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A Non-destructive Ultrasonic Testing Approach for Measurement and Modelling of Tensile Strength in Rubbers

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ABSTRACT

Currently, non-destructive testing is widely used to investigate various mechanical and structural properties of materials. In the present study, non-destructive ultrasonic testing was applied to study the relationship between the tensile strength value and the velocity of longitudinal ultrasonic waves. For this purpose, fourteen specimens of composites with different formulations were prepared. The tensile strength of the composites and the velocity of longitudinal ultrasonic waves inside them was measured. The relevance vector machine regression analysis, as a new methodology in supervised machine learning, was used to define a mathematical expression for the functional relationship between the tensile strength and the velocity of longitudinal ultrasonic waves. The accuracy of the mathematical expression was tested based on standard statistical indices, which proved the expression to be an efficient model. Based on these results, the developed model has the capability of being used for the online measurement of the tensile strength of rubber with the proposed formulation in the rubber industry.

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NOMENCLATURE

$K(.,.)$	Kernel function	**Greek Symbols**	
$N(.\|\mu,\sigma^2)$	Normal distribution with mean μ and variance σ^2	α	Vector of hyper-parameters
$p(.\|.)$	Conditional probability distribution function	μ	Mean Value
t	Vector of targets	σ^2	Variance of Gaussian distribution
W	Vector of weight coefficients		

1. INTRODUCTION

The microstructure of the material shows its macrostructure properties. It is typically believed that the macrostructural properties of a material, such as its physical and mechanical properties, cannot be determined by merely investigating its structural data. One of the conventional approaches to investigate the relationship between the microstructure of materials and some of their macrostructural properties is via the ultrasonic wave velocity through these materials [1]. The characteristics of a pulse traversing among the medium are changed and take information on the medium's microstructure and macrostructure. The application of the ultrasonic wave velocity measurement technique is not confined only to the measurement of physical and mechanical properties but is also used in non-destructive tests.

There are various experimental methods for evaluating the physical and mechanical properties of materials. The samples were taken from the considered sample port which caused destruction. Non-destructive testing is used as one of the analytical techniques to evaluate the properties of many materials without causing damage. The specimen remains usable for the detection of defects and the determination of material

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properties. With the use of an ultrasonic test, it is possible to determine several properties of a material by measuring the time duration between the emission and reflection of ultrasonic waves [2]. The investigation of quality and the determination of the physical and mechanical properties of materials have been practiced by calculating the changes in the ultrasonic wave velocity for a wide variety of materials and applications. The investigations have ranged from the investigation of fruit quality [3] and the determination of limestone properties in historical monuments [4], to the evaluation of weld quality in friction stir welding of aluminum [5]. In this method, the ultrasonic waves and their reflection are displayed on the monitor, and the required data is obtained by interpretation of these signals, i.e., the initial and the reflected pulses, as shown in Figure 1.

As the ultrasonic test parameters are greatly affected by the material's microstructure and mechanical properties, this method has been proven as one of the best and most cost-effective non-destructive testing approaches for investigating mechanical material properties. Due to the recent advances in the electronic components used in the testing equipment, the precise measurement of the ultrasonic wave properties has provided the possibility of evaluating various mechanical properties at a reasonable and satisfactory level. Thanks to high test speeds, lack of part damage during the test, and the ability to perform the test on the parts while being manufactured, non-destructive tests provide a suitable substitute for traditional inspection methods.

Remarkable studies have been conducted on the determination of properties by ultrasonic waves for metals. Grain size, the presence of impurities, elasticity modulus, hardness, toughness, and yield strength in metals are among the items that have been measured by ultrasonic testing [6]. Also, the wave-mode-converted principle was used to calculate the shear wave and longitudinal wave velocities of magnesium-based composite samples; to evaluate the relationship among the reinforcement content and the dual-mode ultrasonic velocities. The elastic modulus is also calculated [7]. Based on the relationship between surface roughness and ultrasonic attenuation, an inverse model for the attenuation, using Weaver's diffuse scattering theory, is fixed to measure grain size in polycrystals [8]. However,

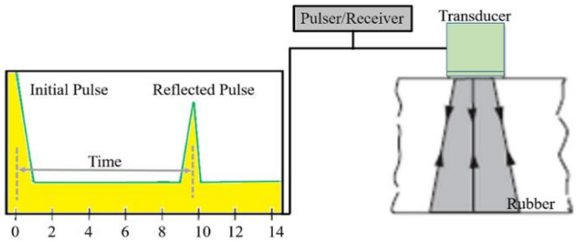

Figure 1. Schematic of Ultrasonic Test

only a few surveys have been performed on the application of ultrasonic testing for the determination of the properties of rubbers.

