

Determining optimal suspension system parameters for spring fatigue life using design of experiment

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Abstract. This paper presents the optimization of spring fatigue life associated with suspension system parameters using the design of experiment approach. The effects of suspension parameters on spring fatigue life were analyzed because this process can improve spring fatigue life from a distinct perspective. A quarter car model simulation was performed to obtain the force time histories for fatigue life prediction where the suspension parameters were adjusted. Multiple input regression and interaction plots were conducted to identify the interaction between these parameters. A full factorial experiment was performed to determine the optimal suspension settings that would maximize the spring fatigue life. For the regression, a high R^2 value of 0.9078 was obtained, indicating good fitting. The established regression showed normality and homoscedasticity for consistent prediction outcome. Reducing the spring stiffness and sprung mass while enhancing the damping coefficient is therefore suggested to enhance fatigue life.

Keywords: Fatigue life / multiple input regression / design of experiment / automotive suspension / finite element analysis

1 Introduction

Automobile springs are subjected to repeated cyclic loading during their operation. The spring fails when a crack is initiated under cyclic loading, and this phenomenon is known as fatigue failure. Hence, fatigue analysis is a main concern during automotive suspension design. In automotive industry, durability analysis of components is usually conducted through simulations before experimental verification [1]. During the fatigue simulation and analyses, the geometry, material properties, and loadings are the main key inputs to the fatigue life predictions [2]. Hence, a critical part of automotive component fatigue life assessment is determining the load associated with the road irregularities [3]. Unrealistic loadings lead to inaccurate automotive design, given that the latter is based on the former.

Improper spring design leads to premature fatigue failure, which can catastrophic accidents [4]. Hence, the spring design, especially in terms of fatigue, must be determined before prototyping [5]. For durability analysis, the spring fatigue design process is usually conducted

through strain data collection from various road conditions because this type of loading is realistic [6]. The actual loadings are important for warranty claims because the automotive suspension components should last at least five years [7]. Therefore, fatigue design and optimization of automotive suspension components is a crucial task. Buciumeanu et al. [8] performed an analysis of an automobile lower arm and proposed innovative component designs for fatigue life improvement, such as introducing washers or adding curvatures. Most fatigue optimization techniques of automotive components clearly depend on the structure. However, optimization of a component could be conducted through analyzing the whole system and interaction between parameters.

To obtain the dynamic behavior effects of suspension systems, a quarter car model is usually used either with a measured [9] or artificial road profile [10]. For example, Kashyzadeh et al. [11] performed fatigue life prediction of an automotive lower arm using quarter car model simulation with artificial road profile input. Saoudi et al. [12] extracted force loading from a quarter car model to optimize the design of an automobile lower arm in terms of fatigue using a strain energy model. Fatigue life predictions of automotive components, such as knuckle [13], lower arm [14], and chassis [15], have also been performed using

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vehicle dynamic model simulations. Fatigue life prediction of automotive components is widely assisted by simulations because of increased convenience and efficiency.

The optimization of automotive components in terms of fatigue was recently adopted to assist in component design, and various approaches have been proposed to perform the optimization process. Heo et al. [16] performed shape optimization of a lower control arm using radial basis function to replace design sensitivity analysis. Fang et al. [17] performed multi-objective fatigue simulation of a truck cab to improve fatigue life and design stability given uncertainties. Song et al. [18] optimized the fatigue design of an upper control arm using response surface method and kriging metamodels. The fatigue life optimization of automotive suspension components such as outer tie rods [19] and connecting rods [20] have also been conducted using shape optimization. Schäfer and Finke [21] performed shape optimization of steel wheels by using design of experiment (DoE). At present, the automotive component analysis design process has shown an increasing utilization trend in fatigue analysis using shape optimization. The DoE approach can determine the factors affecting fatigue life, but the application of DoE in fatigue analysis is notably limited.

Thus, the objective of this study is to perform DoE analysis of suspension parameters in determining the spring fatigue life. We hypothesize that the fatigue life of the automotive coil spring is correlated with the suspension parameters, such as sprung mass, spring stiffness, damping coefficients, and tire stiffness. To the best of the authors' knowledge, no work has utilized the DoE approach to study the relationships and effects of the abovementioned suspension parameters on spring fatigue life. In this study, multivariate quadratic relationships are established to predict the fatigue life of automotive coil springs using suspension parameters. The authors believe that the findings presented in this paper will extend the current body of knowledge on the fatigue analysis of suspension systems, particularly coil springs.

2 Methodology

DoE is the statistical approach used in this work to identify the effects of suspension parameters on the spring fatigue life and the settings of these parameters to optimize the response. The process flow for DoE analysis is shown in Figure 1. A full factorial analysis was initially performed to determine the suitable parameter range because the number of parameters was not large [22]. In this analysis, four suspension parameters, namely, spring stiffness, damping coefficients, tire stiffness, and sprung mass, were used to optimize the spring fatigue life. The configuration of the suspension system was drawn from a locally manufactured car for simulation in virtual environment. The default values of the suspension system setting of the vehicle were as follows: 20,000 N/m spring stiffness, 545.5 Ns/m damping coefficient, 190,000 N/m tire stiffness, and 250 kg quarter sprung mass.

