

Expansion of Statistical Tire Modeling Method to Tire Rolling Resistance Estimation

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ABSTRACT

The “statistical tire model” method, which is used for performance design in the early stages of vehicle development, was applied in order to expand its function to estimate the rolling resistance of tires just from the information of tire size and its inflation pressure. The influence of tire size on RRC became quantified by using measured rolling resistance of tires that have variation in both its sizes and inflation pressures yet that have the same structure and rubber compound. As a result, a model with good precision was obtained that can estimate the increase/decrease of the rolling resistance with respect to the reference tire if the tire size and its inflation pressure were given. The proposed model made it possible to conduct quantitative parameter studies without carrying out time consuming individual tire measurements.

1. Introduction

Automobiles have been providing us with a method of personal mobility and helped our lives become more convenient and enriched, while the performance of automobiles has been advanced so that vehicle performance such as handling performance, collision safety, roominess, riding comfort, resource saving, etc. is achieved at a high level. In recent years, in order to cope with global warming, technologies for fuel saving by power plant innovation have been advanced. Regarding chassis technology, technology to secure handling performance and braking performance has been evolved while improving fuel consumption efficiency using low rolling resistance tires⁽¹⁾.

On the other hand, when looking at development technologies that support these recent performance evolutions, techniques that understand and model the complicated mechanisms and rationally design and examine them based on quantitative prediction⁽²⁾⁻⁽¹⁰⁾ called performance designs have evolved^{(11),(12)}.

In the early stage of vehicle development, using the performance design method, fundamental design process is conducted so that the target performance would be achieved under limited cost and space layout. In the case of platform design, which commonizes fundamental design of multiple models, it is becoming necessary to grasp the characteristics of each part more quantitatively than ever in order to design comprehensively in

consideration of many derived car models.

When we look at the chassis that supports the vehicle dynamics functions of cars, tires is one of the parts with the largest performance contribution, and tire size affects vehicle basic specifications such as wheel base and tread. Also, its characteristics greatly affect important features such as handling performance, braking ability, riding comfort, noise reduction, fuel economy, and so on.

Also in the case of platform development, considering all the types of vehicles that the platform covers, it is necessary to design the space layout beforehand so that the necessary and sufficient tire size can be installed.

Although it has been an important technical challenge to grasp various characteristics of tires, it has not been very easy to get detailed simulation models of tires in the early stages of vehicle development. So, there have not been many options except asking tire manufacturers for characteristics prediction or conducting time-consuming measurements and analysis on available tires by ourselves. Therefore, a technology has long been desired in this field that can quickly and easily estimate tire characteristics.

In order to solve this issue, we have developed a method called a statistical tire model that predicts statistical average characteristics of arbitrary tire size, and applied the method to the initial chassis design⁽¹³⁾⁻⁽¹⁵⁾.

Since this statistical tire model can predict generalized tire characteristics, it is possible to efficiently search Pareto solutions by examining vehicle performance using tire size

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as one of the parameters. As the tire characteristics can be understood more quantitatively, the initial design quality can be matured. In addition, since performance can be studied without carrying out numerous tire measurements, considerable enhancement can be expected in terms of development efficiency.

This statistical modeling method has been mainly applied to the field of vehicle dynamics performance, and, in this report, it is expanded to the prediction of rolling resistance coefficient (RRC) which is often a tradeoff with vehicle dynamics.

2. Statistical Tire Modeling

Many tire models with various complexity and accuracy have been proposed over the past 50 years. They are roughly classified into four categories: detailed physical models and simple physical models both classified as theoretical models, and interpolation approximation models and characteristic identification models classified as experiment identification models⁽¹⁶⁾.

The proposed statistical tire model is one form of the experimental identification model. Whereas almost all previous models including the Magic Formula tire model try to simulate individual tire characteristics accurately, the statistical tire model tries to identify the general characteristics of tires from the measurement characteristics and meta-information like tire size and inflation pressure from various tires. Therefore, it can be called a generalized tire model (Table 1).

This statistical tire model can provide the estimated tire characteristics only from meta information such as tire size and internal pressure so that it could be an efficient means for determining the tire size at the initial stage of development.

In the previously reported statistical tire model, it was possible to estimate the average characteristics of the tire cornering power C_p , tire vertical stiffness characteristic K_z , the dynamic loaded radius DLR , the tire weight WT , and the contact area SS , only from the provided information such as size, inflation pressure P , and normal load F_z ⁽¹⁵⁾.

In order to determine the size of the tire, in addition to the characteristics related to the vehicle dynamics and ride comfort mentioned above, it is also necessary to consider the RRC characteristic, which is a tradeoff to these characteristics. However, in estimating RRC, it is necessary to model the transformation mechanism of tire deformation and the heat energy, but so far there has been no easy method to investigate RRC, due to high technical challenges.

In this report, the statistical tire modeling method is applied to data obtained by arranging experimental conditions for the modeling. The influence of size and internal pressure on RRC was quantified for the first time and its basic idea, identification method, and application method was reported as following.

Table 1 Major prevailing tire models for vehicle dynamics compared with proposed statistical model

Model type	Model name	Modeling approach	Data for model identification	Tire size parameterization
Experimental model	Statistical model	Fitting tire test data from multiple tires using regression technique	From multiple tires	Single model for various size
	Magic Formula, SWIFT, etc.	Fitting full scale tire test data by regression technique	From individual tire	Individual model for each tire
	Interpolation model, etc.	Distorting, rescaling and combining basic characteristics		
Theoretical model	Fiala model, Brush model, etc.	Using simple mechanical representation		
	FEM tire model, FTire, RMOD-K, etc.	Describing tire in greater detail		

3. RRC Estimation

3.1. Tire RRC Characteristics

Rolling resistance of a tire is the reverse resistance force in the direction of travel which occurs when the tire rolls and is represented by RRC where the resistance value is divided by the ground load.