One of the fundamental properties of rubber is its ultimate tensile strength, which is a measure of its ability to withstand a pulling force. The ultimate tensile strength, often shortened to tensile strength, is measured by the maximum stress that a material can withstand while being stretched or pulled before breaking. Although rubber does not reach its ultimate tensile strength, this property is regarded as an index of the quality of the produced rubber. However, online measurement of this property in the production cycle is not possible, and therefore non-destructive testing approaches provide an efficient alternative for this purpose.

In line with previous research by the authors on the use of ultrasonic waves in the rubber industry [9, 10], in this study, an ultrasonic test has been presented as a novel approach for the measurement of the tensile strength of rubber. The proposed method is capable of online measurement of the rubbers' tensile strength while being manufactured. To this end, the tensile strength values in several specimens with different formulations were measured together with the longitudinal ultrasonic wave velocity through them. In addition, the relationship between the tensile strength value and the longitudinal ultrasonic wave velocity was investigated using a novel supervised machine learning algorithm, namely the relevance vector machine (RVM).

Machine learning is a subfield of computer science, in which the study and construction of algorithms that are capable of learning from and making predictions based on a limited set of observed data are explored. Supervised learning is the machine learning task of inferring a function from a set of labeled training data. For this purpose, a model is generated from the dependency of the targets on the inputs based on a set of N observed input vectors $\{x_n\}_{n=1}^{N}$ and the corresponding targets $\{t_n\}_{n=1}^{N}$, in order to predict the targets for inputs that have not been observed [11].

Supervised learning algorithms can be used to establish a global model from the functional relationship between the outputs and the inputs based on a limited number of measurements [12].

Support vector machines (SVMs) are supervised learning models with associated learning algorithms used for the classification and regression analysis [13], which have proven to be efficient in many practical applications [14]. For SVM-based regression, the input space is mapped into a high dimensional feature space, based on a set of kernel functions and then an optimal linear regression is performed in this space, which can be expressed as follows:

$$f(x) = y(x_i, w) = \sum_{i=1}^{N} w_i K(x, x_i) + w_0 \quad (1)$$

where {wi} is the model weights, K (.,.)a kernel function, and N the number of training samples. The most common formulation of the kernel function is the radial basis function (Gaussian) defined in Equation (2) in which σ is the kernel function parameter. Substituting this kernel function in Equation (1) results in function f(x) estimated in the form of Equation (3).

$$K(x, x_i) = exp\left(-\frac{x-x_i{}^2}{\sigma^2}\right) \quad (2)$$

$$f(x) = y(x_i, w) = \sum_{i=1}^{N} w_i exp\left(-\frac{x-x_i{}^2}{\sigma^2}\right) + w_0 \quad (3)$$

Despite its widespread success, the SVM suffers from some disadvantages, which have been overcome in a newer probabilistic approach named the Relevance Vector Machine (RVM) as proposed by Tipping [15]. RVM is a nonlinear pattern recognition model with a simple structure based on the Bayesian Theory and Marginal Likelihood [15]. The main advantage of the RVM over SVM in our application is the fact that in addition to precision and sparseness, it utilizes a fewer number of kernel functions. Therefore, it is suitable for the development of a formula for an input-output relationship.

In this study, the relevance vector machine regression analysis was used to obtain a mathematical expression for the tensile strength based on the longitudinal ultrasonic wave velocity. The accuracy and generalization capability of the obtained expression are verified based on standard statistical indices, which prove it to a suitable model for the rubber tensile strength based on the ultrasonic wave velocity.

2. EMPIRICAL EXPERIMENTS

2. 1. Materials For the fabrication of composites, the following materials have been used: solution caoutchouc styrene-butadiene 1500, butadiene cis caoutchouc, soot, high dispersible silica (HDS), silane, sulphur, sulfonamide accelerator, zinc oxide, stearic acid, zinc stearate.

2. 2. Preparation of Composites In the present research, in order to investigate the relationship between the tensile strength of rubber and longitudinal ultrasonic wave velocity, 14 rubber specimens with different formulations (Table 1) were produced.

