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Prediction of Mechanical Properties of Synthetic Waste Reinforced Polyolefins with GA-LSTM Hybrid Model

Anıl Utku [1], Yılmaz Kısmet [2], Ümit Can [3]
[1] Computer Engineering Department, Munzur University, 62000 Tunceli, Turkey
[2]Department of Mechanical Engineering, Munzur University, 62000 Tunceli, Turkey
[3]Computer Engineering Department, Munzur University, 62000 Tunceli, Turkey.

:ucan@munzur.edu.tr [1] 0000-0002-7240-8713 [2] 0000-0003-3145-6214 [3] 0000-0002-8832-6317

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ABSTRACT

In this study, the effects of the production parameters used in injection molding of particle-reinforced thermoplastics on the product quality and mechanical properties of the produced part are modeled using an optimized Genetic Algorithm-Long Short-Term Memory (GA-LSTM) hybrid deep learning method. Here, LDPE, HDPE, and PP, the most important members of the polyolefins group, were used as thermoplastics, while powdered synthetic paint wastes were evaluated as reinforcement elements. Using different parameters, 819 specimens were produced by injection molding, and mechanical tensile, three-point bending, and izod impact tests were performed on each specimen. The GA-LSTM model was trained with the parameters used and the results obtained during the experimental process, and the predicted values were determined to correspond to the actual values. Well-known methods were used to measure the success of the hybrid GA-LSTM model. The designed GA-LSTM model produced the best outcomes, according to the results attained.

Keywords: Deep Learning, Injection Molding, Machine Learning, Mechanical Properties, Thermoplastic

Sentetik Atık Takviyeli Poliolefinlerin Mekanik Özelliklerinin GA-LSTM Hibrit Modeli ile Tahmini

ÖZ

Bu çalışmada, parçacık takviyeli termoplastiklerin enjeksiyon kalıplamasında kullanılan üretim parametrelerinin ürün kalitesi ve üretilen parçanın mekanik özellikleri üzerindeki etkileri optimize edilmiş bir Genetik Algoritma-Uzun Kısa Süreli Bellek (GA-LSTM) hibrit derin öğrenme yöntemi kullanılarak modellenmiştir. Burada termoplastik olarak poliolefinler grubunun en önemli üyesi olan AYPE, YYPE ve PP kullanılırken takviye elemanı olarak ise toz halde sentetik boya atıkları kullanılmıştır. Farklı parametreler kullanılarak enjeksiyon kalıplama yoluyla 819 numune üretilmiş ve her numune üzerinde mekanik çekme, üç nokta eğme ve izod darbe testleri gerçekleştirilmiştir. GA-LSTM modeli, kullanılan parametreler ve deneysel süreç boyunca elde edilen sonuçlarla eğitilmiş ve tahmin edilen değerlerin gerçek değerlere karşılık geldiği belirlenmiştir. Hibrit GA-LSTM modelinin başarısını ölçmek için iyi bilinen yöntemler kullanılmıştır. Elde edilen sonuçlara göre tasarlanan GA-LSTM modeli en iyi sonuçları üretmiştir.

Anahtar Kelimeler: Derin Öğrenme, Enjeksiyon Kalıplama, Mekanik Özellikler, Makine Öğrenmesi, Termoplastik

INTRODUCTION

Polymers are materials we use in all areas of our daily life because they are simple to produce, low cost, and readily available. In particular, the use of polymer matrix composites developed together with many different reinforcing elements, in addition to their use alone, is widespread [1, 2]. One of the most preferred types of composite is thermoplastic matrix composites. Many organic or inorganic reinforcement elements can be used in these composites, as well as synthetic fillers [3-6]. Especially if the reinforcing element used is in the form of particles, the injection molding method is preferred in production. The injection molding method is a mass production method, and the production parameters used here are critical. Parameters such as temperature, injection pressure, holding pressure, receiving pressure, etc., belonging to the injection part of the injection machine, and parameters such as mold temperature and cooling time belonging to the mold part of the injection machine significantly affect the part quality in production. Knowing these parameters in advance will enable the production to be carried out in series by saving both material and energy without resorting to trial and error at the beginning of the machine in case of changing the type of matrix and reinforcing element to be used in production or changing the mixture ratios [7, 8].

