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Kinematics & Compliance Validation of a Vehicle Suspension and Steering Kinematics Optimization Using Neural Networks

Gurur AĞAKİŞİ*, Ferruh ÖZTÜRK**
**TOFAŞ Türk Otomobil Fabrikası AŞ – R&D Center, Bursa, Turkey, E-mail: gurur.agakisi@tofas.com.tr*
***Bursa Uludag University, Automotive Engineering Department, Bursa, Turkey, E-mail: ferruh@uludag.edu.tr*
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1. Introduction

K&C is a type of suspension analysis in which, kinematics and elasticity, are evaluated together. The suspension systems consist of rigid subcomponents connected by kinematic joints and compliance elements [1]. While kinematics deals with how a mechanism moves, compliance considers the influence of various deformable structures between these links. Thus, both kinematic and elastic properties are evaluated simultaneously in the system. The suspension K&C is more commonly employed for qualitative than quantitative research [2].

The K&C characteristics of vehicle suspension systems are key characteristics by which the vehicle's steering, comfort, ride and handling performance can be evaluated and explained [3]. For example, the vehicle responsiveness to steering input is substantially connected with suspension stiffness in the lateral direction, and steer change rate can be used to estimate the understeering characteristic. In the development phase of the vehicle, by creating a target for each K&C characteristic, design variables such as the position of the suspension hardpoints, and the stiffness of the suspension bushings are tried to be determined optimally [4]. The McPherson suspension system, together with the anti-roll bar and the steering sub-components, creates a complex design environment, and previously they were subjected to an optimization individually [5]. Since these subsystems are kinematically related, the introduction of MBD enabled the analysis of the wheel motion precisely and helped to evaluate and optimize the suspension characteristics [6]. Another goal of the model development is to shorten development time by reducing the requirement for physical tests, observing vehicle characteristics in a continuous loop and test repeatability [7].

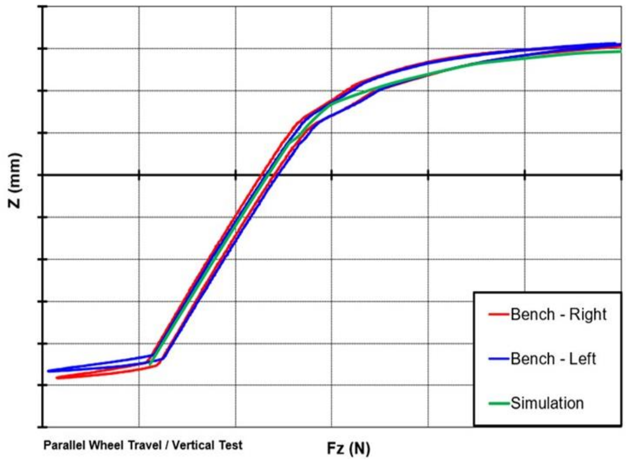
There are some documented papers in the literature on K&C optimization. Steering kinematics are improved focusing on the steering rack [8]. Steering linkage of a bus is optimized using RSM approach [9]. Multi-criteria optimization of a suspension system is realized utilizing the conventional regression models [10]. DOE approach is used for a solid axle of a heavy commercial vehicle on optimizing steering kinematics which used statistical analysis [11]. Double wishbone suspension is optimized within parallel wheel travel tests for the wheel alignment parameters using capability of ADAMS software [12]. DOE with ANOVA is realized for leaf spring suspension to optimize toe angle and wheelbase change using a statistical analysis approach [13]. To the best of the author's knowledge, some publications are available in the literature on the steering kinematic optimization of McPherson suspensions, but none focuses on the suspension hardpoints with multi-objective optimization using NN (neural network) modelling and GA (genetic algorithm), comparing with conventional response surface methods in a limited design environment. As the K&C development is an iterative process and subject to updates based on different vehicle subsystems, it is essential to find the best solutions in available limited and repeatedly varying design space.

Hardpoints are the most fundamental elements of MBD model, as they describe and interpret all the model's critical positions [14]. In this study, we present the results of a project that used a neural network and a genetic algorithm to achieve the K&C targets by defining the optimum hardpoints. Research has shown that combining NN and GA can effectively create significant results [15]. The hybrid NN-GA technique and the traditional RSM approach are compared and used to predict optimum hardpoints. The outcomes of this paper are planned as conducting improved optimization studies: 1. according to frequent changes in the product development process without the need for re-experimentation and re-analysis; 2. solving the problems requiring assumptions and constraints based on experience, mainly by the trial-and-error method of experts, and a solution is sought by carrying over from previous projects; 3. with an intelligent learning algorithms solution approach that can be easily adapted to when different options are encountered that can quickly gather the results at a low cost.

2. K&C model and validation

A compact-sized passenger vehicle is used in the study, and the complete McPherson front suspension system MBD model of the vehicle is created on ADAMS/Car for virtual K&C testing. K&C analyses characterize the suspension system, considering the kinematic properties of the suspension and the deformation due to elastic components. K&C analyzes can be specified as leading analyses evaluated for vehicle dynamics, comfort, and handling. In physical test bench, the examination is performed with the help of an activator that moves the wheel or applies force according to the analysis type and with a test device that records the angles, positions, and kinematic suspension movements of the wheel [16]. While performing these analyzes, the goal is to finalize the design variables with a loop of process that is managed by aligning with all the vehicle subsystems affected by suspension geometry. K&C validation of the prototype vehicle is shared in terms of quasi-static vertical wheel travel and steering tests in this paper and the values from the K&C analysis are hidden for confidentiality purposes.

