



MODELING OF QSTE340TM STEEL FCG CURVE BY NEURAL NETWORK

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Abstract. This study focuses on modeling the fatigue crack growth rate of QSTE340TM steel using a neural network. This material is a thermomechanically rolled high-strength, low-alloy steel with a yield strength of at least 340 MPa, offering a combination of strength, weldability, and excellent cold-forming properties. It's a go-to material for automotive and structural applications where durability and lightweight design are critical. The classical deterministic methods for assessing fatigue crack growth rates are often quite expensive and require a well-equipped testing facility. In contrast, in recent decades, the methods of machine learning have become widespread thanks to their ability to discover previously unobvious data-driven dependencies. Machine learning is a part of artificial intelligence. It is trained on existing data and improves over time without requiring explicit programming. The experimental dataset was taken from open scientific sources. It contained the fatigue crack growth rate data for four stress ratios of 0.1, 0.3, 0.5, and 0.7. The input data comprised of the following features: stress intensity factor range ΔK (MPa \sqrt{m}), fatigue crack growth rate da/dN , and stress ratio R . The target feature was da/dN , and the two rest were treated as input features. The model was shown only the data with stress ratio R that was equal to 0.1, 0.3, and 0.7. The model was tested on fatigue crack growth rate data with a stress ratio (R) of 0.5. The neural network model in the form of multilayer perceptron was built. The model consisted of two hidden layers, each with 100 and 80 neurons, respectively. The activation function was RELU. The solver was chosen as Adam, and maximum iterations parameter was 500. The model's errors were as follows: $MSE = 1.238e-10$, $MAE = 8.594e-06$, and $R^2 = 0.95346$. From the obtained results, neural network gives quite accurate prediction results and can solve such kinds of problems.

Key words: QSTE340TM steel, machine learning, fatigue crack growth rate; neural network, regression problem.

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1. INTRODUCTION

QSTE340TM steel is a thermomechanically rolled high-strength, low-alloy steel with a yield strength of at least 340 MPa, combining strength, weldability, and excellent cold-forming properties [1]. It's a go-to material for automotive and structural applications where durability and lightweight design are critical. Its key advantages are as follows. Initially, this steel is characterized by high strength and low weight. That makes it ideal for automotive lightweighting. Secondly, it possesses excellent cold-forming ability. This means it can be bent and shaped without losing strength. Also, it has good weldability; therefore, it is compatible with standard welding processes. Lastly, but not least, this material is corrosion-resistant, as it contains alloying elements such as Cr, Mo, and Ti [2].

Mechanical properties are typically as follows: yield strength ($\sigma_{0.2}$): ≥ 340 MPa, ultimate tensile strength σ_{UTS} is in the range from 480 to 620 MPa. Its relative elongation (A): is approximately equal to 22% depending on thickness. Its impact toughness is good, suitable for dynamic loads [2].

These properties make it suitable for bending, flanging, folding, and other cold-forming operations without cracking. Chemical composition (approximate limits) are the following: Carbon (C): $\leq 0.12\%$, Silicon (Si): $\leq 0.50\%$, Manganese (Mn): $\leq 1.30\%$, Phosphorus (P): $\leq 0.030\%$, Sulfur (S): $\leq 0.030\%$, microalloying elements: Nb, Ti, V, Al are in small amounts to refine grain and improve strength [2]. This low-carbon composition ensures good weldability and formability.

Among its typical applications, one can name the automotive industry, where it is being utilized for chassis parts, reinforcements, and structural panels. Also, this material is widely employed in construction for load-bearing profiles and beams. QSTE340TM steel is being actively applied in machinery for components requiring strength and formability. It can be seen in the energy sector as well, where it is occasionally used in pipelines and oil/gas equipment [2, 3].

During the service life, the parts of machines undergo cyclic loading in a random manner, which can lead to the initiation of cracks. These cracks gradually propagate and can lead to failure of the respective structural elements or automotive components. Therefore, it is crucial to study the available fatigue crack growth (FCG) data and build some accurate models to describe the FCG rate at various stress ratio.