The composites were prepared in a 2-lit experimental Banbury made by Pomini under similar conditions. The R-E Mccin 305x152 double-roll grind made by Italian Bergamo for material mixing, the experimental 100 tones vulcanizing press made in Japan for the vulcanization of rubber composites, and the Rheometer made by English Alpha co. have been utilized for determination of vulcanization properties. The rotor's revolution in the stages of adding caoutchouc, chemical materials, and filler was a constant value of 20 rev/min. To ensure complete silanization, the rotor's revolution was a set variable during the final stages of mixing to maintain the mixing temperature for a long time within a range of 130–150 °C. The overall mixing duration for the composites was set to be six minutes.

2. 3. Tensile Strength Test To evaluate the tensile strength of the rubber specimens, 14 dumbbell-shaped samples were prepared, as shown in Figure 2,

TABLE 1. The weight of the materials used in final formulations of the sample rubbers used

No	Sulphor (gr)	CBS (gr)	High Dispersible Silica (gr)	Silane (gr)	Soot N330 (gr)	BR CIS (gr)	SBR1500 (gr)	Other Chemicals (gr)
1	5.7	4.95	0	0	386.86	0	773.71	39.43
2	5.7	4.95	0	0	386.86	232.11	541.6	39.43
3	5.56	4.82	377.13	30.17	0	0	754.26	38.44
4	5.56	4.82	377.13	30.17	0	226.28	527.98	38.44
5	6.39	5.54	260.69	26.07	0	260.69	608.27	44.28
6	4.87	4.22	461.29	46.13	0	197.7	461.29	33.58
7	6.53	5.66	0	0	266.48	266.48	621.78	45.26
8	5.06	4.39	0	0	479.74	205.6	479.74	34.92
9	6.29	5.36	377.13	30.17	0	226.28	527.98	38.44
10	7.22	6.16	260.69	26.07	0	260.69	608.27	44.28
11	5.51	4.7	461.29	46.13	0	197.7	461.29	33.58
12	7.02	5.36	377.13	30.17	0	226.28	527.98	38.44
13	8.06	6.15	260.69	26.07	0	260.69	608.27	44.28
14	6.15	4.69	461.29	46.13	0	197.7	461.29	33.58

based on the ASTM D624 standard [16] employed a dynamometer made by Hounsfield.

2. 4. Ultrasonic Test

To investigate the relationship between the tensile strength of rubber and ultrasonic wave velocity, the longitudinal wave velocity for each specimen was measured. To this end, a Tru-Sonic ultrasonic test machine was employed. The specifications of the machine, specimens, and the probe are shown in Table 2. The ultrasonic waves, which are transmitted through the material, always lose a portion of their energy due to the dispersion at microscopic interfaces, as well as the effect of internal frictions in the material. The attenuation effect is actually the drop of the sonic wave energy during the emission of waves through the environment. In this empirical study, regarding the more intense attenuation effect in rubbers [17], a probe with a frequency of 4 MHz was utilized for the determination of the ultrasonic wave' velocity.

The longitudinal ultrasonic wave emission velocity for different specimens was measured by recording the elapsed time between the emission of waves and their reflex, which is displayed on the monitor by the standard electronic circuit. The ultrasonic wave measurement system is shown in Figure 3. The measurement precision of the ultrasonic wave velocity is 1 m/s. Because the calculated duration between the transmission and reception of the wave incorporates the time of the wave's traverse across the probe and coupler during each stage of the wave's travel, the time carries some errors. Consequently, it causes an error in the calculation of the wave emission velocity. First, the travel duration of the longitudinal ultrasonic wave across the probe and coupler was measured using the standard block. It was eliminated from the calculations for the approximation of the longitudinal wave emission velocity, and then the longitudinal wave velocity in specimens was calculated. The measurements were accomplished at a frequency of 4 MHz at the room temperature.