Vertical travel tests include parallel wheel travel and opposite wheel travel analysis with wheels activated only on the Z-axis from the contact patch. Parallel wheel travel simulates when both wheels move up or down simultaneously (e. g., passing over a bump, both suspension wheels are articulated through full jounce and rebound values). The opposite wheel travel analysis mainly controls the same outputs by similarly activating the wheel vertically; however, while one wheel goes for a complete rebound, the other wheel goes to full jounce. This type of analysis is helpful to understand, especially the behavior of the suspension when making a maneuver. The related K&C characteristics for parallel and opposite wheel travel analysis are presented. One of the most fundamental K&C analyses is the wheel rate curve, as shown in Fig. 1. This curve shows the variation of the vertical force on the wheel concerning the wheel stroke. In the parallel wheel travel, the linear region shows the effect of springs. On the left and right sides of the graph, it can be seen in which stroke the rebound-stop and the bump-stop conditions are active. This analysis also enables to check the maximum wheel strokes, as in jounce and rebound conditions. It is also possible to evaluate the suspension hysteresis. In the opposite wheel travel, it is possible to check the anti-roll bar effect on the wheel rate curve as the component is subjected to a deflection in this test configuration [17].



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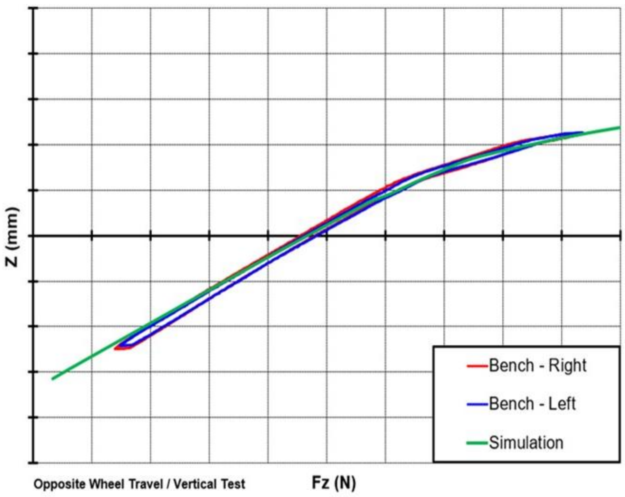

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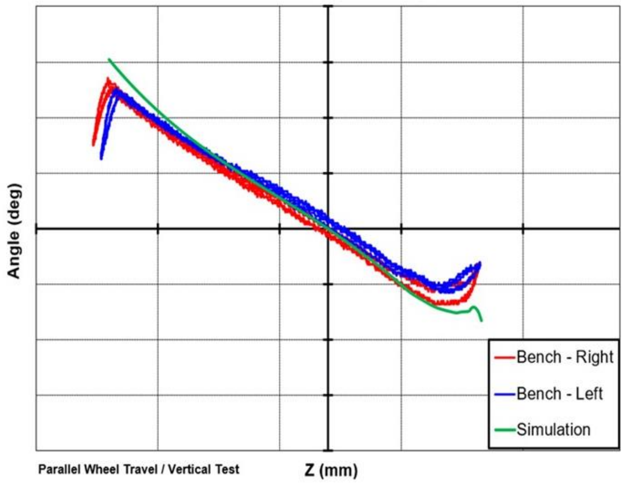
Fig. 1 Front wheel rate: a) parallel; b) opposite travel

Another principal K&C analysis is toe angle change based on the wheel movement, as shown in Fig. 2. Due to handling requirements, an understeer response is desired in the passenger vehicles. To achieve this, the front suspension must have a toe-out, and the rear suspension must have a toe-in angle while driving. Setting up the suspension in this way will increase cornering stability. The toe angle aims to counteract the negative effects of wheel camber and ensure that the wheels roll smoothly and evenly while travelling in a straight path. Generally, the expected variation is below ±0.5° [18]. This is also called ride steer, and targets are defined for the ride steer variation considering specific strokes of wheel articulation on the vertical axis. A lower variation on toe angle improves the straight-line stability and tire wear.



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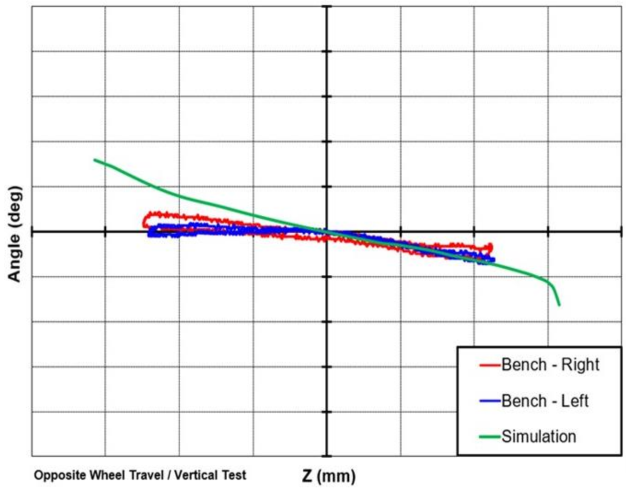