The classical deterministic methods for assessing fatigue crack growth rates are often quite expensive and require a well-equipped testing facility. In contrast, in recent decades, the methods of machine learning (ML) have become widespread thanks to their ability to discover previously unobvious data-driven dependencies. ML is a part of artificial intelligence. It is trained on existing data and improves over time without requiring explicit programming [4].

Recently, ML has become the mainstream of technological society and an inevitable and ubiquitous part of everyday human life. The data emerges very rapidly, and there is a constant need to process it to uncover hidden insights and learn something new and valuable from the data [5].

ML has found its numerous applications in different areas of science and technology [6, 7]. Its algorithms allow us to understand data and its nature [8]. Generally, these algorithms fall into two categories: supervised learning and unsupervised learning. Overall, the primary goal of ML methods is to develop a statistical model that enables predicting or assessing the target feature based on at least one input feature. Such tasks often arise in various fields, including medicine, finance, business, psychology, engineering, and others. On the contrary, unsupervised learning employs the input features, though without the given target. In the latter case, one can study the dependencies and structure of such kind of data.

Therefore, due to the practical use of QSTE340TM steel in structural engineering and automotive technology, it is highly important to predict the FCG data of this steel based on the available open dataset from scientific sources.

There are quite a lot of studies that deal with the FCG and fatigue lifetime of steels and aluminum alloys using numerous methods of ML, for instance [9–11].

However, to the best of the author's knowledge, the study of the FCG rate of QSTE340TM steel using supervised ML methods, specifically an artificial neural network in the form of a multilayer perceptron, remains an uninvestigated task.

This work focuses on modeling the FCG curve of QSTE340TM steel for various stress ratios using a supervised machine learning method.

2. EXPERIMENTAL METHODS

The specimens were machined from the plate made of automotive QSTE340TM with a thickness of 2.5 mm. The mechanical properties were determined through a tensile test. Young's modulus E is equal to 194 GPa, yield strength $\sigma_{0.2}$ is 365 MPa, and ultimate tensile stress σ_{UTS} is 482 MPa [12]. The compact tension specimen (CT) was made according to ASTM E647 standard [13]. The chemical composition of QSTE340TM steel is given in Table 1.

Table 1

The chemical composition of QSTE340TM steel

C	Si	Mn	P	S	Al	Nb	Ti
0.12%	0.50%	1.3%	0.03%	0.03%	0.015%	0.09%	0.22%

3. RESULTS AND DISCUSSION

The experimental dataset was taken from the study [14]. It contained the fatigue crack growth rate data for four stress ratios of 0.1, 0.3, 0.5, and 0.7. The input data comprised the following features: stress intensity factor range ΔK (MPa \sqrt{m}), fatigue crack growth rate da/dN , and stress ratio R . The target feature was da/dN , and the other two were treated as input features.

The dataset was pre-processed using MinMaxScaler to transform the data into the [0, 1] segment. This was done to better train the neural network.

In general, the train dataset contained 596 samples, while the test dataset comprised 171 samples. The model was shown only the data with stress ratios R that were equal to 0.1, 0.3, and 0.7. The model was tested on fatigue crack growth rate data with a stress ratio (R) of 0.5. A neural network model, in the form of a multilayer perceptron, was built. The model consisted of two hidden layers, each with 100 and 80 neurons, respectively. The activation function was RELU. Solver was chosen as Adam, and the maximum number of iterations was set to 500.

The modelling was performed in a script written in Python 3.13 programming language. The MLP was constructed by utilizing the scikit-learn library, especially suited for ML tasks.

Fig. 1 shows the experimental data and the prediction results of the FCG rate of QSTE340TM steel at $R = 0.5$ obtained by using a multilayer perceptron.