During the DoE analysis, full factorial with four parameters was selected to examine the effects on spring

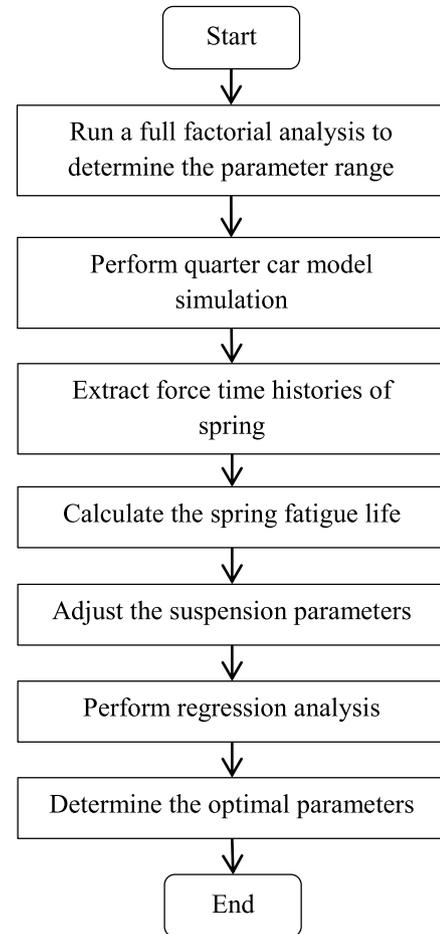


Fig. 1. Process flow for DoE analysis.

Table 1. Levels of influencing parameters.

Parameters	Low (-1)	High (+1)
Tire stiffness	150	230
Spring stiffness	14,000	32,000
Damping coefficient	418	673
Sprung mass	250	350

fatigue life. For two levels of each factor, the design was denoted as 2^k full factorial design, where k is the number of factors [23]. The full factorial method considered all the interactions between the parameters and reduced variability in the analysis. In this case, the number of factors was four, and the replicate number was two, producing a total of 32 runs. In addition, six data points in the center of design were obtained. According to Montgomery [24], the model is fitted with noise when conducting an experiment that has only one run at each test combination. In addition, the pure error and lack of fit are neglected when the design has only a single replicate.

The proposed suspension parameter ranges are listed in Table 1. The tire stiffness range was defined according to different tire pressures, whereas the spring stiffness and

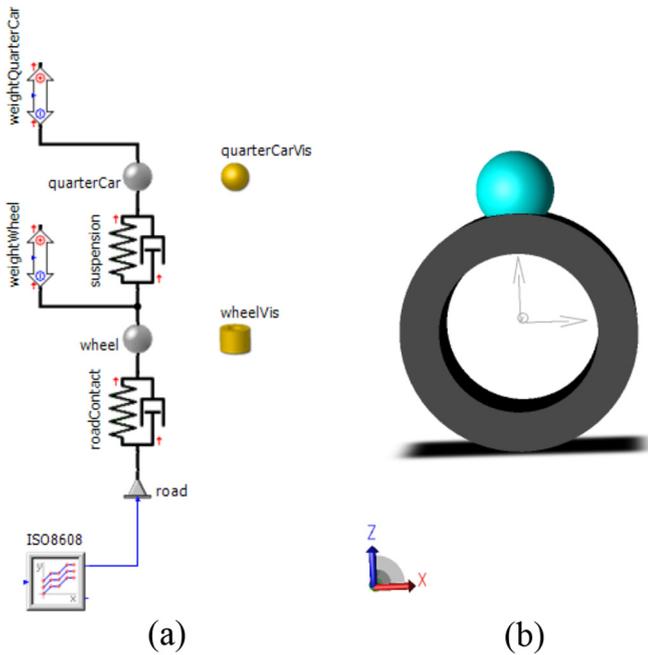


Fig. 2. Quarter car model simulation: (a) block diagram view, (b) 2D view.

damping were defined on the basis of the original value of the actual suspension parameter [25]. The actual vehicle weight was 1200 kg when the vehicle was partially loaded [26]. Hence, the quarter weight of the vehicle was assumed to be 300 kg, given that the weight was evenly distributed among the four wheels. To obtain the data for analysis, a quarter car model was generated for fatigue load data extraction, and the simulation model is shown in Figure 2. An artificial road profile of class “C” according to ISO 8608 was generated and used as input to the quarter car model simulation [27]. This quarter car model was generated according to the equation of motion and consisted of two degrees of freedom.

The quarter car model was run using transient analysis for 90 s to extract the spring force time histories. The spring force time histories were then extracted from the quarter car model for fatigue life prediction. To perform fatigue life analysis, finite element analysis (FEA) of the spring was performed, as shown in Figure 3. The coil spring was meshed with a three-dimensional solid hexahedral element consisting of 9225 nodes and 7168 elements. Furthermore, linear static analysis was conducted to obtain the stress–strain information. The stress–strain information of spring and load time histories were used to predict the spring fatigue life using nCode® DesignLife®, as shown in Figure 4. In this analysis, strain–life (ϵ - N) approach was used to predict the spring fatigue life because this technique is a localized fatigue method with an acceptable safety factor for small components. The vibration signals were applied at the center rigid at bottom of the spring. The automobile coil spring was occasionally subjected to overloads, which caused local yielding. Hence, strain–life approach was suitable for automotive component fatigue analysis, including the suspension elements [28].

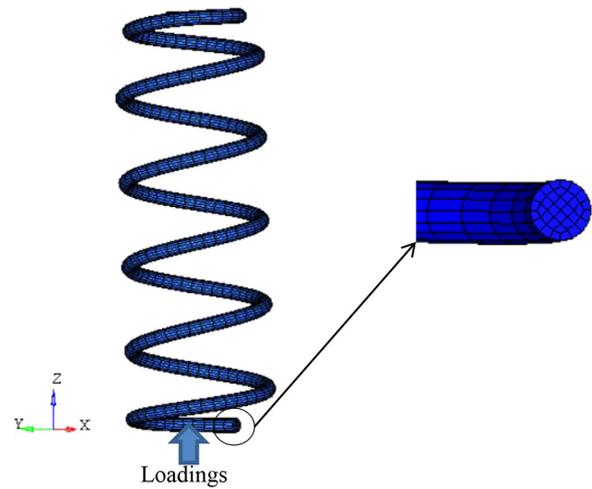


Fig. 3. Solid meshed coil spring.