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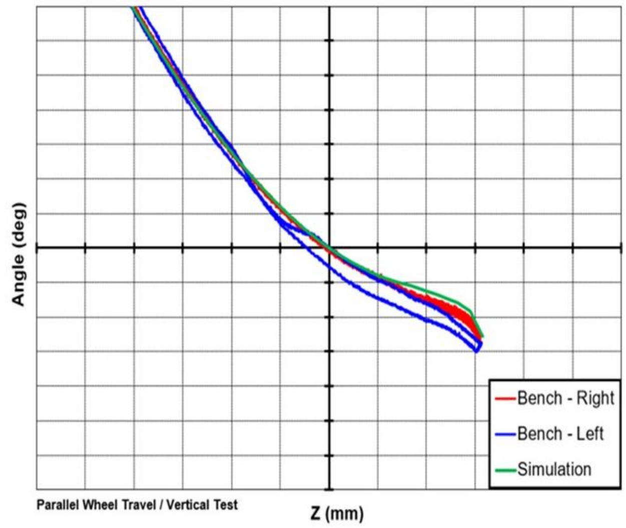
Fig. 2 Ride steer: a) parallel; b) opposite wheel travel

Another parameter that can be evaluated with K&C analysis is the change in camber angle, as shown in Fig. 3. The camber change is aimed to be negative as the dominant wheel (usually the front axle) moves upwards (as the load is applied to the wheel). To increase the cornering ability, solutions are sought to maximize the contact surface of the wheels with the road in suspensions. Generally, the static value and variation are in the range of 0°~1° [19]. This analysis is also called the ride camber. The variation in camber angle aims to have a smaller value to help reduce tire wear [20].

The displacement in the X-axis (as of increasing or decreasing the wheelbase) in response to the vertical movement of the wheels is an essential parameter for comfort performance, especially for longitudinal comfort, as shown in Fig. 4. If the vehicle hits an object and the wheels move toward escaping, this is a comfort-enhancing feature. With the same logic, if the vehicle is moving in the direction of the object as opposed to avoiding it, it can be considered a preliminary analysis that reduces comfort.



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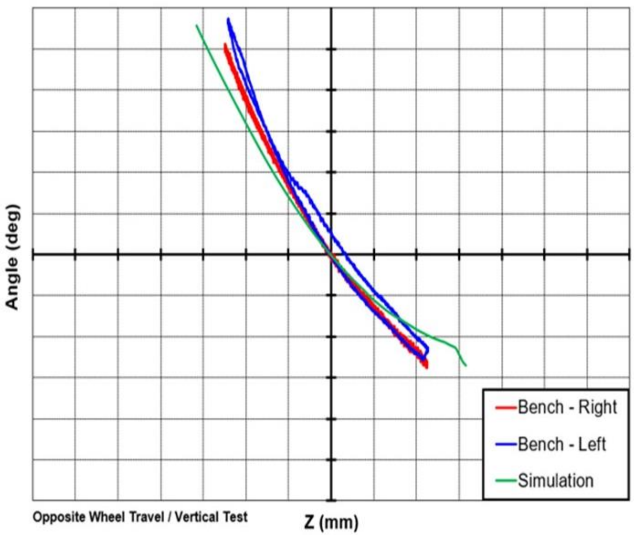

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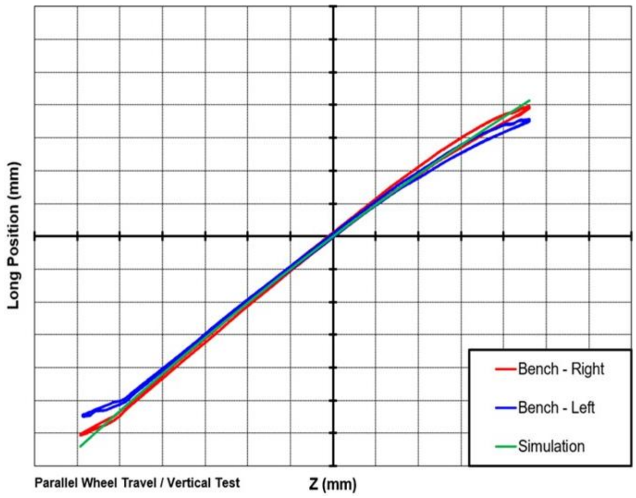
Fig. 3 Camber variation: a) parallel; b) opposite travel

The change of wheel position on the Y-axis (lateral, wheel track) concerning full jounce and rebound articulation is also a parameter checked within the wheel travel K&C testing, as shown in Fig. 5. Apart from a slight variation in rebound condition for the toe and camber angle change, the complete results are acceptable. It can be indicated that the computational MBD model estimates are satisfactorily correlated and reliable in simulating the vertical travel testing.

The steering analysis covers the K&C characteristics checked during the maximum steering wheel rotation in both left and right directions limited by the steering gear rack travel. One of the significant parameters in the steering is the steering ratio, which is the ratio between the steering wheel's angular displacement to the angular displacement of the steered wheels. The camber variation is checked alike the vertical wheel travel tests. Lastly, it is also possible to check the wheel center location change concerning complete steering wheel angle activation, and the related curves can be seen in Fig. 6. Wheel center locus has a critical impact on straight-ahead driving stability. The simulation results show a good correlation with the bench data.