RRC is about 0.0080-0.0100 for ordinary passenger car tires and about 0.0060 for tires using state-of-the-art low loss rubber compounds.

Since energy loss due to rolling resistance of tires contributes about one third of the energy consumption during fuel consumption mode, reducing RRC is an important technique to improve fuel consumption efficiency of the chassis.

This RRC is due to the fact that the deformation of the rolling tire generates heat by the compound hysteresis. Therefore, RRC has speed dependency as shown in Eq. (1)⁽¹⁷⁾.

Since the RRC is affected by the internal structure of the tire that dominates the deformation of the tire, it could be reduced by lowering the hysteresis of the rubber compound, or by decreasing the total amount of rubber used. Or by reducing the deformation itself with a bigger tire size or with higher inflation pressure (Fig. 1).

$$f_R = f_{R0} + f_{R1} \left(\frac{V}{100} \right) + f_{R4} \left(\frac{V}{100} \right)^4$$

$$\text{where } \begin{cases} f_R : \text{RRC}_{[-]} \\ V : \text{Tire rolling speed [km/h]} \\ f_{R0} : 0.0080 \text{ to } 0.0100_{[-]} \\ f_{R1} : 0.0010 \text{ to } 0.0025_{[h/km]} \\ f_{R4} : 0.0002 \text{ to } 0.0004_{[h^4/km^4]} \end{cases} \quad (1)$$

However, these methods might lower important

functions of the tire such as the grip performance, the ability to absorb the impact, and the durability, or ride comfort, by increased stiffness.

Therefore, the fuel efficiency by low RRC and performances like vehicle dynamics and ride comfort required for the chassis generally form a contradictory issue.

In order to efficiently examine the quantitative relationship between tire size and RRC that we focused on, experimental data from tires with the same compound and structure should be acquired and the influence of size and internal pressure on RRC should be extracted, and then the statistical model should be identified.

3.2. Statistical RRC Modeling

In order to clarify the fundamental properties of tire RRC, sample tires were selected from a certain fuel-efficient tire product line that is popular in the market and also has a lot of size variations. And the model identification was carried out using the precisely measured RRC of these sample tires.

Table 2 shows the statistics of measured tire width (W), flatness (H), rim diameter (D), load index (L), internal pressure (P), load (F_z) and measured RRC.

Measurements were carried out with regulated inflation pressure and load after sufficient warm-up. The tire load was set to 80% of the maximum load, which is determined from the size and inflation pressure of each tire.

The measured RRC, with respect to the rolling speed, are shown in Fig. 2. Although these tires have the same compound and structure, measured RRC varies greatly with different size and internal pressure.

As the speed dependency of RRC can be expressed by Eq. (1), in this paper, the RRC values at 80 [km/h] were selected as the representative RRC value of each tire.

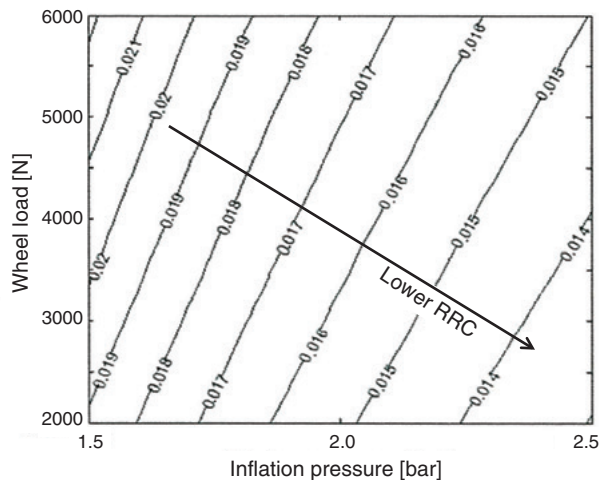


Fig. 1 Example of tire RRC with respect to wheel load and inflation pressure from reference

Table 2 Statistics of tire parameters of 31 cases

	Tread width, W [mm]	Aspect ratio, H [%]	Rim diameter, D [inch]	Load index, L	Inflation pressure, P [kPa]	Normal load, F_z [kN]	RRC at $V=80$, [$\times 10^{-4}$]
Average	202.1	56.3	16.0	89.2	250.6	4.6	69.1
Median	205.0	55.0	16.0	91.0	220.0	4.9	68.4
Std.Dev. σ	17.4	6.2	1.2	5.1	44.9	0.6	7.2
Minimum	155	45	13	73	210	2.89	54.0
Maximum	225	65	18	97	340	5.74	85.8
Max.-Min.	70	20	5	24	130	2.85	31.8
	(4.03 σ)	(3.23 σ)	(4.17 σ)	(4.7 σ)	(2.89 σ)	(4.45 σ)	(4.39 σ)