Table 2. Material cyclic properties for SAE 5160 carbon steel [26].

Property	Value
Ultimate tensile strength (MPa)	1584
Modulus of elasticity (GPa)	207
Yield strength (MPa)	1487
Fatigue strength coefficient (MPa)	2063
Fatigue strength exponent	-0.08
Fatigue ductility coefficient	-1.05
Fatigue ductility exponent	9.56
Cyclic strain hardening exponent	0.05
Cyclic strength coefficient (MPa)	1.940
Poisson ratio	0.27
Modulus of rigidity (GPa)	80

For the fatigue analysis, the Smith–Watson–Topper (SWT) model was selected to perform the fatigue life prediction because this model provides mean stress correction effects with good accuracy when dealing with steel [29]. The SWT strain life model is defined as follows [29]:

$$\sigma_{\max} \epsilon = \frac{(\sigma'_f)^2}{E} (2N_f)^{2b} + \sigma'_f \epsilon'_f (2N_f)^{b+c}, \quad (1)$$

where ϵ is the plastic strain, ϵ'_f is the fatigue ductility coefficient, σ'_f is the fatigue strength coefficient, b is the fatigue strength exponent, c is the fatigue ductility exponent, σ_{mean} is the mean stress, and σ_{\max} is the maximum stress, E is modulus of elasticity and N_f is the fatigue life. The required material cyclic properties are listed in Table 2. Currently, the most widely used strain life fatigue approaches are Coffin–Manson, Morrow and Smith–Watson–Topper. The Smith–Watson–Topper model was suitable for ductility metals fatigue life prediction which

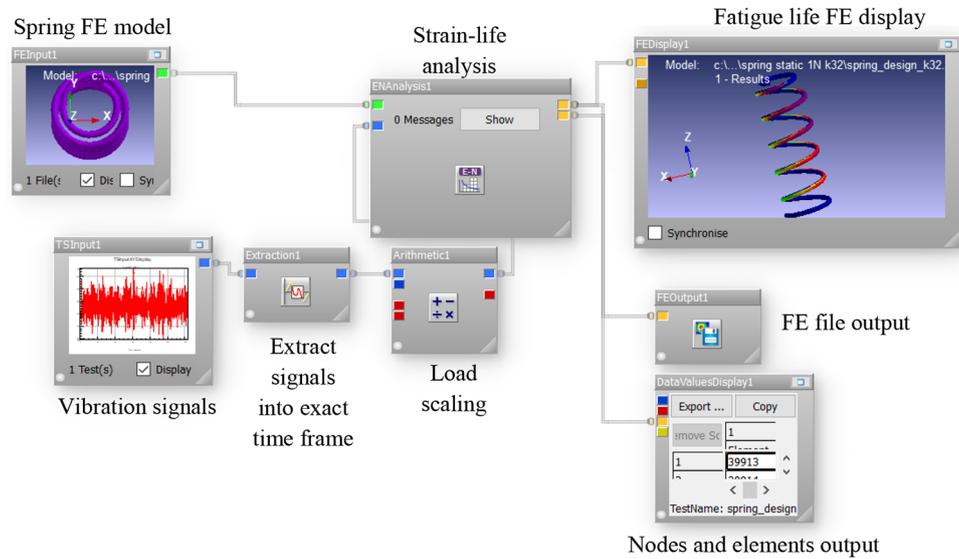


Fig. 4. Setup of fatigue life prediction using nCode[®] DesignLife[®].