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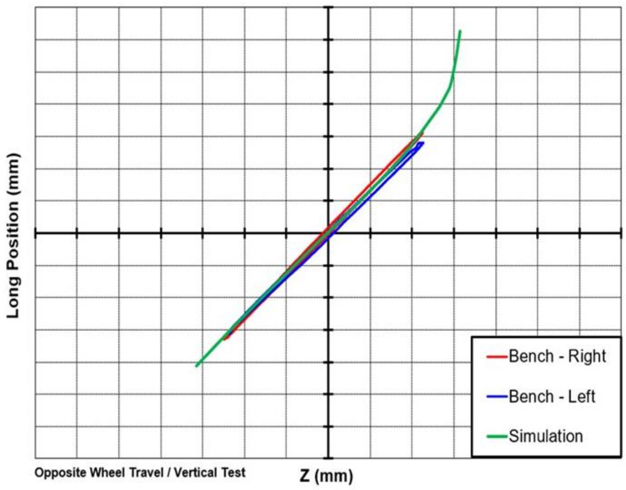

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Fig. 4 Wheelbase variation: a) parallel; b) opposite travel

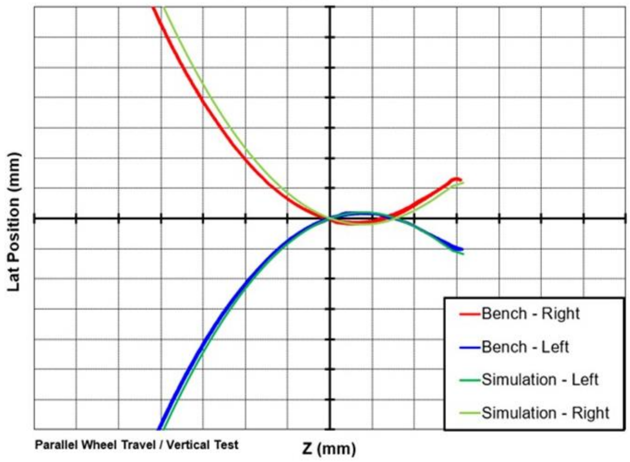

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Fig. 5 Wheel centre lateral change: a) parallel; b) opposite travel

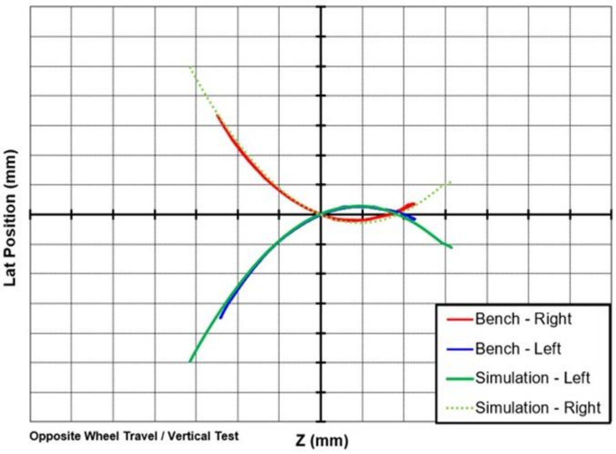

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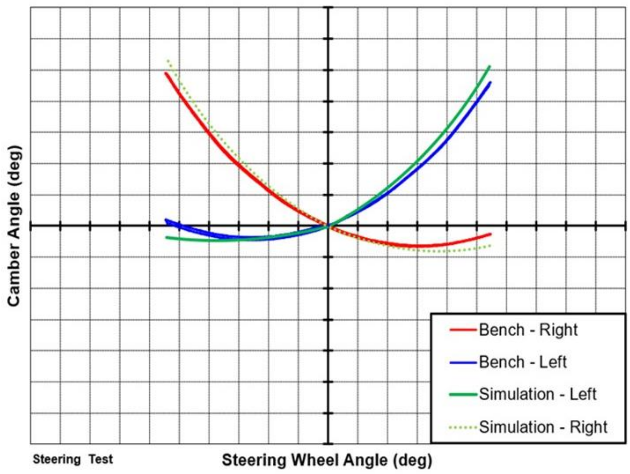
Fig. 5 Continuation



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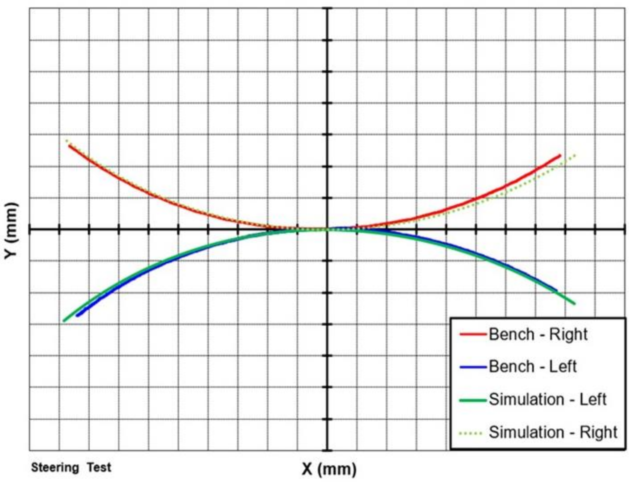

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Fig. 6 Steering outputs: a) front camber angle change; b) wheel centre locus change

Synthesis is available to present the selected major K&C characteristics results according to bench results correlation compared to MBD model, as shown in Table 1. The target values for the characteristics are defined by benchmarking the competitor vehicles, prior experiences and the requested vehicle dynamics targets for this specific vehicle project. The values for each row have been normalized as the maximum target would be 100 % due to confidentiality. The wheel rate values are shown based on the physical bench result for opposite wheel travel accepted as 100% (anti-roll bar effect is the difference between opposite and parallel wheel rate). Briefly, the vertical kinematics are in target, and a good correlation is maintained with the bench testing for both quasi-static vertical travel and steering tests.

