash environment.

Design Space

Robustness analysis within the virtual passive safety design means defining a suitable design space, i.e. a multidimensional space of a number of relevant, independent test parameters of which we believe there may be any form of association to the system responses obtained by simulation.

More concrete, in the context of a FMVSS214 OP 5% crash analysis we are especially interested in the variation of the system responses as listed below since they finally lead to a “fail or pass” in this load case.

- Pelvis: Combined Iliac and Acetabulum Force (CIAF)
- Torso: 12th thoracic spine acceleration (T12)
- Head: Head Injury Criterion (HIC36)

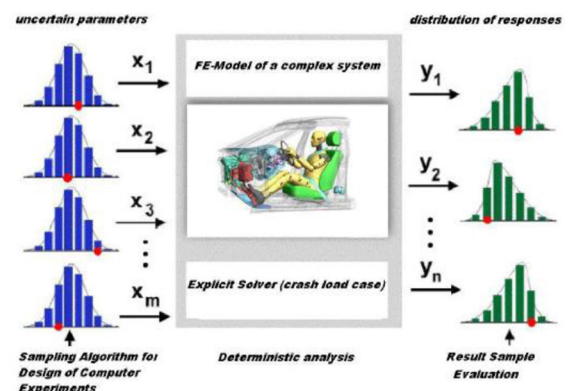


Figure 2. Concept of Robustness Analysis

Now, what are relevant input parameters in this case? There is not the one true answer on this; however it is necessary during the analysis to determine to what extend the system responses can be explained by the variation of the input parameters chosen, and what portion of the system response remains unexplained.

Table 1. Chosen Design Parameters in FMVSS214 OP 5% Occupant Safety Robustness Evaluation: Design parameters which do not require any pre-simulation effort

Design parameter	Explanation
Massflow scale factor	Variation of the available explosive loading to inflate the airbag
Time to fire of airbag	Time delay to fire airbag after impact
Belt pre tensioning	Variation in the belt prestressing level
Friction Parameter SAB vs. Dummy SAB vs. SAB SAB vs. Seat Dummy vs. JacketArm Dummy vs. Seat SAB vs. Env Dummy vs. Env	Taking into account different dummy jacket material conditions, different seat cover (leather, fabric, combinations etc),
Parts & Components Parameter	<i>e.g. thicknesses / thickness distribution due to metal forming / material property e.g. failure modes etc not investigated here since occupant safety parameters were on focus</i>

The design parameters chosen in the robustness analysis are further classified in categories due to their treatment in the further model assembly process. Each parameter is assumed to be normal distributed with mean μ and standard deviation σ based on previous tests experience.

Design parameters such as friction, thicknesses etc are quite easy to handle by merely replacing the corresponding data by the required design parameter variable (e.g. Fric_Sab_Arm). The definition of geometric design parameters however requires a considerable higher amount of modeling effort since all of these parameters demand an individual seating and belting simulation in order to properly position them without any intersections as the present contact algorithms cannot resolve it.

Process Preparation

The flowchart below describes all steps to derive a set of N samples from our design space introduced earlier. Every sample is created in form of a ready to use simulations input decks for which the system responses are then computed.

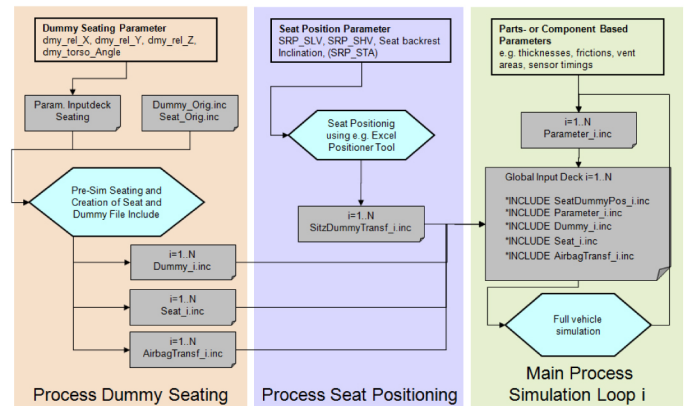


Figure 3. Preprocessing FEA Robustness Environment: Overview Flowchart

This process works quite automated involving several tools and scripts to facilitate the individual steps. Being not in the main focus here, they will only be briefly mentioned. The next section will lead step by step through the flowchart.