Today, artificial intelligence methods have started to be used to learn and predict these parameters. With the emergence of the ease of application of these methods to different fields with the developing technology, artificial intelligence methods are used more easily and widely in various production areas. Thus, the production advantages it brings in production industries have positively affected the sectors economically [9-10]. Due to these important features, it plays an important role in modeling production stages and estimating the optimum values of various parameters (e.g. mechanical properties) used in the production of various parts used in manufacturing. For example, a database was created based on the mechanical results, such as maximum compressive/crushing force, maximum strain, and modulus of elasticity of cylindrical section pipes produced from carbon fibers used in textiles after production. With this database, predictions with high convergence accuracy were developed for pipes containing different proportions of carbon fiber by using methods such as artificial neural networks (ANN) based feedforward backpropagation algorithm (FFBP) and machine learning (ML) [11]. In addition, dog bones were produced by plastic injection molding method using high-density polyethylene, and studies were carried out to increase the efficiency of the samples produced using ANN and ML methods [12]. Similarly, the dimensional stability of injection molded thermoplastics, such as width and thickness, and mechanical properties, such as Young's modulus, tensile stress, and elongation at break, can be predicted using machine learning (ML) [13-15]. Ahmed et al. [16] used Random Forest (RF) and Gradient Boosted Regression Tree (GBRT) algorithms to predict the warpage of a PVC component obtained in the injection molding process. The results achieved using the absolute percentage metric show that the RF algorithm performs better than the other algorithms. In order to reduce the costs of plastic manufacturing companies during injection molding, the correct parameter values should be used. Schulze Struchtrup et al. [17] applied various feature selection methods based on this idea. Then they used ANN, Binary Decision Trees (bDT), k-Nearest-Neighbors (kNN), Support-Vector Machines (SVM), LSBoost, RF, and Gaussian Process Regression (GPR) methods. Kiehas et al. [18] studied Charpy fracture surface images and tried to reveal the mechanisms that cause stress whitening. In this context, they tried to understand the Ductile to Brittle Transition Temperature (DBTT) based on fracture surface features. They also trained a CNN model to predict the DBTT. Wu et al. [19], offered an efficient machine learning-based model instead of the old and time-consuming methods used during the production of polymer materials. The mechanical properties and polymorphic properties of the models to be produced with this model were predicted by RF, Extreme Gradient Boosting (XGBoost), Extreme Tree (ET), and Gradient Boosting Tree (GBT) machine learning methods. Nasri and Toubal [20] tried to predict the impact and mechanical properties of biocomposite materials with pine and flax fibers reinforced with polypropylene using an artificial neural heavy (ANN) model. Many tests and expenses are required to determine the appropriate properties of these materials that degrade prematurely. With this model, this situation was avoided.

In recent years, traditional machine learning and deep learning methods have been applied to solve the problem of accurate prediction of various production parameters due to their ability to solve complex and nonlinear problems [21]. However, there are some situations where the performance of traditional machine learning methods is degraded. For example, in any prediction task, most machine learning algorithms require the user to provide relevant features. However, deep learning models extract the features themselves [22]. In addition, the large amount of data generated during manufacturing, the exceptionally high feature space of this data, and the multimodal data structure all have a negative impact on the performance of traditional machine learning methods. Deep learning models, on the other hand, yield quite successful results in complex tasks such as speech recognition, image processing, and natural language processing. Owing to their multi-layered structure, these methods automatically process data and uncover non-linear and complex relationships. These automatic learning capabilities have made deep learning models an effective tool in complex manufacturing processes [23]. This study created a dataset based on the injection molding production parameters of polyolefins reinforced with synthetic dye wastes and the mechanical test results of the produced samples, and a GA-LSTM hybrid agorithm was designed to predict the mechanical analysis results obtained during the production phase. Linear Regression (LR), RF, SVM, Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), and LSTM models were then applied to measure the accomplishment of this model.

The contributions of this study are listed as below:

- The predictive power of the LSTM model was optimized with the GA method.
- In this study, 819 injection-molded specimens were produced, and each specimen underwent mechanical tensile, three-point bending, and izod impact testing with different parameters.
- The mechanical analysis results of both LDPE-HDPE and LDPE-HDPE-PP were predicted with GA-LSTM.
- The designed GA-LSTM model was compared with RF, LR, SVM, MLP, RNN, and LSTM.
- Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and R squared (R^2) metrics were used to measure the success of the proposed models in predicting mechanical properties.