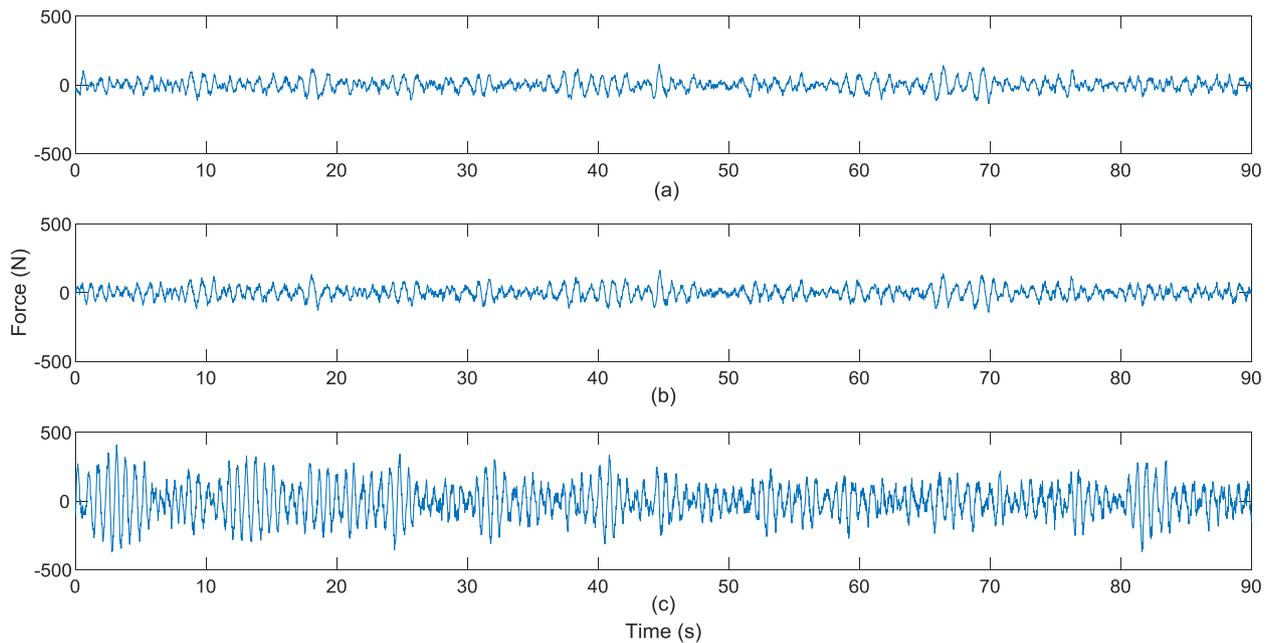


Fig. 5. Simulated force signals for fatigue analysis.

considered mean stress effects [29]. Hence, the SWT model was selected to perform the fatigue life analysis.

To expand the datasets, the suspension parameters were adjusted according to the proposed frequency range of 1–1.5 Hz [30]. After the parameters were adjusted, the simulation was re-run to obtain the force time histories because the dynamic behavior of the model was changed. The force time histories were then used to predict the spring fatigue life. After all the required data were obtained, a regression analysis was conducted to study the effects and interaction of the parameters toward the response. Subsequently, eight axial points and three center points were added, for a total of 49 runs. The optimization

process determined the optimal suspension parameters when the objective function to maximize the spring fatigue life was assigned the constraints, as listed in Table 1.

3 Results and discussions

The preliminary analysis of this research aimed to generate the spring fatigue life prediction according to different suspension parameters. Hence, the force loading signals under the influence of the suspension parameters were simulated from the quarter car model, as shown in Figure 5. These force signals were used to predict fatigue life together

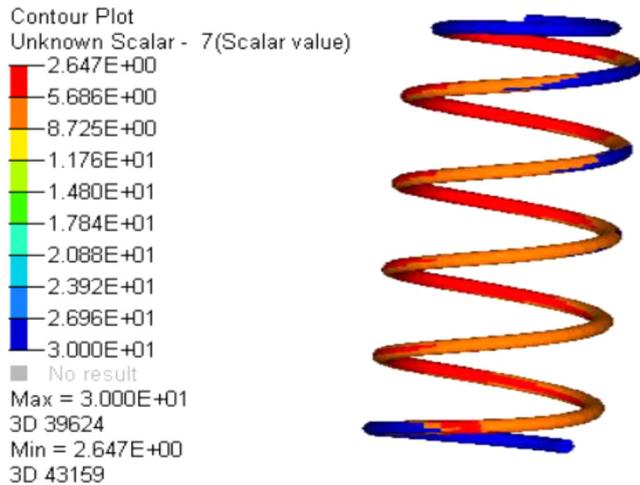


Fig. 6. Fatigue life contour of original spring.

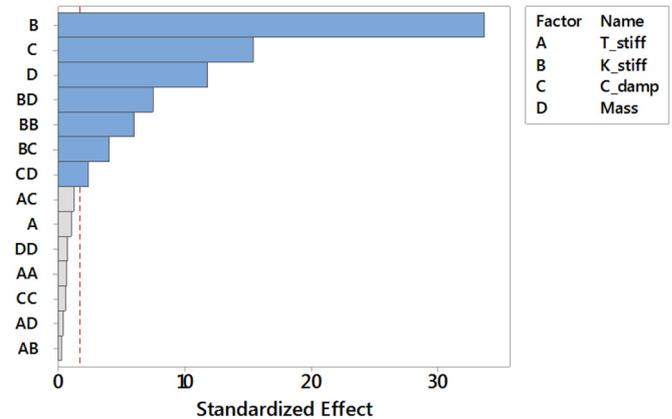


Fig. 7. Pareto chart of standardized effects.
*A: tire stiffness (N/mm), B: spring stiffness (N/mm), C: damping coefficient (Ns/mm), and D: sprung mass (kg)

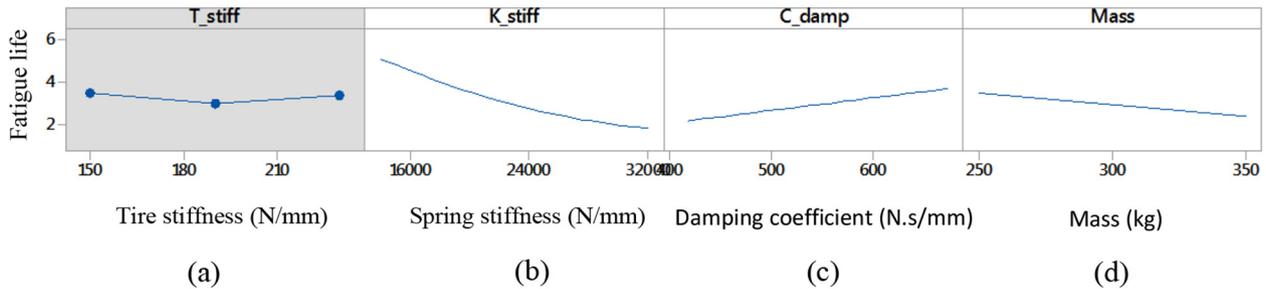


Fig. 8. Main effect plots for fatigue life.

with the FEA analysis of the spring and material cyclic properties. An example of spring fatigue life contour where the localized fatigue life was obtained is shown in Figure 6. A spring sensitivity analysis was performed to determine the effects of different spring designs in terms of fatigue life. The spring sensitivity analysis was performed through adjusting the spring bar diameter.