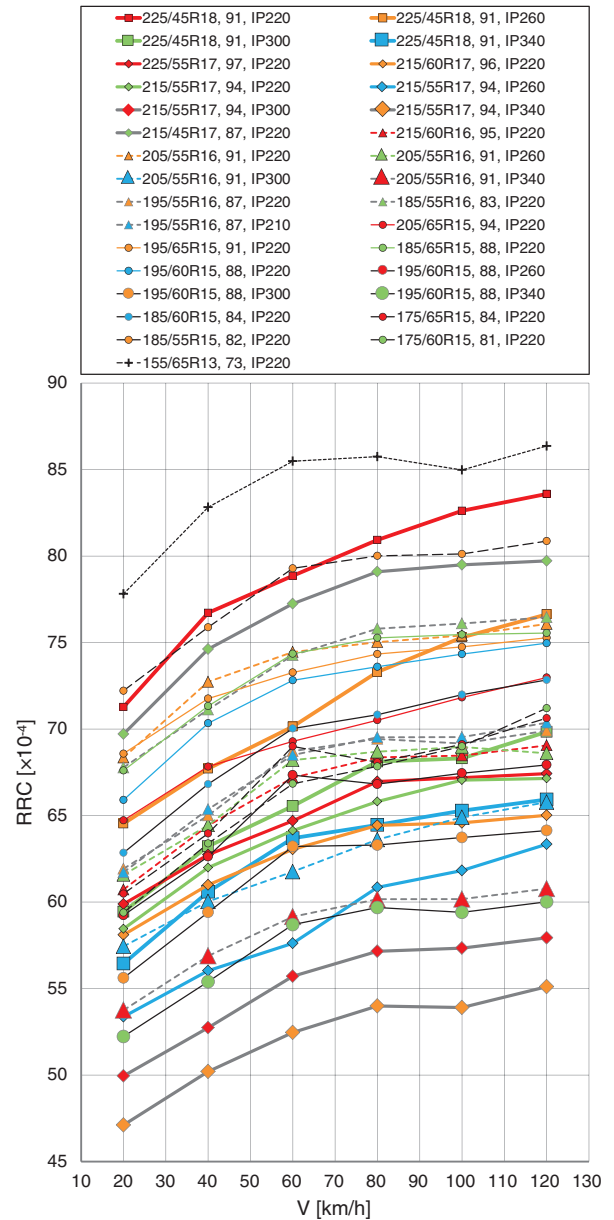


Fig. 2 Measured tire RRC vs rolling speed of 31 cases with normal load F_z equal to 80% of the load index's maximum load and with regulated inflation pressure

In Table 3, the RRC value of each tire at 80 [km/h] is shown as a relative value of No.12 205/55R16 91, $P=220$ [kPa]. The tire size of No. 12, used as the reference, is the median of the tire sizes W , H , D , L , and P of the sample.

Firstly, to analyze correlation between tire size parameters W , H , D , and L , and usage conditions P , F_z , and RRC for the obtained data, a scatter plot was plotted and examined (Fig. 3).

The histogram plotted on the diagonal in Fig. 3 shows the frequency of appearance of each parameter, the scatter plot shows the correlation between each parameter diagonally arranged, and the straight line in the scatter plot represents the linear approximation of correlation.

For example, the plot at the top right of Fig. 3 is a scatter plot with x-axis as RRC and y-axis as tire width W . Since the approximate straight line in the figure goes down to the right, it means that W increases as RRC increases. The bottom left plot is a plot where the x-axis and the y-axis are interchanged.

From the histogram distribution shown in Fig. 3, it can be seen that measured tires have sufficient variations with respect to W , H , and D . If we look at the correlations of W , H , and D , as D becomes larger, W gets larger and H gets smaller. But this is just due to the product line trend on the market that large diameter tires tend to be wider and to have low aspect ratio. It is not a physical causal relationship. Therefore, we adopted W , H , and D as independent input parameters in model identification.

In addition, load index L was used as a parameter of the capacity of the tire, and F_z and P were added to the input parameters that dominate the tire deformation. Since the measured load F_z is set to 80% of the maximum load determined by L in this measurement, the correlation between F_z and L is almost 1, but we regarded there is no causal relationship with this.

There could also be nonlinearity in the correlation between tire size and internal pressure and RRC, so the

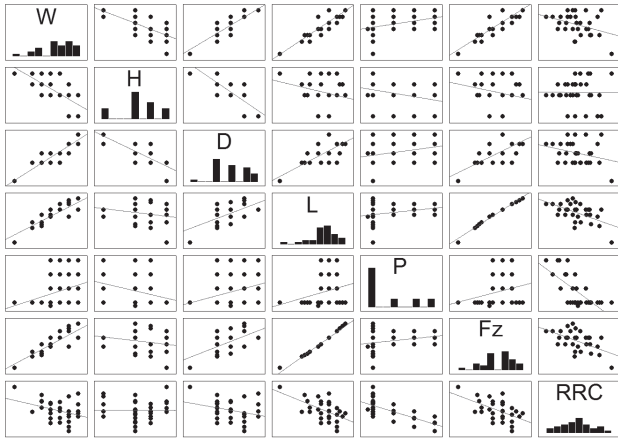


Fig. 3 Correlation overview of sample tire information for “Stat RRC” - W , H , D , L , P , F_z , and RRC

Table 3 Measured RRC relative to No.12* case, with various tire size, load index, inflation pressure, and normal load
* Tire size 205/55R16 of No.12 is a median of sample cases

No.	Tread width, W [mm]	Aspect ratio, H [%]	Rim diameter, D [inch]	Load index, L	Wheel size on measurement	Inflation pressure, P [kPa]	Normal load, F_z [kN]	RRC at $V=80$, [$\times 10^{-1}$]
1	225	45	18	91	18x8J	220	4.85	107.9%
2	225	45	18	91	18x8J	260	4.85	97.7%
3	225	45	18	91	18x8J	300	4.85	90.8%
4	225	45	18	91	18x8J	340	4.85	85.9%
5	215	45	17	87	17x7.5J	220	4.27	105.4%
6	225	55	17	97	17x7.5J	220	5.74	89.3%
7	215	55	17	94	17x7.5J	220	5.25	87.7%
8	215	55	17	94	17x7.5J	260	5.25	81.1%
9	215	55	17	94	17x7.5J	300	5.25	76.2%
10	215	55	17	94	17x7.5J	340	5.25	72.0%
11	215	60	17	96	17x7.5J	220	5.59	85.9%
12*	205	55	16	91	16x6.5J	220	4.85	100.0%
13	205	55	16	91	16x6.5J	260	4.85	91.6%
14	205	55	16	91	16x6.5J	300	4.85	84.8%
15	205	55	16	91	16x6.5J	340	4.85	80.2%
16	195	55	16	87	16x6.5J	220	4.27	92.5%
17	185	55	16	83	16x6J	220	3.82	101.0%
18	215	60	16	95	16x6.5J	220	5.44	91.1%
19	185	55	15	82	15x6J	220	3.73	106.7%
20	195	60	15	88	15x6J	220	4.41	98.1%
21	195	60	15	88	15x6J	260	4.41	89.1%
22	195	60	15	88	15x6J	300	4.41	84.4%
23	195	60	15	88	15x6J	340	4.41	79.6%
24	185	60	15	84	15x5.5J	220	3.92	94.4%
25	175	60	15	81	15x5.5J	220	3.63	90.4%
26	205	65	15	94	15x6J	220	5.25	94.0%
27	195	65	15	91	15x5.5J	220	4.85	99.1%
28	185	65	15	88	15x5.5J	220	4.41	100.3%
29	175	65	15	84	15x5.5J	220	3.92	90.7%
30	155	65	13	73	13x4J	220	2.89	114.3%
31	195	55	16	87	16x6J	210	4.27	92.7%