MATERIAL and METHOD

The matrix materials used in the production are LDPE, HDPE, and PP obtained from PETKIM A.Ş. The reinforcement elements are three different synthetic paint wastes belonging to epoxy, epoxy/polyester (hybrid), and polyurethane systems.

Production of Test Bars

Powder coating wastes were mixed with each matrix material separately by %5, 10%, 20%, and 30% by weight, first mechanically and then homogeneously using a single screw extruder device in the Polymer Science and Technology Laboratory of Munzur University Mechanical Engineering Department. After these mixtures were cooled at the extrusion outlet, they were passed through a crusher to 2 to 3-mm granules. These granules were separately produced into test bars using the "EKİN 100 T" brand/model plastic injection molding machine shown in Figure 1 in the Polymer Science and Technology Laboratory.

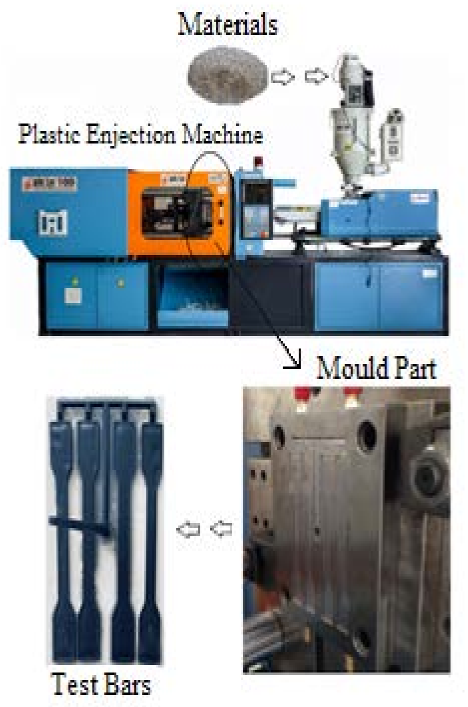

Figure 1. Production Flow chart of test bars

During these productions, the injection machine temperature, injection pressure, secondary pressure, holding pressure, mold temperature, cooling time, and cycle time values vary depending on the type and mixing ratio of each matrix material and reinforcing element.
Samples were also produced using pure LDPE, HDPE, and PP without reinforcements, and the production parameters varied for each. For example, the number of samples produced according to the AYPE and paint waste used for these experiments is given in Table 1. In addition, the same number of test bars were produced for other thermoplastics

Table 1. Test LDPE matrix samples used in mechanical tests

Materials/Mechanical Tests	**Tensile Test**	**Three-point bending**	**Izod Impact Test**
AYPE pure	7	7	7
AYPE+%5 Epoxy	7	7	7
AYPE+%10 Epoxy	7	7	7
AYPE+%20 Epoxy	7	7	7
AYPE+%30 Epoxy	7	7	7
AYPE+%5 Hybrid	7	7	7
AYPE+%10 Hybrid	7	7	7
AYPE+%20 Hybrid	7	7	7
AYPE+%30 Hybrid	7	7	7
AYPE+%5 P-Pure	7	7	7
AYPE+%10 P-Pure	7	7	7
AYPE+%20 P-Pure	7	7	7
AYPE+%30 P-Pure	7	7	7

A total of 819 test bars were produced as specified, and the mechanical properties of each of these test bars were analyzed. In addition, tensile, three-point bending, and izod impact tests were performed as mechanical tests.

Mechanical Tests

Tensile and three-point bending tests for the bars were performed using the 100 kN "Shimadzu AG-X" device in the Mechanical Engineering Laboratory of Munzur University. The device used in the experiment for the produced specimens is shown in Figure 2.

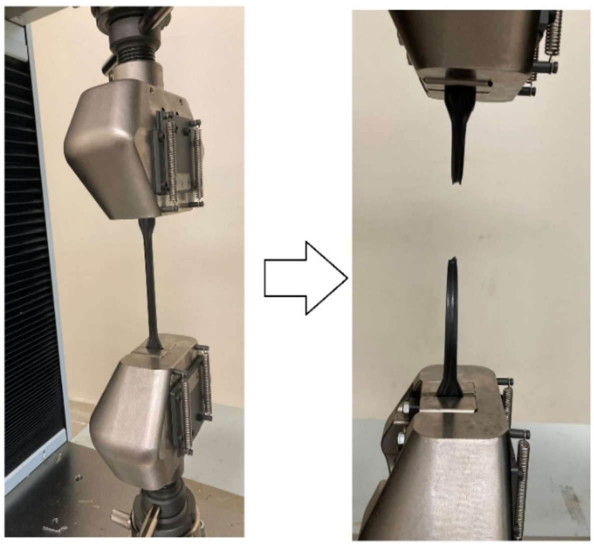

Figure 2. Tensile test performed for the produced specimens.