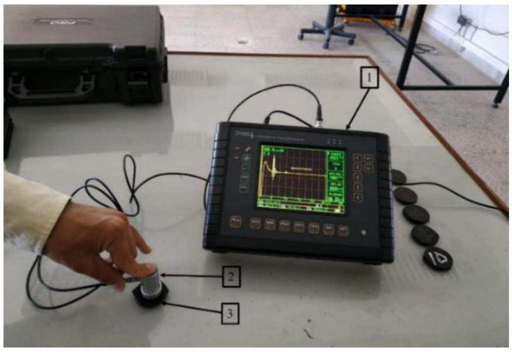

Figure 3. A System for Measuring Ultrasonic Waves Velocity: (1) Ultrasonic Instrument, (2) Probe, (3) Rubber Compound Sample

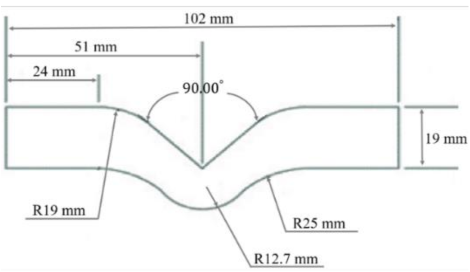

Figure 2. Tensile strength test sample based on the ASTM D624 standard [16]

TABLE 2. Specification of Instrument, Probe, and Samples

Specification	Value
Manufacturer	tru-sonic
Probe diameter (mm)	12
Probe frequency (MHz)	4
Sample diameter (mm)	41
Sample thickness (mm)	6

3. THEORY of RELEVANCE VECTOR MACHINE

In RVM-based regression, to predict a function based on a set of N input-target pairs$\{x_n, t_n\}_{n=1}^{N}$, each target is modeled as a function of the corresponding inputs with additive white Gaussian noise to accommodate measurement error on the target:

$$t_i = y(x_i, w) + \varepsilon_i \tag{4}$$

ε_i is assumed to be mean-zero Gaussian with variance σ^2 and similar to the SVM, $y(x, w)$, is considered as a linear combination of N kernel functions centered at the training samples inputs, in the form of Equation (3). Therefore, with the assumption that we know $y(x_n)$, each target is of normal independent distribution with the mean $y(x_n)$ and variance σ^2, expressed as [17]:

$$p(t_n|x) = N(t_n|y(x_n), \sigma^2) \tag{5}$$

Due to the assumption of independence of the targets, the likelihood function of whole samples can be obtained by the multiplication of the probability distributions as

$$p(t|w,\sigma^2) = \frac{e^{\left\{\frac{-t-\varphi\, w^2}{2\pi\sigma^2}\right\}}}{(2\pi\sigma^2)^{\frac{N}{2}}} \tag{6}$$

where

$$t = (t_1 \dots t_N)^T \tag{7}$$

$$w = (w_0 \dots w_N)^T \tag{8}$$

and $\boldsymbol{\varphi}$ is an N*(N+1) matrix, calculated as follows:

$$\varphi_{N*(N+1)} = \begin{bmatrix} 1 & k(x_1, x_1) & k(x_1, x_2) & \dots & k(x_1, x_N) \\ 1 & k(x_2, x_1) & k(x_2, x_2) & \dots & k(x_2, x_N) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & k(x_N, x_1) & k(x_N, x_2) & \dots & k(x_N, x_N) \end{bmatrix} \quad (9)$$

To avoid over-fitting, a 'prior' zero-mean Gaussian probability distribution is assumed for the weights as:

$$p(w|\alpha) = \prod_{i=0}^{N} N(w_i|0, \alpha_i^{-1}) \quad (10)$$

where $\boldsymbol{\alpha}$ is a vector of N+1 hyper-parameters [17]. The variance of this Gaussian probability distribution, α_i^{-1} controls how far from zero each weight can deviate.

The posterior over w can be obtained based on the Bayesian posterior inference as:

$$p(w|t, \alpha, \sigma^2) = \frac{p(t|w,\sigma^2)\ p(w|\alpha)}{p(t|\alpha,\sigma^2)} = (2\pi)^{-\frac{N}{2}} |\textstyle\sum|^{-\frac{1}{2}} e^{\left\{-\frac{(w-\mu)^T \sum^{-1} (w-\mu)}{2}\right\}} \quad (11)$$

In this formulation, $\sum$ is the variance and is calculated as

$$\textstyle\sum = (\sigma^{-2}\varphi^T\varphi + A)^{-1} \quad (12)$$

wherein A is a diagonal matrix formulated as

$$A = diag(\alpha_0, \alpha_1, \dots, \alpha_N) \quad (13)$$

The mean value μ can be obtained as

$$\mu = \sigma^{-2}\textstyle\sum\varphi^T t \quad (14)$$

It can also be concluded based on this formulation that when $\alpha_i \to \infty$, $\mu_i \to 0$.