As initial vehicle steering K&C targets have not been satisfied for the Ackerman error and the camber angle variation, a DOE and NN study is planned to optimize by predicting the hardpoints.

3. Hardpoint optimization by RSM

In this section of the paper, a design of experiment is conducted to find the key hardpoints that most affect the camber angle variation and Ackerman error performance in steering analysis. Once the key hardpoints are defined, an RSM study is conducted to optimize the hardpoints and improve steering kinematics followed by NN and GA in the next chapter. In ADAMS/Car, two design objectives are created for Ackerman error and camber angle variation and in ADAMS/Insight, the design matrix is created by selecting seven hardpoints that include twenty-one factors of the front suspension assembly. The selected hardpoints are the X, Y and Z coordinates of the lower control arm (front and rear linkage with subframe and outer linkage with the knuckle), McPherson strut lower knuckle connection, top mount, and outer and the inner steering gear tie-rod connections.

DOE screening with a linear model and fractional factorial design type, 232 runs are completed. The screening objective is also realized with the Plackett-Burman design type linear model to check whether this approach can result with similar critical factors. As the Plackett-Burman requires low number of trials, the time needed to accomplish the task is considerably less. The five most influential factors are selected for optimization based on the results, as shown in Table 2. The points are specifically, outer tie-rod (X and Y coordinates), knuckle linkage of the lower control arm (Y coordinate), inner tie-rod (X coordinate) and top mount (X coordinate).

According to results realized with 24 runs with Plackett-Burman, it is seen that the key parameters having more than 10 % effect on two design objectives are the same five hardpoints defined in the fractional factorial study. This shows that Plackett-Burman can be a feasible selection for sensitivity analysis on McPherson K&C suspension tests. Goodness-of-fit is expressed as positive for both screening objectives utilizing coefficient of determination, R2 (R-Squared) and R2adj (Adjusted R-Squared), as the values are close to 1, as shown in Table 3. It is requested an R2adj value of more than 0.85 for similar K&C activity [21].

Ackerman error and the camber angle variation is first optimized with the DOE response surface objective method to achieve values below the maximum. The five factors used are the hardpoints defined by the DOE screening method. Since there is a tight zone in design environment point of view for the vehicle, the values available for each factor (hardpoint coordinates) are within the +/- 5 mm range. The response surface approach combines statistical experimental designs with empirical model construction using regression for optimization. DOE's primary concept is to diversify all relevant parameters concurrently throughout a series of prepared trials and integrate the findings using a mathematical model [22].

Table 1

Vehicle kinematics & compliance vertical travel and steering tests performance table

Analysis	K&C Characteristic	Min. target	Max. target	K&C bench	MBD
Parallel wheel travel	Ride steer variation at +10 mm bump	35 %	100 %	53 %	63 %
	Ride steer variation at +40 mm bump	24 %	100 %	40 %	43 %
	Ride camber variation at +40 mm bump	43 %	100 %	46 %	50 %
	Caster angle	73 %	100 %	87 %	96 %
	Parallel wheel rate at ground	-	-	43 %	42 %
Opposite wheel travel	Opposite wheel rate at ground	-	-	100 %	104 %
	Anti-roll bar effect	-	-	57 %	62 %
	Ride steer variation at +10 mm bump	35 %	100 %	37 %	43 %
	Ride steer variation at +40 mm bump	24 %	100 %	26 %	27 %
	Ride camber variation at +40 mm bump	43 %	100 %	69 %	51 %
Steering	Steering ratio	81 %	100 %	92 %	93 %
	Caster trail	83 %	100 %	83 %	86 %
	Kingpin inclination	80 %	100 %	84 %	85 %
	Ackerman error	56 %	100 %	119 %	126 %
	Kingpin offset	83 %	100 %	95 %	98 %
	Camber angle variation	65 %	100 %	120 %	12 8%

Table 2

Sensitivity analysis

	Fractional factorial % Effect	Plackett-Burman % Effect
Ackerman error		
tie-rod outer, Y	36.7	32.73
lca outer, Y	30.34	25.28
tie-rod inner, X	10.5	11.48
Camber angle		
tie-rod outer, X	20.9	18.79
lca outer, Y	15.46	12.93
top mount, X	14.47	14.06
tie-rod outer, Y	13.69	10.78

Table 3

Goodness-of-fit results for screening analysis

	Fractional factorial		Plackett-Burman	
	R2	R2adj	R2	R2adj
Ackerman error	0.999	0.9883	0.9926	0.9771
Camber angle	0.9983	0.9801	0.9865	0.9581

The DOE design matrix is created using three different methods. Quadratic central composite faced (CCF), quadratic Box-Behnken, and linear interactions full factorial models conduct the optimization study. Using a full factorial design in quadratic is very costly because of the high number of simulations; hence the CCF and Box-Behnken are checked if these models can show promising results. The optimized hardpoints are found by defining the cost function as the squared sums of targeted K&C characteristics. After the definition of optimized (by regression) hardpoints, the coordinates are further inserted into the MBD model by adjusting the relevant hardpoints, and with the virtual test rig, the K&C testing is again realized. The results from the MBD simulation test rig are considered as the as the final results indicating each method's performance as shown in Table 4.