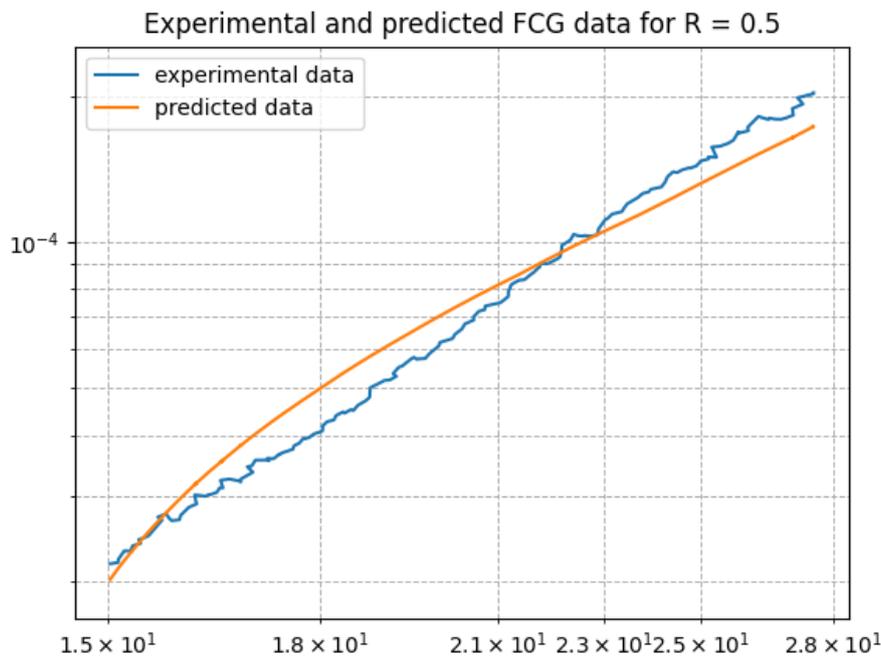


Figure1. Experimental and predicted FCG data of QSTE340TM steel at $R = 0.5$
 The model's errors were as follows: MSE: 1.238e-10, MAE: 8.594e-06, R^2 : 0.95346

As shown in Fig. 1, the predicted results are quite accurate. Fig. 2 shows the actual versus predicted plot for the FCG rate of QSTE340TM steel at $R = 0.5$.

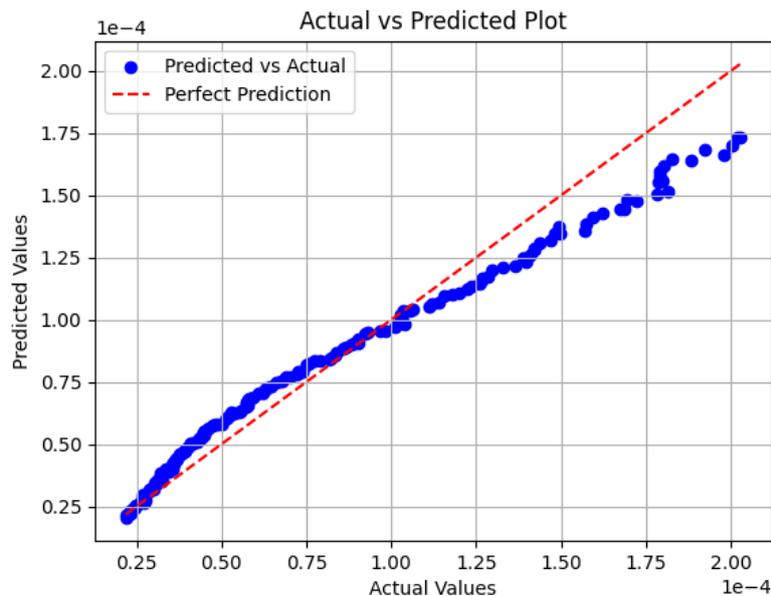


Figure 2. Actual versus predicted plot for FCG rate of QSTE340TM steel at $R = 0.5$

The red line is the bisector of the first coordinate angle. The blue points correspond to the abscissa equal to the actual value of FCG and the ordinate equal to the predicted value of FCG. The closer the blue points are to the red line, the better the prediction is.