square terms of these parameters were also taken into account as an input parameter. The validity of the adopted input parameters will be discussed later.

Based on the above assumptions, the statistical RRC model that estimates RRC by the tire size parameters W , H , D , and L , and the usage condition parameters P and F_z , was defined by Eq. (2).

The measurement data of Table 3 was applied to this model definition formula and model coefficients a_1 to a_{12} were identified from the least squares method of estimation error (3).

$$\begin{aligned}
 &RRC(a_1, a_2, \dots, a_{12}/W, H, D, L, P, F_z) \\
 &= a_1 W + a_2 W^2 + a_3 H + a_4 H^2 + a_5 D + a_6 D^2 \\
 &\quad + a_7 L + a_8 L^2 + a_9 P + a_{10} P^2 + a_{11} F_z + a_{12}
 \end{aligned} \tag{2}$$

where

- W : Tread width [mm]
- H : Aspect ratio [%]
- D : Rim diameter [inch]
- L : Load index
- P : Inflation pressure [kPa]
- F_z : Normal load [kN]
- a_i : Coefficients of RRC multi-regression model

Table 4 Identified model parameters for statistical RRC model

Model coefficient	Identified value	Note
a_1	3.62E-2	W
a_2	-1.07E-4	W^2
a_3	-1.06E-1	H
a_4	7.51E-4	H^2
a_5	-8.34E-1	D
a_6	2.38E-2	D^2
a_7	8.61E-2	L
a_8	-9.61E-4	L^2
a_9	-4.09E-3	P
a_{10}	4.55E-6	P^2
a_{11}	7.78E-1	Fz
a_{12}	5.90E+0	y-intercept

$$\frac{\partial J}{\partial a_k} = 0 \rightarrow a_k \left| \frac{\partial J}{\partial a_k} = 0 \right. \quad (k = 1 \text{ to } 12)$$

where

$$J = \sum_{i=1}^n [RRC_i - RRC(a_1, a_2, \dots, a_{12}/W_i, H_i, D_i, L_i, P_i, Fz_i)]^2 \quad (3)$$

The coefficients of the statistical RRC model obtained in this procedure are shown in Table 4.

4. Calculation Results

4.1. Estimated RRC

The RRC estimates obtained by applying the tire size, load index, internal pressure and load to the identified statistical RRC model are shown in Table 5. And the correlation between these estimated values and the measured RRC is shown in Fig. 4.

The corrected R^2 , which represents the correlation with the measured value of the statistical RRC model, was 0.913.

Corrected R^2 is a degree-of-freedom adjusted coefficient of determination (also called contribution rate), indicating that the proposed model explains about 90% of variations due to size and internal pressure of RRC. Therefore, when conducting parameter studies on performance, including RRC while changing tire size and its internal pressure at the early stage of development, we think that the statistical RRC model proposed in this paper has sufficient accuracy for the investigation.

However, from Fig. 4, the standard error is still $\sigma = 2.13 \times 10^{-4}$, and the contribution ratio, which cannot be estimated by the prediction equation, remains about 10%. When conducting performance design, we should consider these estimation errors in mind.

The RRC estimated values vs tire width W , aspect ratio H , rim diameter D , load index L , and inflation pressure P are plotted along with measured values and are shown in Fig. 5.

Table 5 Estimated RRC by statistical RRC model

Tire size and IP	Measured RRC at V = 80 in relative form	Estimated RRC at V = 80 in relative form	Error [c]
225/45R18, 91, IP220	107.9%	105.7%	-1.0%
225/45R18, 91, IP260	97.7%	98.0%	0.2%
225/45R18, 91, IP300	90.8%	91.9%	0.5%
225/45R18, 91, IP340	85.9%	87.2%	0.6%
215/45R17, 87, IP220	105.4%	105.4%	0.0%
225/55R17, 97, IP220	89.3%	87.5%	-0.8%
215/55R17, 94, IP220	87.7%	89.3%	0.8%
215/55R17, 94, IP260	81.1%	81.7%	0.3%
215/55R17, 94, IP300	76.2%	75.5%	-0.3%
215/55R17, 94, IP340	72.0%	70.8%	-0.5%
215/60R17, 96, IP220	85.9%	86.7%	0.4%
205/55R16, 91, IP220	100.0%	99.3%	-0.3%
205/55R16, 91, IP260	91.6%	91.6%	0.0%
205/55R16, 91, IP300	84.8%	85.5%	0.3%
205/55R16, 91, IP340	80.2%	80.7%	0.3%
195/55R16, 87, IP220	92.5%	94.6%	0.9%
185/55R16, 83, IP220	101.0%	94.8%	-2.9%
215/60R16, 95, IP220	91.1%	89.7%	-0.6%
185/55R15, 82, IP220	106.6%	104.8%	-0.9%
195/60R15, 88, IP220	98.1%	97.2%	-0.4%
195/60R15, 88, IP260	89.1%	89.6%	0.2%
195/60R15, 88, IP300	84.4%	83.4%	-0.5%
195/60R15, 88, IP340	79.6%	78.7%	-0.4%
185/60R15, 84, IP220	94.4%	95.1%	0.3%
175/60R15, 81, IP220	90.4%	96.4%	2.8%
205/65R15, 94, IP220	94.0%	96.8%	1.3%
195/65R15, 91, IP220	99.1%	99.6%	0.2%
185/65R15, 88, IP220	100.3%	95.5%	-2.3%
175/65R15, 84, IP220	90.7%	91.2%	0.2%
155/65R13, 73, IP220	114.3%	114.0%	-0.1%
195/55R16, 87, IP210	92.7%	96.7%	1.9%