CCF design type with quadratic model only required 31 runs to accomplish the task. Compared to the baseline front suspension geometry, 14.4% improvement on Ackerman error and 25.7% improvement on camber variation is achieved. However, Ackerman error remained over the target. In contrast, the Box-Behnken design type with a quadratic model required 46 runs to finalize the objective. Compared to the baseline front suspension geometry, 23.84% improvement on Ackerman error and 24.45% improvement on camber variation is achieved. Both quadratic models show lower errors, hence exporting similar results as the MBD software. The results are further compared with linear interactions full factorial study that has run 32 times. Full factorial has presented comparable improvement with fewer runs proposed by Box-Behnken despite a worse prediction performance. For both the Ackerman error and the camber angle variation, the values are normalized to 1 as a maximum allowable target for each specific characteristic enabling confidentiality of the data. The baseline suspension has the Ackerman error of 1.26 and camber angle variation of 1.28 as can be seen in Table 1.

Table 4

Optimization results of RSM

		CCF	Box-Behnken	Linear full factorial
Ackerman error	Predict	1.074	0.958	0.975
	Test-rig	1.081	0.962	0.987
	Error	0,68 %	0.39 %	1.15 %
	Improve	14,4 %	23.84 %	21.84 %
Camber angle variation	Predict	0.956	0.97	0.96
	Test-rig	0.951	0.967	0.952
	Error	-0.53 %	-0.27 %	-0.82 %
	Improve	25.7 %	24.45 %	25.61 %

4. Neural network approach for hardpoint optimization

A neural network is a mathematical model of how the brain works neurologically. It mathematically models the web of linked nerve cells to imitate the brain's learning process. A neural network is a data-driven model of interconnected items called neurons included in layers, and adequate input and output data are necessary for neural network modelling. An input and output layer with the hidden layer(s) make up a conventional neural network [23]. The network can calculate complicated correlations between the input and output variables thanks to the neurons in the hidden layer having configurable weights. Adjusting weights is realized by the process called "training", and it is similar to calculating the regression coefficients in the response surface matrix. A supervised learning technique with cross-validation is used for this purpose [24]. The weights are chosen at random at first, and then an iterative process is used to discover the weights that minimize the variances between the real and the network outputs.

The feed-forward neural network is the most popular neural network architecture. A feed-forward network is one in which information or signals are only sent in one direction, from input to output. Any nonlinear continuous function may be approximated precisely using a three-layered feed-forward neural network with a back-propagation method [25]. The backpropagation algorithm is the most often utilized. The backpropagation learning algorithm employs a gradient search strategy to reduce the network's mean square error [26]. In this training procedure, the error between the output neurons' results and the actual outputs is calculated and transmitted back through the network. The algorithm modifies the weights in each successive layer to decrease inaccuracy. This process is continued until the difference between the actual and calculated outputs meets a pre-determined error specification. In this study, the neural network model included two output neurons as Ackerman error and the camber angle change, and five input neurons as outer tie-rod (X and Y coordinates), knuckle linkage of the lower control arm (Y coordinate), inner tie-rod (X coordinate) and top mount (X coordinate).

The strength of ANN over RSM comes from the fact that it can learn from prior data, does not need the definition of a suitable fitting function in advance, and has universal approximation capacity, which means it can approximate practically any non-linear functions [27]. For optimization, neural network models could be treated as objective functions. However, optimizing a neural network model using traditional approaches such as gradient-based methods is challenging due to the difficulty of calculating the model's derivatives. Genetic algorithms, founded on the concepts of evolution through the natural selection approach, have shown to be an effective search and optimization tool for problems with non-continuous or non-differentiable objective functions. Using a population, the genetic algorithm examines all the solution space. At first, a population is created at random. An objective function is used to assess each individual's fitness. The neural network models are used as the objective function in this manner [28]. Following the conclusion of the fitness evaluation, genetic algorithm procedures such as mutation and crossover are conducted on individuals chosen based on their fitness to generate the next generation. This method is repeated until an optimal solution is discovered. Implementation of genetic algorithms as a problem-solving and optimization tool is possible and MATLAB R2021a has been used to implement the NN models and genetic algorithms presented in this study.

Defining the network's topology is the initial stage in developing a neural network modelling technique. Because the topology of a neural network is mainly specific to the problem, there is no concrete set of rules for the design parameters. As a result, choosing design parameters for a neural network is frequently a combination of trial and error. The neural network configuration developed in this work has a 5-14-2 structure: five input neurons, fourteen neurons in one hidden layer and two output neurons, as shown in Fig. 7.

For each dataset, 70% of the data are used as training, 15% for the test and 15% for the validation. The training is realized with Bayesian regularization, and the performance is evaluated in terms of mean squared error (MSE) and Pearson determination of coefficient R, as shown in Table 5.