Tensile tests were performed under EN ISO 527 standards with a 50 mm/min tensile speed. And three-point bending tests were performed under EN ISO 178 standards with a bending speed of 10 mm/min, and a maximum travel of 6 mm. Izod impact tests followed EN ISO 180 standards using the Italian brand "Ceast Fractovis Plus" impact device in Dokuz Eylül University Mechanical Engineering Department.

Classification Models

Popular artificial intelligence methods used in many current researches were used to measure the performance of the GA-LSTM hybrid model developed in this study. These methods are briefly described in this section.

LR: Linear regression is a commonly used method in statistical data analysis. LR is used for linear and continuous variables and is one of the popular machine learning methods. LR shows the relationships between one or more independent variables and a dependent variable [24]. There are two different types of LR: Simple Linear Regression and Multiple Linear Regression models. The first one deals with one independent variable, while the other has more than one independent variable [25].

RF: It is one of the most promising ensembles learning methods that aims to find more successful solutions to problems by combining different methods. The random forest algorithm is an ensemble of multiple decision trees [26]. The algorithm comprises decision trees that independent of the input vector of each classifier. For the classification of the input vector, each tree produces a unit vote result [27]. The RF algorithm achieves successful results from both large data sets and small data sets. It can also work with a combination of discrete and continuous data types.

SVM: It is a trained statistical learning method used for classification and regression and successfully solves machine learning problems. SVM, developed by Vapnik [28], has gained popularity due to its many efficient features and good performance in solving nonlinear problems. The version used to solve regression problems is called the Support Vector Regression model [29].

MLP: This model is a nonparametric artificial neural network technique that performs many detection and prediction tasks. It is a general-purpose, flexible, non-linear model consisting of units (neurons) organized in multiple layers [30]. It consists of many layers, and for each neuron in these layers, it takes the sum of the product of the connection weight and the input signals and calculates its output as a function of this sum. This model is also known as feedforward ANN, as the learning is done from the previous layer to the following layer [31].

RNN: In RNN, a type of artificial neural network, the output data depends on the calculation of the sequential time series inputs of the neural network. These models are networks where the connections between units form a directed loop. RNN allows a system to exhibit dynamic temporal behavior [32]. Unlike feedforward neural networks, RNNs can process inputs using their own input memory. RNN performs processing time series data in application areas such as handwriting, speech, and activity classifications [33-34].

LSTM: This effective model is a variant of RNN and is used to solve various problems where the RNN method does not provide the desired solution power. LSTM is designed to overcome error-backflow problems. It was proposed by Hochreiter and Schmidhuber [35]. There are four layers in the LTSM architecture: input, forget, output, and cell. The cells that are the key to the architecture can keep or remove the information because of the features in the LTSM architecture, which are expressed as gates [36]. The other layers in the architecture, namely the input, output, and forgetting layers, constitute the memory of the network in the cell state. LSTM achieves very effective results in classification and regression problems, especially in text and audio-related tasks.

Developed Hybrid Deep Learning Model

This section describes the development process of the deep learning-based model, which successfully predicts the actual experimental results by using the production parameter values used and obtained experimental results in the real experimental environment and thus realistically models this experimental process. First, a data set was created using real experimental results, and then the data was given as input to the model after preprocessing steps. The developed GA-LSTM hybrid model inputs the experimental parameters and generates predictions for mechanically tensile, three-point bending, and izod impact tests as output. The architecture of the developed GA-LSTM model is shown the Figure 3.