Integrating $p(\boldsymbol{w}|\boldsymbol{t}, \boldsymbol{\alpha}, \sigma^2)$ over the weights w, the marginal likelihood [13] for the hyper-parameters is calculated as

$$p(t|\alpha, \sigma^2) = \int p(t|w, \sigma^2)\ p(w|\alpha)\ dw \quad (15)$$

The above integral is a convolution of Gaussians, which can be calculated as

$$p(t|\alpha, \sigma^2) = (2\pi)^{-\frac{N}{2}} |\Omega|^{-\frac{1}{2}} e^{\left\{-\frac{t^T \Omega^{-1} t}{2}\right\}} \quad (16)$$

The matrix Ω in the marginal likelihood can be obtained as

$$\Omega = \sigma^2 I + \varphi A^{-1}\varphi^T \quad (17)$$

The optimal parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\sigma^2}$ can be obtained by maximizing the marginal likelihood $p(\boldsymbol{t}|\boldsymbol{\alpha}, \sigma^2)$ over the training dataset. They are estimated in an iterative re-estimation procedure in the learning process of RVM. Following the approach of MacKay [18], the following iterative relationships were proposed for this purpose:

$$\alpha_i^{new} = \frac{1 - \alpha_i \Sigma_{ii}}{\mu_i^2} \quad (18)$$

$$(\sigma^2)^{new} = \frac{\boldsymbol{t} - \boldsymbol{\varphi\mu}^2}{N - \sum_{i=0}^{N}(1 - \alpha_i \Sigma_{ii})} \quad (19)$$

The iterative calculation of the parameters α_i and σ^2 from Equations (18) and (19) concurrent with updating of the following statistics $\sum$ and μ from Equations (12) and (14) is repeated until some suitable convergence criteria have been satisfied.

At the end of this procedure, the maximizing values $\boldsymbol{\alpha}_{MP}$ and σ_{MP}^2 are obtained, and the predictions for the new samples are made based on the posterior distribution over the weights conditioned on them. For a new sample x^*, a Gaussian predictive distribution is assumed for the output, expressed as [19]:

$$p(t^*|t) = N(t^*|y^*, \sigma_*^2) \quad (20)$$

where

$$y^* = \mu^T \varphi(x^*) \quad (21)$$

$$\sigma_*^2 = \sigma_{MP}^2 + \varphi(x^*)^T \textstyle\sum \varphi(x^*) \quad (22)$$

$$\varphi(x^*) = [1, K(x^*, x_1), \dots, K(x^*, \boldsymbol{x}_N)]^T, \quad N = 1, \dots, N \quad (23)$$

The mean value of the distribution y^* is considered as the predicted output value and the variance, σ_*^2, provides an index of uncertainty in prediction.

In the iterative calculation of hyper-parameters α_i, many of them tend to infinity. This means that the probability distribution of the corresponding weights w_i is peaked at zero and they are estimated to be zero; thus, pruning many of the kernel functions used in Equation (1), which results in the sparseness of the model. The training set, which associates with the remaining nonzero weights, is called the relevance vector.

4. RESULTS AND DISCUSSION

In this survey, non-destructive tests using ultrasonic waves were used to examine the tensile strength of rubber composites, and a database of fourteen values of tensile strength and the corresponding longitudinal ultrasonic wave speed was obtained, as shown in Table 3. The RVM model was trained by eleven values of the measurements listed in Table 3, and it was tested by three of them, marked in bold. The Sparse Bayes package for Matlab [20] was used for the implementation of the model. Using the Gaussian kernel function formulated as Equation (25), with the parameter of $\sigma = 45$, the relevance vector contains only two of the training samples. Therefore, based on the calculated weights, the functional relationship between the tensile strength and the longitudinal wave speed can be defined as

$$\hat{y} = 1.483 * exp\left(-\frac{(x-1749.5)^2}{2025}\right) - 8.796 * exp\left(-\frac{(x-1483.2)^2}{2025}\right) + 16.153 \quad (24)$$

TABLE 3. The resilience and longitudinal ultrasonic waves' velocity of the samples used