Dummy Seating

The dummy and seat model with an undeformed cushion are taken as an initial parameterized meta model. All geometric parameters are set to their design vales as specified in the regulation of FMVSS214 OP 5%. In a pre-simulation the dummy will now be seated in N variations by sampling according to [Table 2](#) and [Table 3](#).

Table 2. Chosen Design Parameters in FMVSS214 OP 5% Occupant Safety Robustness Evaluation: Dummy seating parameters which require extensive pre-simulation effort

Dummy Seating Parameter dmy_rel_X dmy_rel_Y dmy_rel_Z dmy_Torso_Angle	Parameter that describe the relative position of the dummy on the seat in X,Y,Z direction and in torso angle around Y. Refer to Figure 5.
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Table 3. Chosen Design Parameters in FMVSS214 OP 5% Occupant Safety Robustness Evaluation: Seat positioning parameters which require extensive pre-simulation effort

Seat Position Parameter SRP_SLV SRP_SHV Seat inclination angle	Parameters describe the seat adjustment (including, Dummy/SAB etc) relative to the interior environment e.g. door trim (in seat longitudinal and seat height adjustment d.o.f. as well as backrest rotation)
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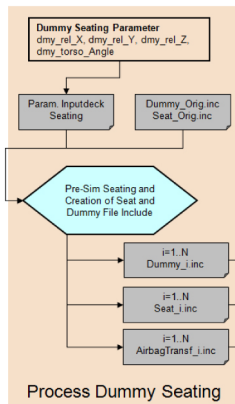


Figure 4. Preprocessing FEA Robustness Environment: Dummy Seating

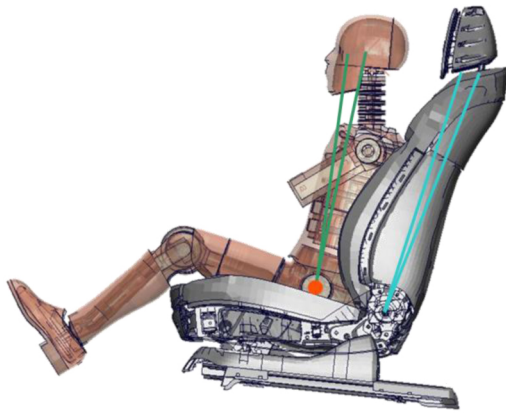


Figure 5. Dummy Seating Parameter dmy_rel_X , dmy_rel_Y , dmy_rel_Z , dmy_Torso_Angle

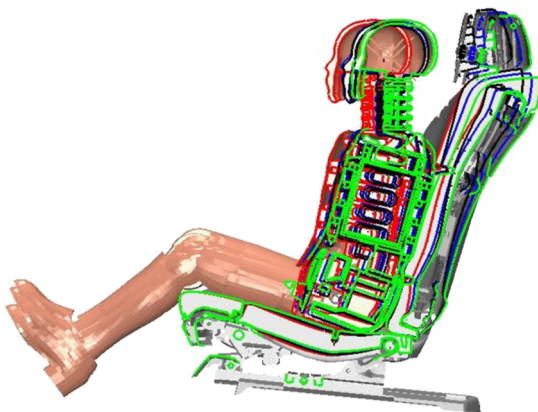


Figure 6. Section-cut through the dummies mid surface for 3 realizations of N samples

After every i -th seating simulation a sub input deck for dummy, seat and airbag is derived from the meta model inheriting the calculated geometric seating properties according to the i -th sampling of the population. As an

example three realizations of N samples are illustrated below in a section through the dummies mid surface.

With this statistical seating process it is ensured that we do acknowledge the uncertainties in positioning the hardware dummy SID2s in its design position. Sources for uncertainty may arise from variation of seat or dummy properties but also due to the fact that the seating in the laboratory is a highly manual task. We therefore also have to expect variations depending on the physiognomy of who is actually doing the dummy seating.