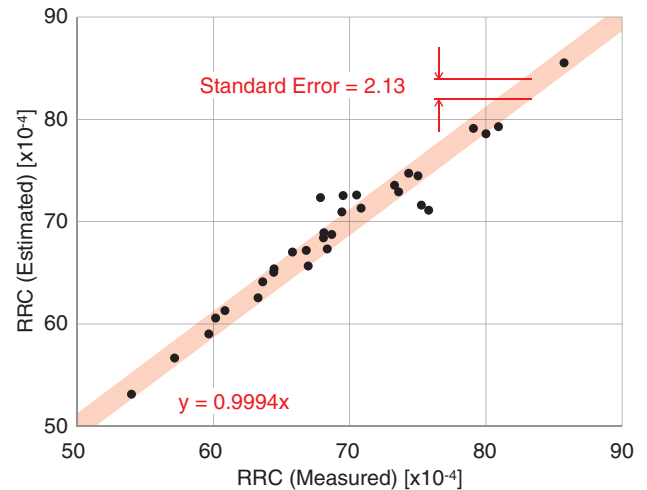


Fig. 4 Correlation between measured RRC and estimated RRC from statistical RRC model with W , H , D , L , P , and Fz given

Table 6 Multiple regression model - Stepwise verification using forward selection method

Model ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Independent parameters	W	W,H	W,H,D	W,H,D,L	W,H,D,L,P	W,H,D,L,P,Fz	W,H,D,L,P,Fz,W ²	W,H,D,L,P,Fz,H ²	W,H,D,L,P,Fz,D ²	W,H,D,L,P,Fz,L ²	W,H,D,L,P,Fz,P ²	W,H,D,L,P,Fz,Fz ²	W,H,D,L,P,Fz,W ² H ²	W,H,D,L,P,Fz,W ² H ² D ²	W,H,D,L,P,Fz,W ² H ² D ² L ²	W,H,D,L,P,Fz,W ² H ² D ² L ² P ²	W,H,D,L,P,Fz,W ² H ² D ² L ² P ² Fz ²
Statistics																	
R	0.367	0.516	0.554	0.639	0.906	0.907	0.912	0.957	0.935	0.926	0.908	0.947	0.960	0.968	0.968	0.972	0.973
R ²	0.135	0.266	0.307	0.408	0.821	0.823	0.831	0.916	0.875	0.857	0.824	0.897	0.922	0.937	0.937	0.945	0.946
Adjusted R ²	0.105	0.213	0.230	0.317	0.785	0.779	0.780	0.891	0.836	0.814	0.771	0.865	0.894	0.910	0.906	0.913	0.910
Standard error	6.832	6.404	6.336	5.967	3.345	3.395	3.385	2.384	2.920	3.117	3.455	2.650	2.349	2.169	2.260	2.132	2.163
Coefficients																	
y-Intercept	1.33E+0	2.16E+0	2.78E+0	1.80E+0	2.66E+0	3.19E+0	4.79E+0	8.36E+0	9.14E+0	-5.89E+0	3.39E+0	6.83E+0	7.56E+0	9.65E+0	4.88E+0	5.90E+0	2.37E+0
W	-2.04E-3	-3.97E-3	-1.73E-3	9.64E-3	8.12E-3	7.21E-3	-2.42E-2	-5.69E-3	-3.18E-3	8.74E-3	7.21E-3	8.15E-3	2.34E-2	4.51E-2	3.08E-2	3.62E-2	4.18E-2
H		-7.82E-3	-1.20E-2	8.07E-3	-1.46E-3	-3.21E-3	-9.33E-3	-1.33E-1	-1.91E-2	1.11E-3	-3.40E-3	2.88E-3	-1.47E-1	-1.31E-1	-1.08E-1	-1.06E-1	-1.19E-1
D			-5.24E-2	-2.36E-2	-5.75E-2	-5.98E-2	-8.15E-2	-9.39E-2	-9.75E-1	-5.24E-2	-6.08E-2	-3.67E-2	-7.77E-2	-7.24E-1	-7.33E-1	-8.34E-1	-1.08E+0
L				-3.26E-2	-2.25E-2	-2.81E-2	1.11E-2	-1.32E-2	3.57E-2	1.97E-1	-2.80E-2	-1.77E-1	-4.97E-2	-3.93E-2	9.68E-2	8.61E-2	2.40E-1
P					-1.50E-3	-1.49E-3	-1.54E-3	-1.46E-3	-1.71E-3	-1.51E-3	-2.94E-3	-1.68E-3	-1.41E-3	-1.54E-3	-1.54E-3	-4.09E-3	-3.81E-3
Fz						6.53E-2	-1.46E-1	2.46E-1	-1.76E-1	1.04E+0	6.54E-2	2.80E+0	4.82E-1	4.57E-1	7.62E-1	7.78E-1	6.06E-2
W ²							7.12E-5	9.77E-4					-7.03E-5	-1.32E-4	-9.25E-5	-1.07E-4	-1.27E-4
H ²													1.13E-3	9.56E-4	7.78E-4	7.51E-4	8.25E-4
D ²									2.78E-2					2.04E-2	2.05E-2	2.38E-2	3.11E-2
L ²										-2.03E-3					-1.02E-3	-9.61E-4	-1.75E-3
P ²											2.63E-6					4.55E-6	4.09E-6
Fz ²												-1.79E-1					7.24E-2

It is confirmed that the RRC estimated value for each size parameter has a good accuracy and is distributed within approximately ± 2.13 of the measured value.