As shown in Figure 2, neural network prediction results can effectively solve such problems.

4. CONCLUSIONS

In the current study, the modeling of the FCG rate of QSTE340TM automotive steel at $R = 0.5$ was performed using a supervised machine learning method, specifically an artificial neural network, considering the stress ratio.

The dataset contained the FCG curves for four stress ratios of 0.1, 0.3, 0.5, and 0.7. The input data comprised of the following features: stress intensity factor range ΔK (MPa \sqrt{m}), fatigue crack growth rate da/dN , and stress ratio R . The target feature was da/dN , and the other two were treated as input features. The model was shown only the data with stress ratios R that were equal to 0.1, 0.3, and 0.7. The model was tested on fatigue crack growth rate data with a stress ratio (R) of 0.5. A neural network model, in the form of a multilayer perceptron, was built. The model contained two hidden layers with 100 and 80 neurons, respectively. The activation function was RELU. The solver was chosen as Adam, and the maximum number of iterations was set to 500. The model's errors were as follows: MSE: 1.238e-10, MAE: 8.594e-06, R^2 : 0.95346. From the obtained results, neural networks give quite accurate prediction results and can solve such kinds of problems.

The input data consisted of the next features: stress s (MPa), cycle number N , and loading frequency f (Hz). Based on these data, for each loading cycle, and for each loading cycle, the dissipated energy was calculated.

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МОДЕЛЮВАННЯ ДІАГРАМИ ВТОМНОГО РУЙНУВАННЯ СТАЛІ QSTE340TM НЕЙРОННОЮ МЕРЕЖЕЮ

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Резюме. Дослідження стосується моделювання росту втомних тріщин у сталі QSTE340TM за допомогою нейронної мережі. Цей матеріал є термомеханічно прокатана високоміцна, низьколегована сталь з границею плинності 340 МПа, яка поєднує міцність, здатність до зварювання і чудові властивості холодного формування. Це матеріал, який успішно застосовують у автомобілебудуванні та елементах конструкцій, для яких ресурс та легке проектування є критичними. Класичні детерміновані методи оцінювання росту втомних тріщин є часто досить дорогими і вимагають добре обладнаної лабораторії для проведення експериментів. На противагу ним, за останні десятиліття методи машинного навчання стали широко поширеними завдяки їх властивості виявляти неочевидні залежності на основі даних. Машинне навчання є частиною штучного інтелекту. Воно навчається на існуючих даних і удосконалюється з часом без потреби явного програмування. Експериментальний набір даних взято з відкритих наукових джерел. Він містив дані швидкості росту втомної тріщини для чотирьох асиметрій циклу навантаження: 0,1; 0,3; 0,5; і 0,7. Вхідні дані склалися з наступних ознак: розмах коефіцієнта інтенсивності напружень ΔK (МПа \sqrt{m}), швидкість росту втомної тріщини da/dN та коефіцієнт асиметрії циклу навантаження R . За вихідну змінну вибрано da/dN , а дві інші слугували в якості вхідних змінних моделі машинного навчання. Модель тренували тільки на даних швидкості росту втомної тріщини з коефіцієнтом асиметрії циклу навантаження R , який дорівнював 0,1; 0,3; та 0,7. Модель перевіряли на даних швидкості росту втомної тріщини з коефіцієнтом асиметрії циклу навантаження R , котрий дорівнював 0,5. Побудовано модель у вигляді багатошарового перцептрона. Модель містила два прихованих шари з кількістю нейронів 100 та 80, відповідно. Функція активації була RELU. В якості оптимізатора обрано Adam, а параметр максимум ітерації дорівнював 500. Помилки моделі були наступними: $MSE = 1.238e-10$, $MAE = 8.594e-06$, $R^2 = 0.95346$. З отриманих результатів, можна побачити, що нейронна мережа забезпечує досить точні результати прогнозування і може розв'язувати задачі такого типу.

Ключові слова: сталь QSTE340TM, машинне навчання, швидкість росту втомної тріщини, нейронна мережа, задача регресії.