No	Longitudinal ultrasonic waves' velocity (m/s)	Tensile Strength (MPa)
1	1717	17.04
2	1537.5	15.25
3	1749.5	18.46
4	**1494**	**7.53**
5	1469.6667	7.47
6	1536.75	14.9045
7	1501.16667	7.63
8	**1573.75**	**15.34**
9	1559.833	13.65
10	1500.8	10
11	1483.2	7.67
12	**1599**	**16.94**
13	1467	10.03
14	1467.125	6.06

The accuracy of the proposed expression was evaluated based on root-mean-square error (RMSE) and the coefficient of determination (R^2) of statistical indices, defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(y_i - y_i\right)^2}{N}} \tag{25}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i - y_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2} \tag{26}$$

In these equations, y_i and $\hat{y_i}$ are the measured and the predicted outputs, respectively. N is the number of training samples, y_{max} and y_{min} are the maximum and minimum values of the measured outputs, and $\bar{y}$ is the mean value of the measured output, calculated as follows:

$$\bar{y} = \frac{\sum_{i=1}^{N} y_i}{N} \tag{27}$$

The calculated values of the indices are listed in Table 4. As it can be observed, the RVM method provides the possibility of defining an explicit mathematical expression along with reasonable accuracy and a generalization capability. The measured outputs, together with the outputs predicted by the RVM method, are depicted in Figure 4, showing a good agreement between them.

TABLE 4. Statistical indices for evaluation of the RVM model

Database	RMSE	R^2
Training	1.2957	0.9023
Testing	0.6259	0.9768

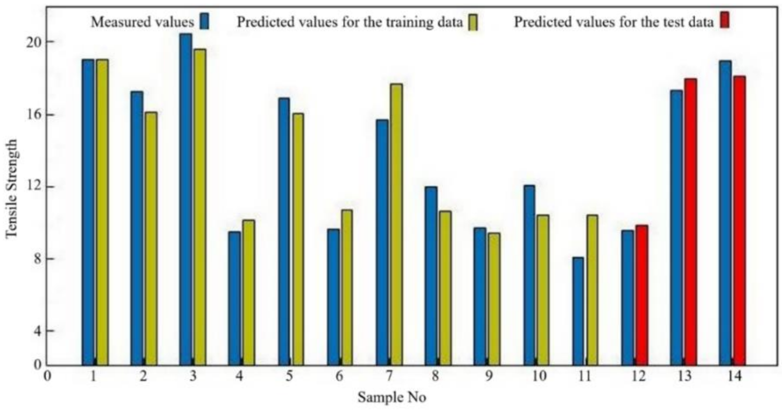

Figure 4. The measured outputs and the outputs predicted by RVM

5. CONCLUSION

In this paper, the application of ultrasonic testing for the measurement and modeling of the tensile strength of rubber has been proposed. For this purpose, the tensile strength of a set of rubber samples together with longitudinal ultrasonic wave velocity is measured. Based on these measurements, the relevance vector machine regression analysis is used to define an explicit mathematical expression to model the relationship between the tensile strength and the wave velocity, which is proven to provide reasonable accuracy and generalization capability. Based on these results, the developed model has the capability of being used for the online measurement of the tensile strength of rubber with the proposed formulation in the rubber industry.

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Persian Abstract

چکیده

امروزه، استفاده از بازرسی غیرمخرب برای بررسی ویژگی‌های مختلف مکانیکی و ساختاری مواد گسترش فراوانی یافته است. در پژوهش حاضر، از آزمون غیرمخرب فراصوتی برای بررسی رابطه بین مقدار استحکام کششی و سرعت امواج فراصوتی طولی استفاده شده است. برای این منظور چهارده نمونه کامپوزیت با فرمول‌های مختلف تهیه شده و استحکام کششی کامپوزیت‌ها با سرعت امواج فراصوتی طولی در داخل آن‌ها اندازه‌گیری شده است. تحلیل رگرسیون ماشین بردار رابط، به عنوان یک روش جدید در یادگیری ماشین تحت نظارت، برای پیدا کردن رابطه ریاضی بین مقاومت کششی و سرعت امواج فراصوتی طولی مورد استفاده قرار گرفته است. ارزیابی دقت بیان ریاضی براساس شاخص‌های آماری استاندارد ثابت کرد که مدل پیشنهادی یک مدل کارآمد است. براساس نتایج به دست آمده، مدل ارائه شده قابلیت استفاده در اندازه‌گیری برخط استحکام کششی لاستیک را در صنعت لاستیک دارد.