Seating positioning

The next important source of uncertainty regarding the seat is the position of the seat itself. Typical automotive seats provide several degrees of freedom for adjusting its position. As most common ones we have seats with a longitudinal, a height and backrest rotation adjustment. Additionally some seats are equipped with a seat tilt adjustment providing different position for the seat pan angle. The statistical influence of the backrest rotation had been considered during the seating process since this requires an individual seating simulation. Putting these degrees of freedom (d.o.f) together, the reference point of the dummy's hip describes the area in which the seat can be adjusted. As mentioned earlier the required seat position in the FMVSS214 OP 5% test is defined to be seat longitudinal adjustment (SLA) full frontal, seat height adjustment (SHA) middle and seat tilting adjustment (STA) at lowest point. At this design position the variation of seat positions are taken as normally distributed with a standard deviation derived from data gathered of typical seat position measurements.

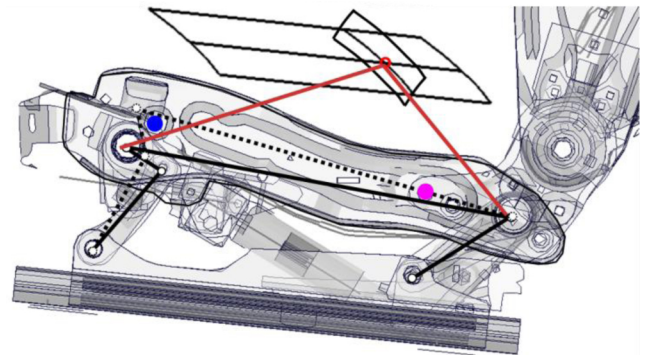


Figure 7. Seat Position Parameter SRP_SLA , SRP_SHA , SRP_STA

To actually create one realization out of the seating position input variables from Table 2 and Table 3 a tool is used that creates the seat position information based on the existing seat kinematics. This information is stored as pure non structural position information ($\rightarrow$ SitzDummyPos_i.inc) which will be applied to seat structure and to all components such as dummy belt and airbag that depend on it.

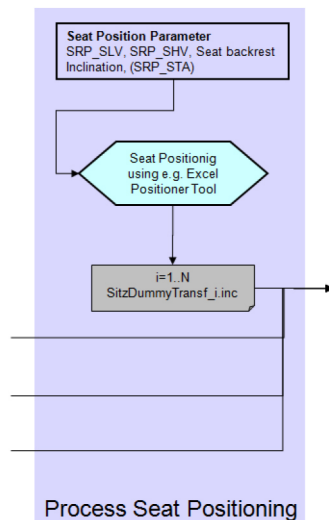


Figure 8. Preprocessing FEA Robustness Environment: Positioning

The remaining design variables as shown in [Table 1](#) are directly set in the global input deck of the simulation. Those of them that required a pre-simulation or a seat position will enter the main simulation via their inclusion as a complete file [Seat|Dummy|AirbagTransf|SeatDummyPos]_i.inc.

ROBUSTNESS ANALYSIS

In this paper the DAKOTA Tool (Design Analysis Kit for Optimization and Terascale Applications) was used for the sample generation, where there are a lot of the available methods for the DOE [[Adams et al., 2011](#)]. Latin Hypercube Sampling (LHS) and random Monte Carlo Sampling (MCS) methods support different distributions of variables within DAKOTA. However among them only the LHS Algorithm makes it possible to include the distributions of the variables into the sampling procedure.

After gathering the experimental data is to infer causal relationships between the independent and dependent variables. Taking into account the stochastic nature of the sampling method and strategy chosen to obtain the data, as well as the sample size, it is decided to fulfill sensitivity study within two steps. The first step can be fulfilled by means of correlation analysis applying nonparametric concepts. In the second step the data are subjected to conventional and robust regression analysis.

In this paper basic concepts and tests regarding nonparametric Spearman Rank Correlation Coefficient, conventional t-statistics and permutation tests on significance will be performed. The concepts will be used in the final evaluation procedure. Basic robust estimator - concept of nonparametric bootstrap, being part of nonparametric statistics will be used in the current paper as well. Nonparametric bootstrap of the correlation coefficients, mean, standard deviation, as well as bootstrap percentile method for Confidence Intervals computations will be

applied in the current work, since the technique provides with the unbiased estimators [[Gentle,2003](#)].