A total of 49 datasets were used in this analysis to determine the optimal solution of the suspension parameters for spring fatigue life. All effects of suspension parameters were analyzed using a Pareto chart because the goal was to maximize the spring fatigue life, as shown in Figure 7. The parameters, namely, spring stiffness (K_{stiff}), tire stiffness (T_{stiff}), damping coefficient (C_{damp}), sprung mass (Mass), and interactions between parameters, were then analyzed. According to Figure 6, the parameters B, C, D, BD, BB, BC, and CD were related to spring fatigue life at the 0.1 level of significance. Meanwhile, the parameters of AC and below (red dot line) did not show significant effects, indicating that the tire stiffness had minimal effect on spring fatigue life. A flat line was also obtained for the spring fatigue and tire stiffness plots [31], indicating no direct relationship between these two parameters as shown in Figure 8a. The changes in tire vertical stiffness were not linear to the

Table 3. Percentage variations of suspension parameters and interactions.

Factor	Percentage variation (%)
B	33.68
C	15.46
D	11.80
BD	7.45
BB	5.96
BC	4.00
CD	2.34

spring fatigue life. Hence, tire stiffness was excluded from the regression analysis.

The significance level of each parameter, explained by variation percentage after the less significant parameter was removed, is shown in Table 3. The table shows that the designated spring stiffness had the highest variation (33.68%) on the spring fatigue life because the fatigue life of a spring depends on the geometry, which is derived on the basis of the spring stiffness. The relationship between spring stiffness and fatigue life, where the fatigue life of the

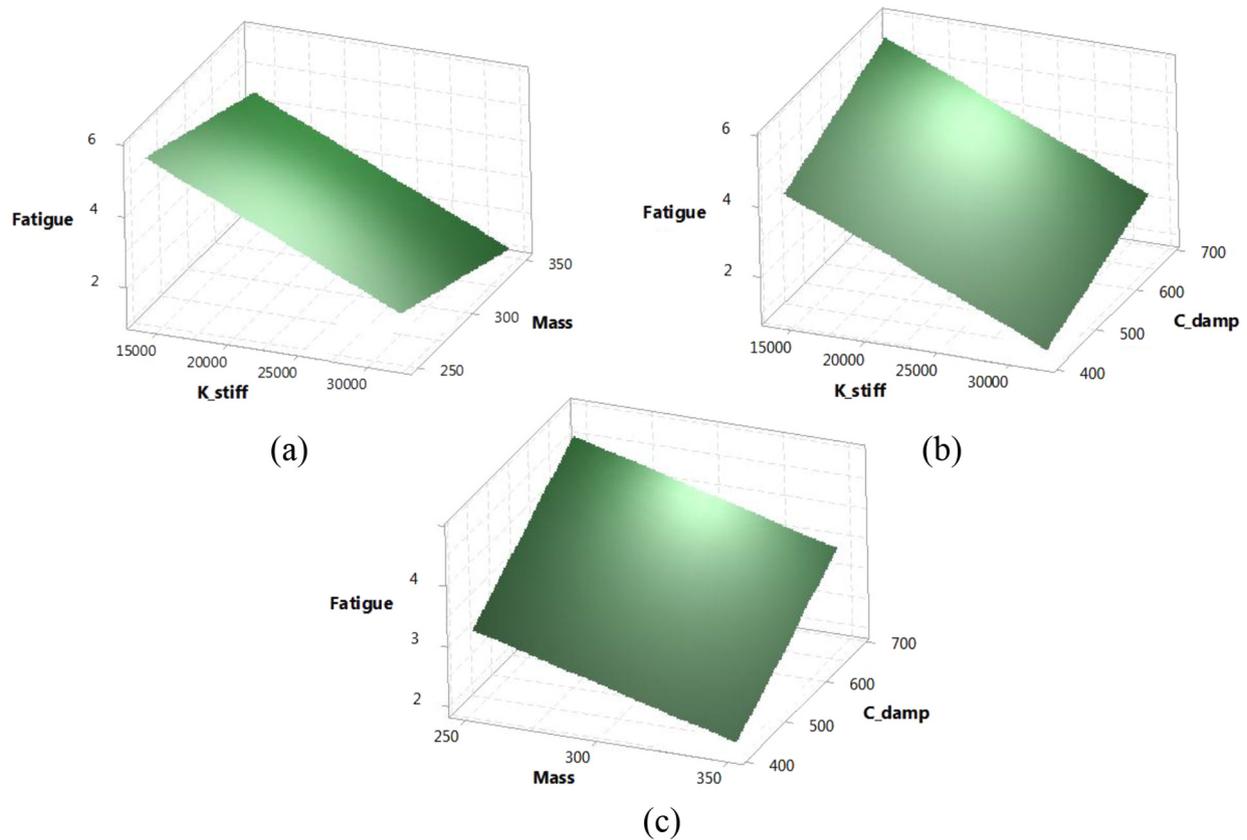


Fig. 9. Response surface plot of fatigue life for different parameters: (a) spring stiffness and sprung mass, (b) spring stiffness and damping coefficients, and (c) sprung mass and damping coefficients.

spring reduced with every increment of spring stiffness, is plotted in Figure 8b. The second important parameter was the damping coefficient, which also affected the spring fatigue life [32]. The reason was that the damper transforms shock from road excitations into heat and dissipates it. Therefore, the damping properties play a critical role in determining the fatigue behavior of automotive components, including the spring.