4.2. Model Verification

In order to verify the identified statistical RRC model, using the stepwise variable increasing method of multiple regression analysis, the accuracy of several models with various input parameter combinations were obtained and compared with the proposed model. The results are shown in Table 6 and the proposed model is Model 16. The

coefficient of determination and standard error of each model are shown in Fig. 6 and Fig. 7, respectively.

From Table 6, increasing the number of variables generally increases the coefficient of determination, enhancing the correlation, and reduces the standard error, therefore enhancing the accuracy of the model.

For example, Model 1 has only input parameter W and its coefficient of determination (contribution rate) is 0.105, and Model 2, which has two input parameters, W and H , exhibits 0.213 of coefficient of determination. So the contribution rate of parameter W and H to RRC can be

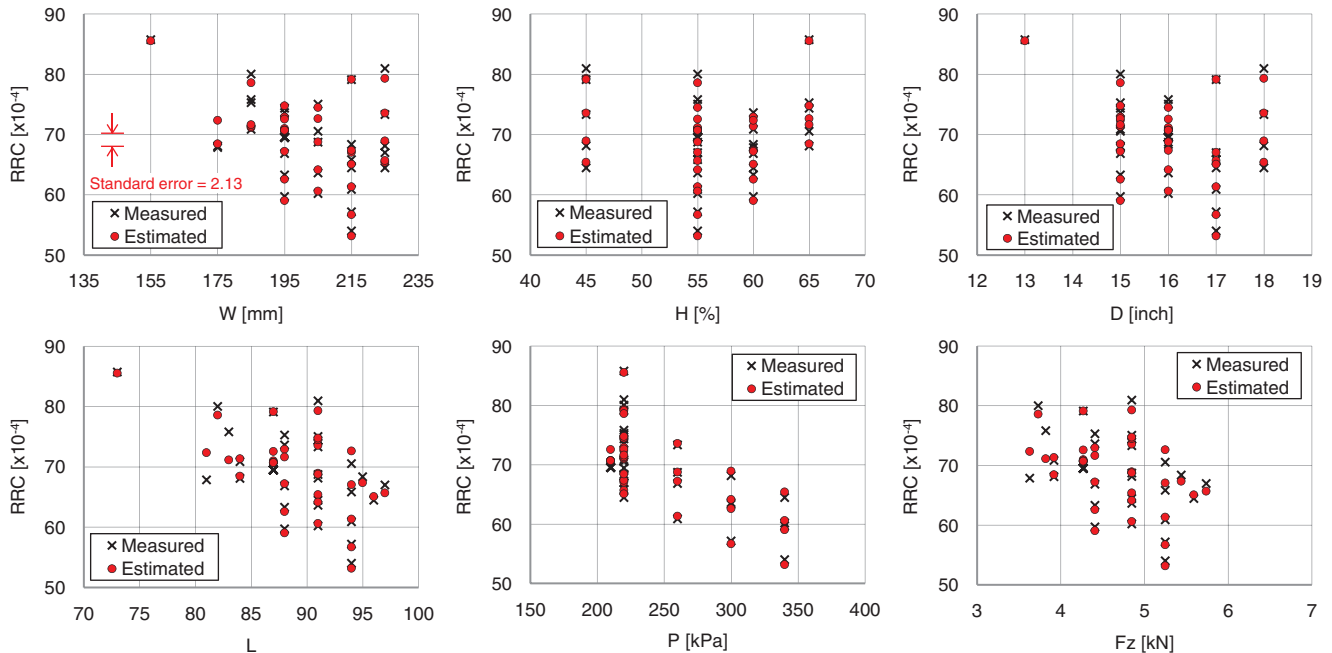


Fig. 5 Comparisons between measured RRC and estimated RRC with respect to W , H , D , L , P , and Fz

analyzed as about 10% each.

Focusing on differences in Models 4 to 5 and Models 7 to 8, when the internal pressure P and the square of the aspect ratio H^2 are added as variables, respectively; the

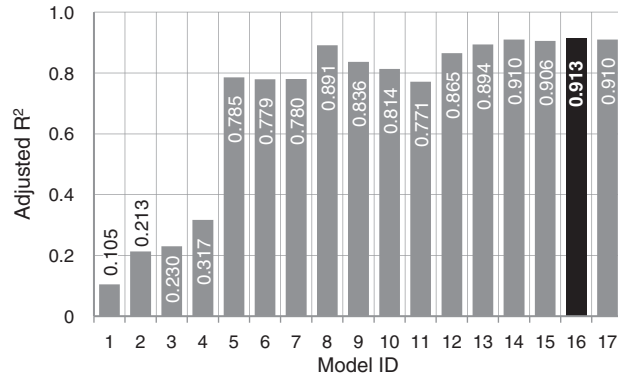


Fig. 6 Adjusted R^2 of multiple regression models

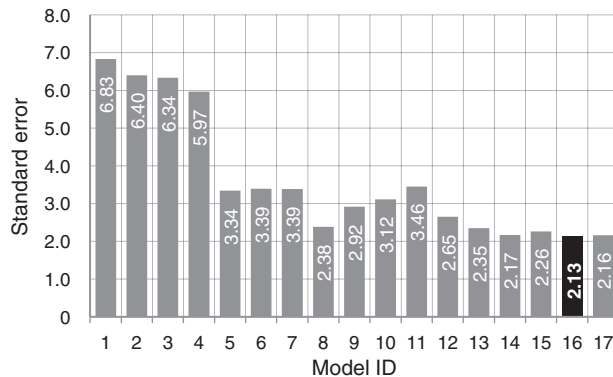


Fig. 7 Standard error of multiple regression models

coefficient of determinations are greatly increased from 0.317 to 0.785 and 0.780 to 0.891, respectively. It can be understood that the internal pressure P of the input parameter and the square of aspect ratio H^2 contribute about 47% and 11%, respectively.