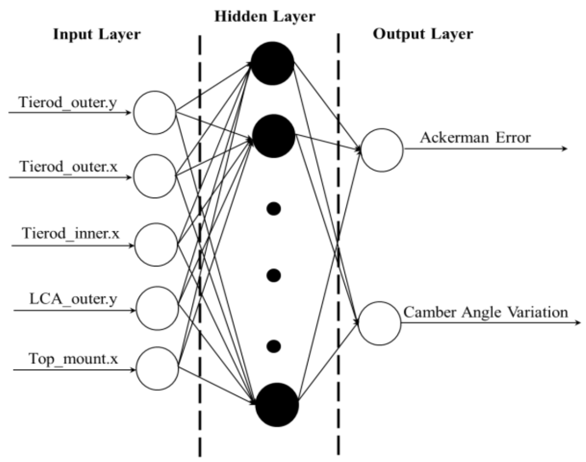

Fig. 7 Schematic of the NN architecture utilized

Table 5

Performance of NN models

Dataset	CCF	Box-Behnken	Linear full factorial
Number of Experiment	31	46	32
Training (MSE)	3.60e-17	4.60e-15	6.64e-15
Testing (MSE)	0.001208	0.000707	0.000202
Training (R)	1	1	1
Testing (R)	0.99902	0.99645	0.99774
All (R)	0.99985	0.99962	0.99986

Cross-validation is a statistical technique to evaluate networks by partitioning the data into subsets of specified ratios. In this research, a hold-out method for cross-validation is used by partitioning the data into subsets, which are the data used for the test, validation and the other for the neural network model training [29]. This technique is preferred since the data set is almost rare and used for training, testing, and validation. It is seen that the accuracy of the network is higher, there is no over-fitting, the network does not have a complex structure, and the data is also rare. The ANN model and predictions are saved in this study when the test's Pearson correlation co-efficient R is higher than 0.99 and gets better mean square error (MSE) values. The reason for choosing MSE besides the R-value is to prevent over-fitting and increase accuracy. The present neural network model offers an NN model with higher prediction ability. The experimental results related to RSM studies are taken and used as the input set for neural network models. NN calculated predictions are compared to the experimental data as shown in Figs. 8 and 9. As it can be seen from the related curves, the NN model perfectly fits the training data, and the predictions are quite close to the experimentations in the validation dataset. This demonstrates the neural networks' potential as an empirical model.

The surrogate-based optimization method plays an essential role in the optimization processes, especially when the optimization model is established based on computationally expensive evaluations [30]. NN has the advantage to provide better predictions in case of uncertainties and noise in data sets [31]. It is also preferable to predict the outcomes in case of out of design space evaluations since NN can learn from previous cases, and it may act efficiently in case of

a b c

Fig. 8 NN model with Box-Behnken dataset performance: a) training; b) test; c) all data

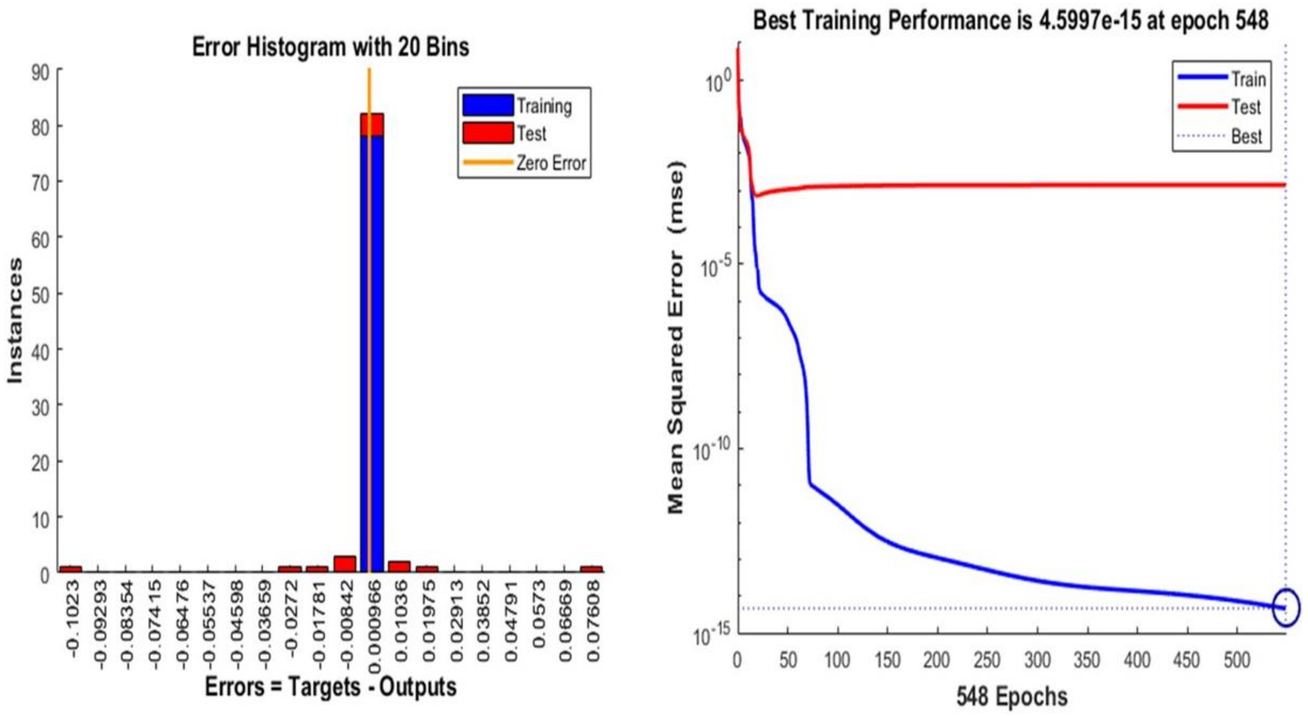

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Fig. 9 NN with Box-Behnken dataset performance: a) error histogram; b) learning curve

predictions for new cases. It is possible to start the optimization after an acceptable neural network model has been developed.