The damping coefficients showed a positive increasing relationship toward the spring fatigue life, as illustrated in Figure 8c. Apart from spring stiffness and damping coefficients, the sprung mass was an important parameter which affected the spring fatigue life. Kamal and Rahman [33] proposed that the sprung mass changed the equilibrium position where the spring deformed to counter the road disturbances. The effects of sprung mass were clear because it had direct effects on the spring which was designed to support heavy loads. When the sprung mass was high, the load exerted on the spring was also high, thereby reducing the spring fatigue life. Hence, a negative relationship for spring fatigue life and sprung mass was obtained, as shown in Figure 8d. Subsequently, the interactions between parameters toward spring fatigue life were also investigated because the combination of every parameter led to varying effects on spring fatigue life.

Table 3 shows that the interactions between spring stiffness and sprung mass had only a small percentage of variation. To further investigate the relationship between

spring stiffness and sprung mass, a response surface plot for fatigue life is shown in Figure 9. This condition could be explained using an interaction plot, which described how the mean of fatigue life changed when the two other relevant factors were altered. In Figure 10, the interaction plots for spring stiffness and sprung mass indicate that an increment in spring stiffness reduced the fatigue life. When the sprung mass was increased, the fatigue life was further reduced, but the magnitude was small. The interaction of spring stiffness and damping coefficient was then considered, as shown in Figure 9b. According to the interaction plot, increasing the damping could enhance the spring fatigue life where an apparent increment of spring fatigue life was illustrated. According to the damping coefficient and sprung mass interaction plot, the enhancement of fatigue life through increasing damping coefficient could be further improved using reduced sprung mass. Regarding the design aspect, the interaction plots between parameters provided important information when the combination effects of parameters toward response were required.

Subsequently, multiple regression modeling was performed for the parameters, with spring stiffness, damping coefficients, and vehicle sprung mass as the independent variables and spring fatigue life as the dependent variable. The fatigue model was obtained as follows:

$$N_f = 17.25 - 0.00063 * K_stiff + 0.00438 * C_damp - 0.04048 * Mass + 0.00002C_damp * Mass. \quad (2)$$

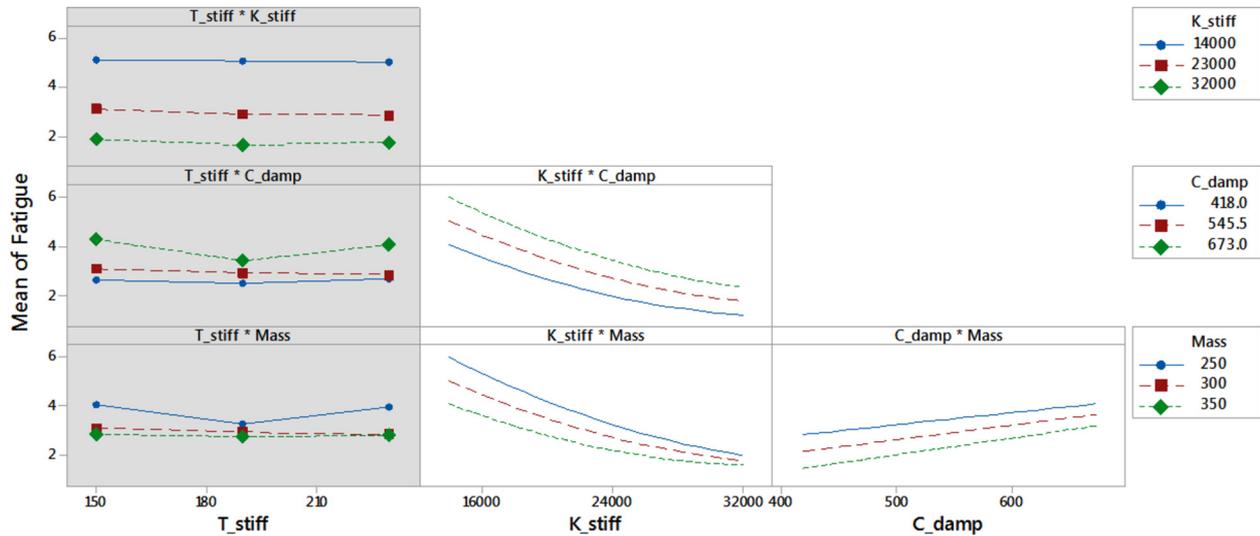


Fig. 10. Interaction plots of parameters for fatigue life.

This regression was obtained using un-standardized coefficients where the original units of the parameters were applied. The unit for spring stiffness (K_stiff , T_stiff) is N/m, damper damping coefficient (C_damp) is N s/m and sprung mass (Mass) is kg. This process meant that an increment in fatigue life led to a reduction of 0.00063 N/m spring stiffness, 0.00438 N s/m damping coefficient, 0.04048 kg mass, and 0.00002 increment in interaction effect of damping and sprung mass from a constant of 17.25. The predicted fatigue life was with unit of blocks to failure in natural logarithm. In this study, the obtained coefficients for both quadratic spring stiffness (BB) and spring-damping (BC) are approximately zero which caused very minimum effects on the fatigue life. Hence, the fatigue life model was presented with only the spring stiffness, damping, sprung mass and damping-sprung mass as independent variables.