However, in Model 17 where the square of load Fz^2 is added to the proposed Model 16, the coefficient of determination decreases and the standard error increases. For RRC, it can be safely said that the linear approximation of the load Fz is more appropriate.

Through the above verification work, it was confirmed that the proposed Model 16 is a highly correlated model that can predict the contribution of size factors and internal pressure to RRC with good accuracy. Note that Model 8 is simpler, but the coefficient of determination is 0.891 and its prediction accuracy is relatively good, so we will consider it from the viewpoint of robustness of the estimation in the next chapter.

5. Application Examples and Discussions

5.1. Discussion on Model Robustness

Figure 8 compares the estimated RRC from both the proposed Model 16 and the simpler Model 8 with the measured values for various tire sizes.

Model 8 is a simpler model with only W , H , D , L , Fz , and H^2 as variables, but its estimate is close enough to the measured value, and its standard error is also about $\sigma = 2.38$, which is just 11% larger than the error of Model 16.

Figure 9 shows the RRC estimate obtained by varying only the tire width W from 145 to 235, with respect to reference tire 205/55R16 91, IP=220.

The RRC estimate has an upwardly convex shape in the case of Model 16 and it estimates extremely low RRC values in the ranges of $W < 155$ and $W > 225$. On the other

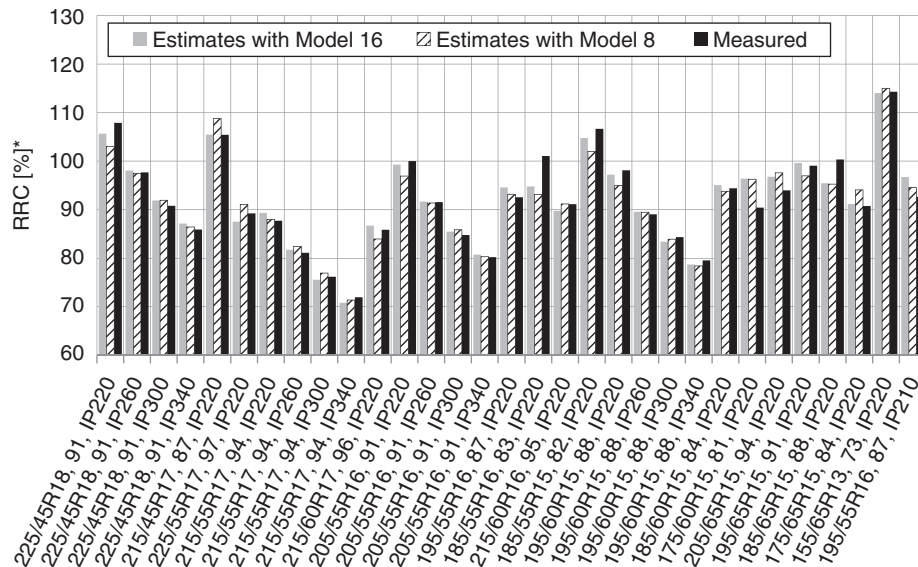


Fig. 8 Comparison of estimates of RRC from Model 16 and Model 8 with measured RRC (relative to 205/55R16's)

hand, RRC is linearly predicted to be decreased with respect to W in the simpler case of Model 8.

Considering the relation between the tire width and RRC, when the tire width gets narrower under a constant load condition, the contact length of the tire becomes longer and the bending deformation of the tire contact patch occurs, which causes hysteresis to increase. Therefore, prediction of Model 16 that the RRC will decrease in the extrapolated area of $W < 155$ does not agree with this general trend. On the other hand, the simple Model 8 approximates the relationship between the tire width W and the RRC in a linear fashion, so the trend agrees with this qualitative consideration and seems rational.

From the above discussion, with regard to at least the tire width, it can be seen that Model 16 shows high reproducibility in the range of the given sample, but its prediction accuracy may decrease if the estimation range is out of sample's range. When using the statistical RRC model, it is important to consider carefully whether to emphasize on the precision within the range given, or to examine under general trends, and to select an appropriate model according to the purpose.

5.2. Sensitivity Analysis

In the early stages of vehicle development, tire size determination, including size for derived models, is performed not only in terms of fuel consumption performance but also in consideration of load capacity and handling stability. In that case, it is necessary to measure all the RRC characteristics and cornering characteristics of the candidate tire with the conventional method⁽¹⁸⁾, and a new method to reduce the time and cost has been needed. Combining the proposed statistical RRC model with the

previously reported statistical C_p model makes it possible to search for initial specifications with good fuel economy and good handling performance in various derived models.

The predicted sensitivity of C_p and RRC by statistical model is calculated and shown in Fig. 10. The tire parameters W , H , D , P were varied with respect to 205/55R16, $L = 91$, $P = 220$ [kPa] respectively.

Plot D +1 is a case where the rim diameter D is raised from 16 inch to 17 inch. It is predicted that C_p will increase by 4% and RRC will also be reduced by 5%. Therefore, although the outer diameter of the tire increases, it can be seen that increasing the rim diameter can achieve both handling stability and fuel economy.

Likewise, if tire width W is increased by +10, the C_p increases by 4%, the RRC also reduced by 8%, and similar compatibility can be expected.

On the other hand, even if the inflation pressure P is increased by +20, the enhancement is only 1% for C_p and 4% for RRC. Therefore, the effect of the countermeasure for the handling performance by the tire inflation pressure will be limited if compared with the size change. Also, the decreasing aspect ratio H by -5 increases C_p by just 5% while it increases RRC by 13%. So handling performance and fuel economy becomes a tradeoff with this size change case.

For example, when trying to make an SUV with weight increase as a derivative model from a basic platform, and good fuel consumption should be realized while securing handling performance that can compensate for weight increase, it is suggested that a space layout, which allows both a larger rim diameter and wider tire, should be prepared in advance.