As seen in Figure 3, the GA-LSTM architecture consists of an input layer, LSTM layers, and an output layer. The input layer is taken to the input layer after the data has gone through a certain preprocessing process in the first stage of the model. This layer receives time series data and prepares it in a format suitable for the LSTM layers. LSTM layers are used to learn and model long-term dependencies of consecutive data. Each LSTM layer contains an input gate, an output gate, a forget gate, and a cell state. The input gate determines how to process newly arriving data. The forget gate decides how much of the previous state information to forget. The output gate outputs the updated state information. The cell state stores and updates the long-term information. These gates and the memory cell control how the data is updated and stored at each time step. Hidden layers, the outputs obtained from the LSTM layers, are passed to the hidden layers. These layers represent the learned features at a higher level and increase the learning capacity of the model. The output layer provides the final prediction results of the model. Information from the hidden layers is passed to the output layer to produce the model's predictions.

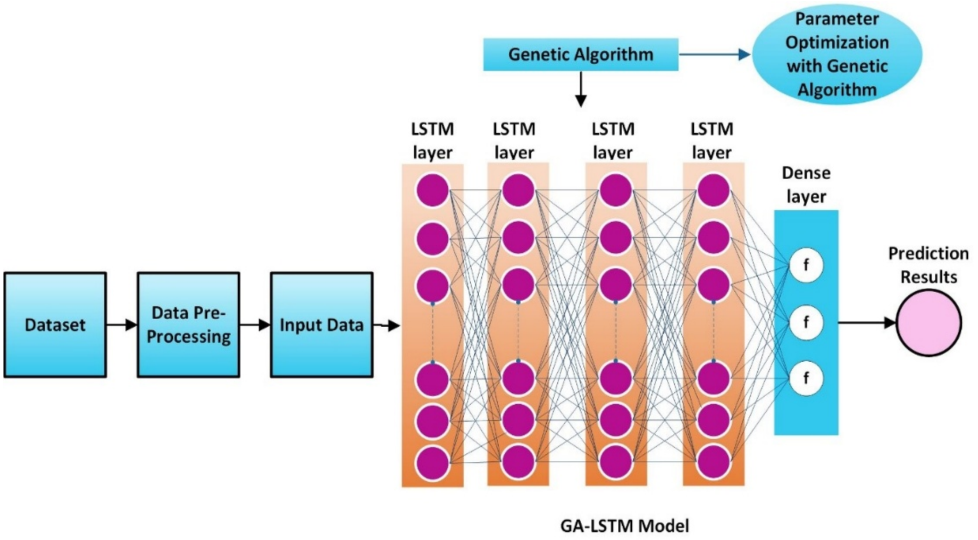

Figure 3. The architecture of the developed GA-LSTM model

Dataset

The dataset used in this study comprises three mechanical test results: tensile, three-point bending, and izod impact results of the samples produced with the parameters used during the injection molding of polyolefins reinforced with synthetic dye wastes. The dataset consists of 819 real test results obtained in the laboratory. Table 2 shows the attributes and value ranges in the dataset.

Table 2. Attributes and value ranges in the dataset

Attributes	***Value ranges***
Percentage contribution	≥ 0 ≤ 0.3
Temperature (°C)	≥ 165 ≤ 200
Injection pressure (bar)	≥ 60 ≤ 90
Secondary pressure (bar)	≥ 50 ≤ 0.3
Holding pressure (bar)	≥ 0 ≤ 80
Mold temperature (°C)	≥ 25 ≤ 90
Cooling time (s)	≥ 30 ≤ 80
Cycle time (s)	≥ 60 ≤ 110
Tensile strength	≥ 5.13 ≤ 56.783
Tree point bending strength	≥ 10.54 ≤ 68.55
Izod impact strength	≥ 2.11 ≤ 23.87

Evaluation Metrics

In prediction problems, the metrics Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R Squared (R2) are mainly used to determine the error between predictions and actual values. MSE is calculated by subtracting the predicted values from the actual values, squaring them, and calculating the average. MSE is calculated using Eq.1, where y is the actual value, $\hat{y}$ predicted values and n is the number of samples.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y-\hat{y})^2 \quad (1)$$

RMSE calculates the standard deviation of the prediction errors. The square root value of MSE represents RMSE, as shown in Eq.2.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|y-\hat{y}|)^2} \quad (2)$$

MAE takes the absolute value of the difference between the actual values found and the values predicted by the methods and then calculates their average. It calculates the mean of the prediction errors. MAE is calculated using Eq.3.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y-\hat{y}\,| \quad (3)$$