Initially, the full factorial with replicate was performed to ensure the design was fully orthogonal. Subsequently, quadratic model was fitted for suspension parameters and fatigue life relationship. By cross-validation, the optimised fatigue life quadratic model was obtained [34]. The optimized suspension parameter was determined using steepest ascent algorithm [35]. The fitted regression was evaluated using the coefficient of determination (R^2) value. As proposed by Sivák and Ostertagová [36], the regression for fatigue fitted with R^2 value above 0.90 was considered as very good. In this case, the R^2 value was 0.9078, which indicated that the data had good fit. When the linear regression was applied, the datasets were assumed to be linear. To investigate the normality of the datasets, a normal probability plot for the datasets was plotted, as shown in Figure 11. Figure 11 shows that the data points followed a straight diagonal line at the center. However, a data point lay far from the diagonal center line and was thus a possible deviating point. The existence of an outlier point could lead to inaccurate prediction results [37]. Nevertheless, to determine whether a data is an outlier, the value of the data was usually exceeded value of three

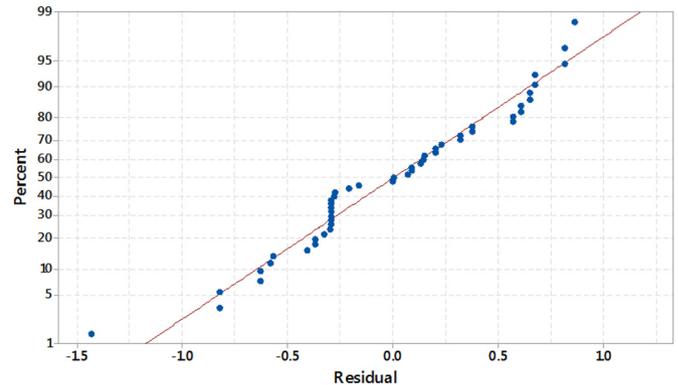


Fig. 11. Normal probability plot for fatigue life.

standard deviation [38]. In this case, the high deviation data point value was within one standard deviation.

The residual of prediction was further examined using an error histogram, as shown in Figure 12. An apparent point lay beyond the range of the predictions, and the point consisted of a high residual value of -1.5 . Nevertheless, the standard deviation of the fatigue life was 1.6651, showing that the deviation was not extreme in affecting the predictions. In addition, only a single high deviation point was observed, and the obtained R^2 value of the regression was high. To check the homoscedasticity of the generated regression, a scatter plot of the regression was plotted as shown in Figure 13. When the regression was homoscedastic, the prediction outcomes were consistent and did not show any specific pattern. Figure 13 shows that the data points were evenly distributed along the zero line, which proposed equal variation. However, a deviation point (red dot) was detected from the scatter plot. In addition, the higher deviation point was reported in the error histogram. According to the scatter plot and the histogram, the regression exhibited normality and homoscedasticity; the regression was acceptable and produced consistent predictions.

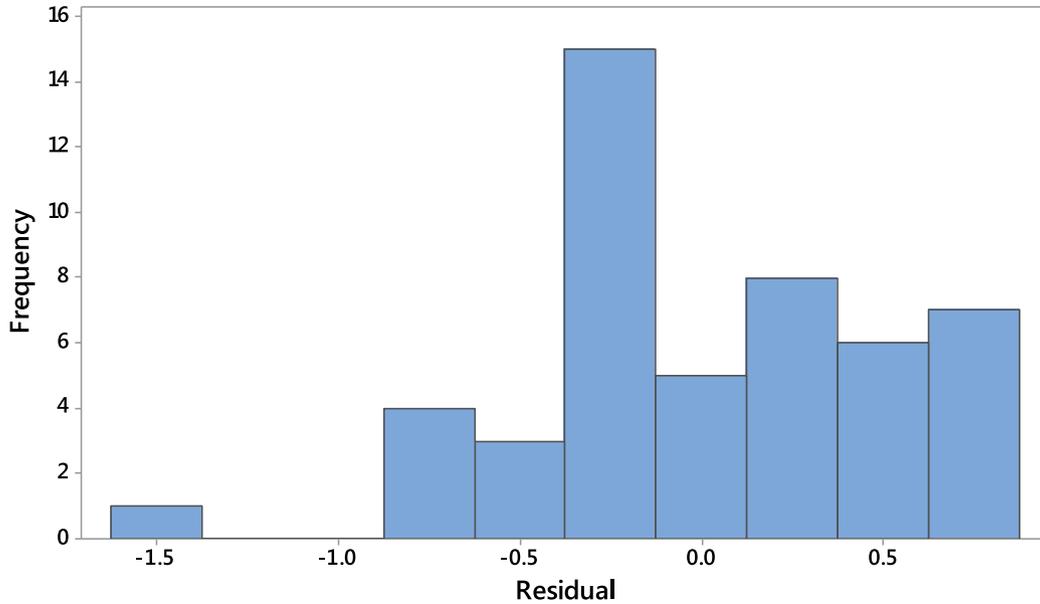


Fig. 12. Error histogram for fatigue life response.