More detailed explanation of the methods chosen in this work can be found in [[Adams et al., 2011](#)], [[Giunta, 2003](#)], [[Sallaberry, 2006](#)], [[Sprent and Smeeton, 2001](#)], [[Bethea et al., 1995](#)], [[Cohen et al., 2003](#)], [[Good, 2005](#)], [[Tanizaki, 2006](#)], [[Wilcox, 2005](#)], [[Milliken, 1989](#)], [[Rousseeuw and Leroy, 2003](#)], [[Atkinson and Riani, 2000](#)] and [[Davison, 1997](#)].

RESULT INTEPRETATION

Sampling Procedure

Design parameters as described in the earlier section in [Table 1](#), [Table 2](#) and [Table 3](#) are chosen for robustness analysis. These parameters have been normalized by their maximum absolute value such a way that every parameter varies within $[-1; 1]$ and represented in [Table 4](#) and [Table 5](#). Sampling procedure is divided into two steps. First, LHS algorithm is used to generate the 20 configurations from [Table 4](#) which are related to pole-dummy-seat parameters. Sample size is limited to 20 as it requires extensive pre-simulation effort. Next step is to fulfill continuous LHS sampling on parameters shown in [Table 5](#) and couple with the prepared pole-dummy-seat configurations as the discrete values. Each of such configuration is the output of the geometry after the pre-simulation work in the form of a separate Abaqus/Explicit input deck. Therefore, 140 crash simulations are carried out with the 20 discrete configurations as discrete parameter that has equal probability for each of the generated samples during the sampling run. Two tabular files are obtained as the result of the sampling. The first one contains the samples generated according to [Table 4](#) and the second one contains the parameters generated according to [Table 5](#) with one discrete uniformly distributed parameter mentioned. These two tabular files will be merged by MATLAB script. Robustness analyses are performed based on the merged tabular file.

Table 4. Pole-dummy-seat configuration parameters, participating in the first stage of sampling. The values are indicated relative to basis.

Parameter	Characteristics of the distribution			
pole rel pos x (mm)	normal	$\sigma = 0.4$	$\mu = 0$	pole rel pos x $\in [-1; 1]$
dmy rel X	normal	$\sigma = 1.0$	$\mu = 0$	dmy rel X $\in [-1; 1]$
dmy rel Y	normal	$\sigma = 1.0$	$\mu = 0$	dmy rel Y $\in [-1; 1]$
dmy rel Z (mm)	normal	$\sigma = 1.0$	$\mu = 0$	dmy rel Z $\in [-1; 1]$
dmy Torso Ang (rad)	normal	$\sigma = 1.0$	$\mu = 0$	dmy Torso Ang $\in [-1; 1]$
SRP SLV	uniform			SRP SLV $\in [-1; 0]$
SRP SHV (mm)	normal	$\sigma = 1.0$	$\mu = 0$	SRP SHV $\in [-1; 1]$
seat inclin ang (rad)	normal	$\sigma = 1.0$	$\mu = 0$	seat inclin ang $\in [-1; 1]$

Table 5. Uncertain input variables participating in the second stage of sampling.

Parameter	μ	σ	Lower/Upper Bounds
Massflow scale factor	0.909	0.045455	[0.81818; 1.0]
Time to fire of airbag (s)	0.005	0.0005	[0.0; 1.0]
Belt pre tensioning (mm)	-0.85	0.07	[-1; -0.714]
Friction Parameter:			
SAB vs. Dummy	0.175	0.05	[0.0; 1.0]
SAB vs. SAB	0.025	0.025	[0.0; 1.0]
SAB vs. Seat	0.075	0.025	[0.0; 1.0]
Dummy vs. JacketArm	0.45	0.025	[0.0; 1.0]
Dummy vs. Seat	0.15	0.025	[0.0; 1.0]
SAB vs. Env	0.175	0.05	[0.0; 1.0]
Dummy vs. Env	0.15	0.025	[0.0; 1.0]

One can refer to [Figure 35](#) and [Figure 36](#) for the definition of the directions of variations for seat and dummy uncertain parameters as illustrated below.