R^2 is a statistical measure of the proportion of variance. R^2 is calculated using Eq.4. $\bar{y}$ is the average of the actual values. The values of y and $\hat{y}$ were mentioned at the beginning of the section and are not repeated here.

$$R^2 = \frac{\Sigma(y-\hat{y})^2}{(y-\bar{y})^2} \quad (4)$$

Proposed Hybrid GA-LSTM Prediction Model

In this research, the hybrid model was designed and compared with RF, LR, SVM, MLP, RNN, and LSTM models in practice. First, this dataset was normalized in between 0 and 1 values with the MinMaxScaler method belongs to the Scikit Learn library and then artificial intelligence models were applied. After the normalization step, the data were divided into training, test, and validation sets. As a result of the experimental studies, the highest prediction accuracy was achieved in the combination of 80% training and 20% testing, so these values were chosen for the experimental studies. In

addition, 10% of the training data was reserved for validation. The validation data was used to optimize the parameters of the applied models. The model parameters were optimized using the GridSearchCV method from the Scikit Learn library to ensure the applied models get the best prediction outcomes. GridSearchCV uses a different combination of all specified hyperparameters and their values and selects the best value for the hyperparameters by calculating the performance for each combination. However, in the GA-LSTM model, parameter optimization was carried out using the GA algorithm to create the ideal parameter configuration for accurately predicting mechanical properties. Initially, 3x3 and 5x5 kernel sizes were tried for kernel sizes. These sizes were evaluated in a wide range to ensure that the model could learn different features and as a result of the experimental studies, 3x3 kernel size was selected.
For epoch numbers, 50, 100 and 150 epoch values were used in the training process and as a result of the experimental studies, 100 epoch number was selected.
For number of neurons, 50, 100 and 150 values were tried as the neuron numbers used in different layers and as a result of the experimental studies, 50 neurons were selected.
For learning rate, 0.001, 0.01 and 0.1 values were tried and as a result of the experimental studies, 0.01 learning rate was selected.
The LSTM can learn and model the sequential data more efficiently. This allowed LSTM to learn long-term patterns better. The following equations show the stages of the LSTM algorithm.

LSTM algorithm

For the input sequence $T_1, T_2, \ldots, T_N$ the hidden state h_t and the output y_t can be calculated as in Equations 1 and 2.

$$h_t = H(W_{ih}T_t + W_{hh}h_{t-1} + b_h) \quad (1)$$

$$yt = W_{ho}h_t + b_o \quad (2)$$

W_{ih}, W_{hh} *and* W_{ho} refer to the weight matrices between the input, hidden, and output layers. Here, an input x_t is received at time *t*. C_{t-1} denotes long-term memory and h_{t-1} denotes the transaction memory.
The following equations are used for learning and prediction by the LSTM deep learning model.

$$i_t = \sigma(w_{xi}x_t + w_{hi}h_{t-1} + w_{ci}c_{t-1} + b_i) \quad (3)$$

$$f_t = \sigma(w_{xf}x_t + w_{hf}h_{t-1} + w_{cf}c_{t-1} + bf) \quad (4)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(w_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (5)$$

$$o_t = \sigma(w_{xo} + w_{ho}h_{t-1} + w_{co}c_{t-1} + b_o) \quad (6)$$

$$h_t = o_t \odot h(c_t) \quad (7)$$

where, i_t represents the input gate, o_t the output gate, f_t the forgetting gate, *c* denotes the cell activation vector, w weight matrix, and b is the bias vector. ʘ is a the scalar product of two vectors. x_t and h_t denotes input-output sequences.
The parameters used in the experiments performed in this study were given as input to the LSTM model. These parameters were used in the construction of the algorithms to be selected while building the model. The selection of the activation function and the construction of the optimization algorithm can be given as examples. In order for the model to make effective and high performance predictions, the optimum values of the hyperparameters should be selected, and also the limits of the hyperparameters should be considered during this selection. Some of these hyperparameters to be selected are the kernel size, epochs, neurons, and layers numbers. However, finding the optimum values of the hyperparameters is a time-consuming process. The first hyperparameters obtained while designing the model usually do not give successful results. In the following process, many trials are made to achieve the highest success of the model and optimum results are obtained. The model is trained with these hyperparameter values. By adjusting the most successful hyperparameter combination, the best results are tried to be obtained by using success metrics. In this study, the hyperparameter values are optimized using GA to increase the success of the LSTM model. Thus, the most successful model was tried to be found.