The ideal values of Ackerman error and camber angle change for the case studied in this paper are found by optimizing the input space of the NN model constructed using a genetic algorithm. The NN responses effectively converged to the optimal values below 1000 generations with a population of 500 and a crossover rate of 0.8. Based on the results plotted on the Pareto front curve in Fig. 10, the solution pair with the minimum sum of the squared Ackerman error and the camber angle variation has been considered as the optimization result as realized for response surface method.

The optimization study with a NN model with full factorial dataset has improved the Ackerman error by 28.27% and the camber angle variation by 26.83%, resulting in better improvement than all the RSM methods. This

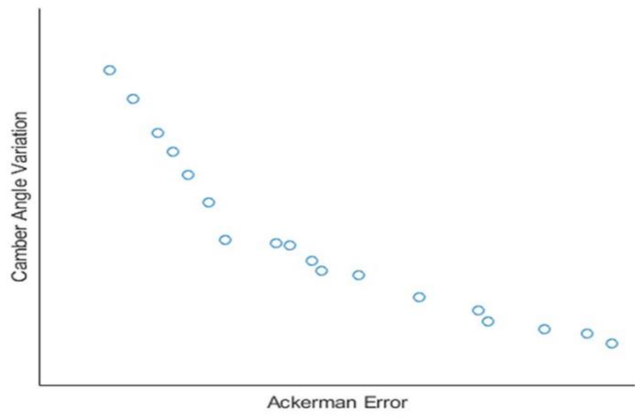

Fig. 10 Pareto front of NN model with GA trained on full factorial dataset

method also showed lower error than the RSM linear interactions full factorial method. The study with the CCF dataset has improved the Ackerman error by 26.39% and the camber angle variation by 26.76%, resulting in better performance than all the RSM methods in terms of improvement and prediction error. The study with the BB dataset has improved the Ackerman error by 23.99% and the camber angle variation by 28.38% with similarly better improvement performance than RSM methods as can be seen from the Table 6. The total cost is evaluated as in the DOE RSM section, obtained by the squared sum of Ackerman error and the camber angle variation values gathered from the virtual test rig. Consequently, all NN models have performed better than RSM methods using the same dataset for training.

5. Conclusions

The developed MBD simulation model correlates to physical K&C test bench data in this paper. The model shows satisfactory results for the suspension kinematics in overall K&C compact-sized passenger vehicle McPherson front suspension characteristics. The most effective geometry coordinates are found for Ackerman error and the camber angle change, that are out of target, within suspension steering kinematics by DOE screening. Further hardpoint optimization is done with the DOE RSM and NN on the selected vital hardpoints. Different strategies for screening and optimization studies are evaluated. Defining Plackett-Burman for screening and NN model trained using a DOE dataset with GA optimization is selected as the primary process since neural network modelling shows promising results over the conventional regression methods. Compared to traditional RSM methods, NN models trained with the same design of experiment datasets could offer 14% more improvement on Ackerman error and 5,2 % more improvement on the camber angle variation.

Table 6

Optimization results of NN with GA

		NN with CCF	NN with Box-Behnken	NN with full factorial
Ackerman error	Predict	0.93	0.962	0.899
	Test-rig	0.929	0.96	0.906
	Error	-0.13%	-0.25%	0.74%
	Improve	26.39%	23.99%	28.27%
Camber angle variation	Predict	0.938	0.919	0.932
	Test-rig	0.937	0.917	0.937
	Error	-0.12%	-0.22%	0.52%
	Improve	26.76%	28.38%	26.83%

Since finding the optimum hardpoints is a complex task with a limited design space available from the vehicle, engineers must find the best outcomes out of the available design environment. The optimization with NN trained models shows improvement on Ackerman error and on camber angle change that is not achievable with the RSM methods within +/- 5 mm design space range for the critical hardpoints of the baseline front suspension. Consequently, it is shown that the hybrid NN-GA technique proposed in this paper is a promising alternative to the usual RSM approach for the modelling and optimization of K&C characteristics of vehicle suspensions.

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G. Ağakişi, F. Öztürk

KINEMATICS & COMPLIANCE VALIDATION OF A VEHICLE SUSPENSION AND STEERING KINEMATICS OPTIMIZATION USING NEURAL NETWORKS

S u m m a r y

Physical and virtual K&C analyses are performed to achieve the vehicle dynamics targets by finding the optimum variables such as the position of hardpoints or stiffnesses of bushings. However, finding appropriate design variables that meet all the aims is challenging. This paper evaluates a hardpoint optimization approach to attain suspension K&C characteristic objectives with the design of experiments, neural networks, and genetic algorithm, based on a reference compact-sized prototype vehicle. The MBD model correlation is provided to optimize the hardpoints to improve the vehicle's steering kinematics concerning Ackerman error and camber angle variation that are out of target in baseline suspension. The results showed that NN based optimization strategy to define the hardpoints has significantly improved targeted characteristics compared to conventional response surface methods in the limited design space.

Keywords: steering kinematics, neural networks, hardpoint optimization.

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