Robustness Evaluation of CIAF

CIAFmax is the maximum value of the curve after the summation of the Iliac and Acetabulum Force Y response curve. Scatter plot in [Figure 9](#) shows that there is one outlier for CIAFmax. It is due to the termination of one simulation because of some implicit error. Since the data contains neither missing nor a big percentage of outlier, robustness evaluation can be started with the sensitivity analysis after deleting the point marked.

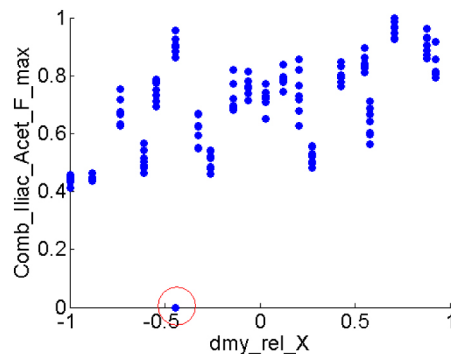


Figure 9. Outlier in the response Combined Iliac Acetabulum Force Max

Correlation analysis

Significant level or probability of making the error Type I is chosen on the level 5%, or $\alpha=0.05$ as it is the optimal value for hypothesis testing for the small sample size data as described in [Sprent and Smeeton, 2001]. The hypotheses that are tested for any statistics θ in current evaluation are: $H_0: \theta=0$ against $H_1: \theta \neq 0$. The significance is checked in terms of p-values computed for all tests and referred to the two-tail

tests. Confidence Intervals, α , namely 95% CI are computed for all estimator to validate the values.

Table 6. Nonparametric data analysis: correlating with CIAF_max data, significance of Spearman Rank Correlation with the help of t-statistics and permutation tests.

Spearman Rank Correlation $\rho_{xi,yj}$	p-value
Permutation test (repeated for P=1000 and P=10000)	
$\rho_{Fric_Sab_Seat\ CIA_F_max}=0.23196$	p=0.006
$\rho_{Dmy_rel_X\ CIA_F_max}=0.6318$	p=0.06e-027
$\rho_{SRP_SHV\ CIA_F_max}=-0.51612$	p=0.879e-021
$\rho_{SRP_SLV\ CIA_F_max}=-0.34799$	p=0.879e-021
t-statistics test	
$\rho_{Fric_Sab_Seat\ CIA_F_max}=0.23196$	p=0.0061054
$\rho_{Delta_ZZP\ CIA_F_max}=-0.17633$	p=0.037977
$\rho_{Dmy_rel_X\ CIA_F_max}=0.6318$	p=1.1102e-016
$\rho_{SRP_SHV\ CIA_F_max}=-0.51612$	p=7.8799e-011
$\rho_{SRP_SLV\ CIA_F_max}=-0.34799$	p=2.6976e-005

The results of the non-parametric analysis of the Spearman Rank Correlation are illustrated in [Table 6](#). The tests are carried out according to the hypothesis $H_0: \rho_{xi,yj}=0$, against $H_1: \rho_{xi,yj} \neq 0$. Rejection happens if the p-values are smaller than the α -value. There is no significant correlation between input variables based on the t-statistics test and permutation test.

Table 7. Bootstrap method (10000 samples with replacement) for testing the significant of Spearman Rank Correlations, concerning CIA_F_max.

Original $\rho_{xi,yj}$	Bootstrapped $\rho_{xi,yj}$	95% Confidence Interval
$\rho_{Fric_Sab_Seat} = 0.23196$	0.23166	[0.083341; 0.37033]
$\rho_{Delta_ZZP\ CIA_F_max} = -0.17633$	-0.17636	[-0.33477; -0.014413]
$\rho_{Belt_Tension} = -0.16373$	-0.16407	[-0.3201; -0.0022427]
$\rho_{Dmy_rel_X} = 0.6318$	0.63102	[0.50563; 0.7393]
$\rho_{SRP_SHV\ CIA_F_max} = -0.51612$	-0.51537	[-0.62146; -0.39687]
$\rho_{SRP_SLV\ CIA_F_max} = 0.34799$	0.34662	[0.19823; 0.48079]

[Table 7](#) illustrates the generalization of the significant data out of the [Table 6](#). Non-parametric bootstrap is used to validate the Confidence Interval since it gives unbiased estimators [Gentle, 2003].