Next, in the case of size 225/45R18, the same sensitivity

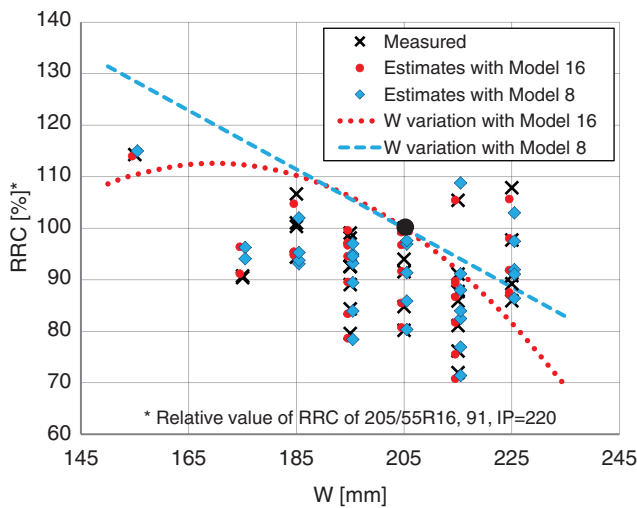


Fig. 9 Comparison of estimates of RRC from Model 16 and Model 8 with measured RRC with regard to tread width W

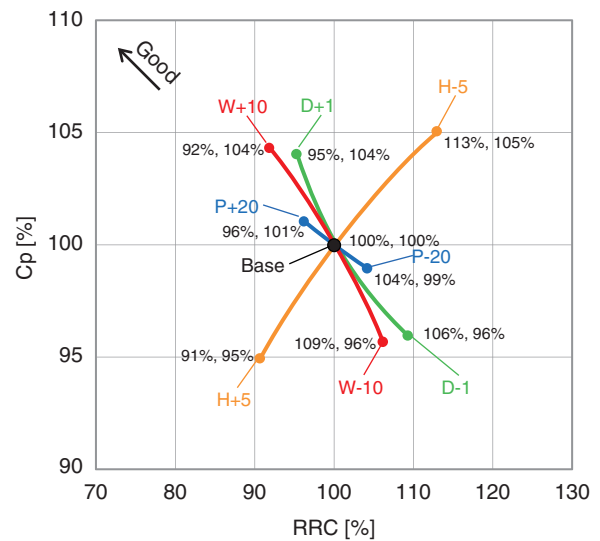


Fig. 10 Sensitivities of tire parameters W , H , D , and P of 205/55R16 tire on both cornering stiffness and RRC

is shown in Fig. 11. It is the case of the outermost size of the sample tire.

The sensitivity tendency of the size parameters W , H , and P is almost the same as 205/55R16, but the C_p sensitivity is slightly lower and the RRC sensitivity is slightly higher. In addition, the sensitivity of D to RRC is considerably low, and for the $D+1$ plot case, even if the rim diameter is increased, RRC increases and it is a prediction result that is highly unlikely to occur in reality.

In this example, the sensitivity analysis is performed on the size having W , H , and D , which are outermost in the sample statistics shown in Table 2. When the size parameter is extrapolated from the data sample used for modeling, it can be seen that the correlation cannot be guaranteed in this model.

In order to circumvent this, it is necessary to increase the number of samples with more variations, and/or to separate the data for model identification and the data for verification, and perform the verification. Also, when applying this method to development studies, it is necessary to accumulate know-how to select models appropriately depending on the application cases.

Regarding the prediction of tire RRC, correction method considering tire temperature, etc. is also being proposed⁽¹⁹⁾. As the fuel economy of automobiles advances, technologies for predicting RRC with higher precision are increasingly required.

By expanding this statistical tire modeling method, it is possible to conduct an initial examination utilizing existing tire measurement data, and it is possible to greatly support efficiency improvement of conventional chassis development.

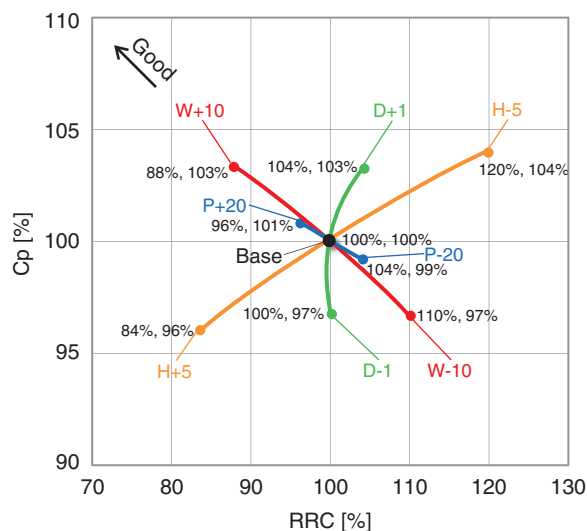


Fig. 11 Sensitivities of tire parameters W , H , D , and P of 225/45R18 tire on both cornering stiffness and RRC

6. Summary

In this paper, we extend the method of statistical tire models, which can decide the characteristics and size of tire rationally and efficiently at the initial development stage, to the prediction of rolling resistance coefficient of tire and obtained the following knowledge:

- (1) From the RRC measurement data that made the compound and structure of the tire the same brand, it turned out that the tire size and internal pressure are important factors affecting RRC.
- (2) Under certain compound and tire structures, it is possible to construct a model that estimates RRC based only on tire size and internal pressure, and the proposed model can explain about 90% of actually measured RRC fluctuation.
- (3) When the statistical RRC model is combined with the statistical C_p model, it became possible to study the tire size that can achieve both handling performance and fuel efficiency without conducting tire measurement.

The statistical RRC model reported in this paper would be able to be further expanded by incorporating measurement data of tire such as hysteresis characteristics of compound, tire weight, contact area of tire and contact length in the future.

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