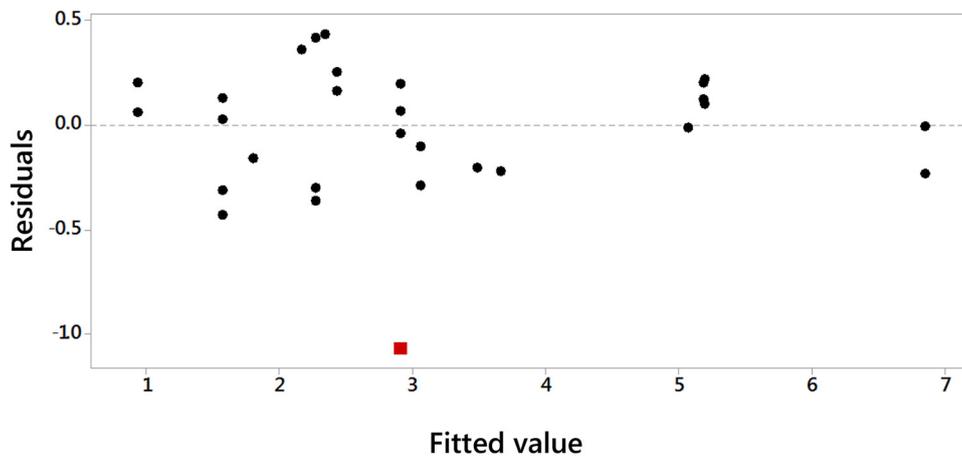


Fig. 13. Scatter plot of residuals.

The scatter plot was plotted into observation order to determine non-random patterns, as shown in Figure 14. In this figure, we examined the trends of the residuals for large values and shifting of the mean. A large residual, which was caused by the resonance of the suspension model, was observed on the number order of 38. When the suspension system resonated, added deflection and vibration were introduced to the suspension system, thereby causing the deviation [39]. Figure 14 shows that this plot also ensured that the data had no increasing or cyclical trend, suggesting that the error terms were independent; hence, the generated regression assumption was satisfied.

After evaluating the regression, the next step was to determine the optimal settings of the suspension parameter for spring fatigue design. To obtain the optimal suspension parameter, the objective of optimization to maximize the spring fatigue life was assigned. According to this objective function, the proposed optimal suspension parameter

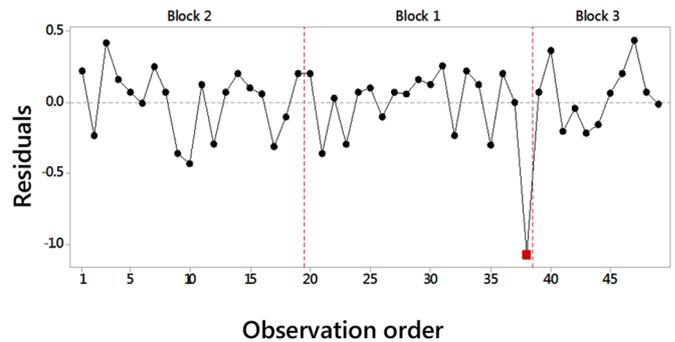


Fig. 14. Residual versus observation plot.

settings were as follows: spring stiffness of 14,000 N/m, damping coefficient of 673 N s/m, and sprung mass of 250 kg. With this set of suspension parameter settings, the

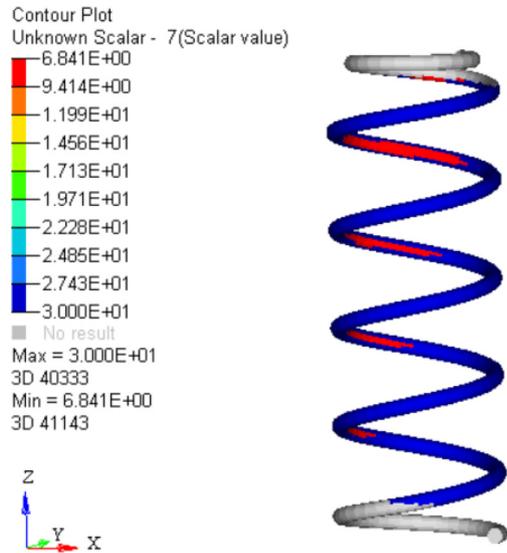


Fig. 15. Optimized fatigue life of the spring.

spring fatigue life could be maximized. The predicted optimized fatigue life was 7,012,938 blocks to failure, and the fatigue contour of the spring is shown in Figure 15. The lowest fatigue occurred at the inner surface, where the crack was initiated, and propagated toward the outer surface [40]. To estimate and reduce the uncertainties, 2 replicates were used to increase accuracy and variability of estimates. The 95% confidence interval is the range of likely values for the mean fatigue life which between 3,162,278 and 12,589,254 blocks to failure.

When observing the parameter sensitivity, the fatigue life could be enhanced through reducing the spring stiffness and sprung mass. This analysis was significant in determining the suspension parameter configuration that led to the optimal spring fatigue life. A good spring design results in sufficiently long fatigue life, but current coil spring design always depends solely on the spring geometry and materials. This analysis proposes the effects of suspension parameter toward the spring fatigue life and thus serves as guidance for suspension designers. In terms of vehicle dynamics, engineers have attempted to maximize vehicle ride comfort through reducing the spring stiffness and increasing sprung mass and damping coefficients. However, the effects of changing the spring stiffness and damping coefficients toward spring's fatigue life are significant but have not been conducted. Through utilizing the developed multiple regression, spring fatigue life can be predicted under constrained suspension parameters.

4 Conclusion

In this study, design of experiments was developed on the basis of SWT strain-life models to predict the fatigue life of an automotive coil spring using suspension parameters, namely, spring stiffness, damping coefficients, and sprung mass. The interactions between parameters were examined, and the spring stiffness showed the largest influence

on spring fatigue life. A multiple-input regression was conducted, and the R^2 value was 0.9078. This value indicated that more than 90% of the variability in the fatigue life of the automotive coil spring was described by the models. The regression showed normality and homoscedasticity in a residual scatter plot and an error histogram. The optimal suspension parameters that must be set to obtain maximum spring fatigue life were obtained. The spring stiffness and sprung mass must be minimized while maximizing the damping coefficient.

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