Genetic Algorithm

GA is a population-based and stochastic method. It is also an efficient classification and search algorithm. Its ability to adapt to problems, its fast operation, and the fact that it does not get stuck in local solutions in the search space make it stand out. This algorithm was introduced by John Holland [37]. GA is a method developed based on Darwin's theory of evolution and the principle that the best-adapted individual will survive [38]. The operators that form the basic structure of the algorithm are crossover, mutation, and selection operators. When adapting GA to problems, the representation of individuals should be done correctly, the fitness function should be created efficiently, and the correct genetic operators should be selected.
In GA, each solution corresponds to a chromosome, and gene represents each variable. GA calculates the fitness of each candidate solution in a population, and the individual with the best fitness after all iterations is presented as the solution. The GA algorithm first generates a random initial population. The aim here is to expand the solution space by creating a wide variety of individuals [39]. The pseudocode of GA is given in Figure 4.

```
Input:
   Set initial population size (n)
   Set the maximum (MAX) number of iterations
   Define objective function
Output:
   Return the best X_best solution
begin
   Generate an initial population of n chromosomes, X_i (i = 1,2, ..., n)
   Set iteration counter t=0
   Calculate the fitness value of each chromosome
   while (t < MAX)
      Select a chromosome pair from the initial population, taking into account the fitness value
      Perform the crossover operation with a crossover probability on the selected chromosome pair
      Apply the mutation operation to the offspring with a certain mutation probability
      Replace the old population with the new population
      Increase the current number of iterations by one
   end while
   Return the best solution X_best
end
```

Figure 4. The pseudocode of GA

The selection operator determines whether chromosomes will participate in the reproduction process. In other words, individuals selected by the selection operator are eligible to enter the crossover pool, while unselected individuals are destroyed. In some studies, the selection operator is also called the reproduction operator. This operator affects the convergence process of the algorithm. Various selection methods include the Roulette wheel, rank, tournament, and Boltzmann [41]. The crossover process, which is used to create new generations in the evolutionary process, comes to life in the genetic algorithm as a crossover operator that produces better solutions. The crossover operator creates a new generation from individuals selected by the selection operator. New chromosomes are produced at this stage, just as new ones are produced from parent chromosomes. After the replication process is finished, two chromosomes are randomly selected from the new population to be crossed. Generally, single-point, double-point, k-point, partially matched, uniform, shuffle, order, and cycle crossover operators are used [40]. The last operator is the mutation operator. With this operator, a process similar to the natural mutation process is carried out. It diversifies the solutions formed after the selection and crossover processes with a certain probability. This increases the diversity of the population, recovers good features that may be lost due to crossover, and prevents the algorithm from getting stuck in local solutions [39].

In the process of optimizing the LSTM model with the genetic algorithm, 20 iterations were performed for each experiment. In the implementation of the GA, the Python-based Distributed Evolutionary Algorithms in Python (DEAP) package was used. In addition, the Keras and PyGAD packages were used for the LSTM model to integrate the GA into the LSTM. In the optimization process with the GA, the population size was determined as 50 agents. This number of agents was found to be sufficient to reach optimum results by scanning a large part of the solution space. The tanh transfer function was preferred as the activation function used in the LSTM. This function was chosen to ensure that the LSTM cells learn long-term dependencies better. In the output layer, since it was a regression problem, the linear activation function was used. Finally, the KerasGA class generates the initial population of parameters of the LSTM model. The MSE metric served as a fitness measure. Through the algorithm's operation, these values were attempted to be maximized. In other words, an effort was made to identify the maximum fitness value. As a result, GA optimized the parameters of the LSTM. Additionally, the LSTM's weights were initially set to random numbers. Here the sliding window size parameter and the LSTM cells number are represented as chromosomes and encoded in binary bits. Recombination and selection operators work to discover the best solution from the population. As a result, the solutions with the best fitness values were selected for reproduction. If the condition to terminate the algorithm is reached after the reproduction operator is applied, it means that the optimal solution is approached. If the desired quality solutions are not reached as a result of iterations, crossover and mutation operators are applied again in order for the model to generate better solution candidates. The flowchart of the developed model is shown in Figure 5.

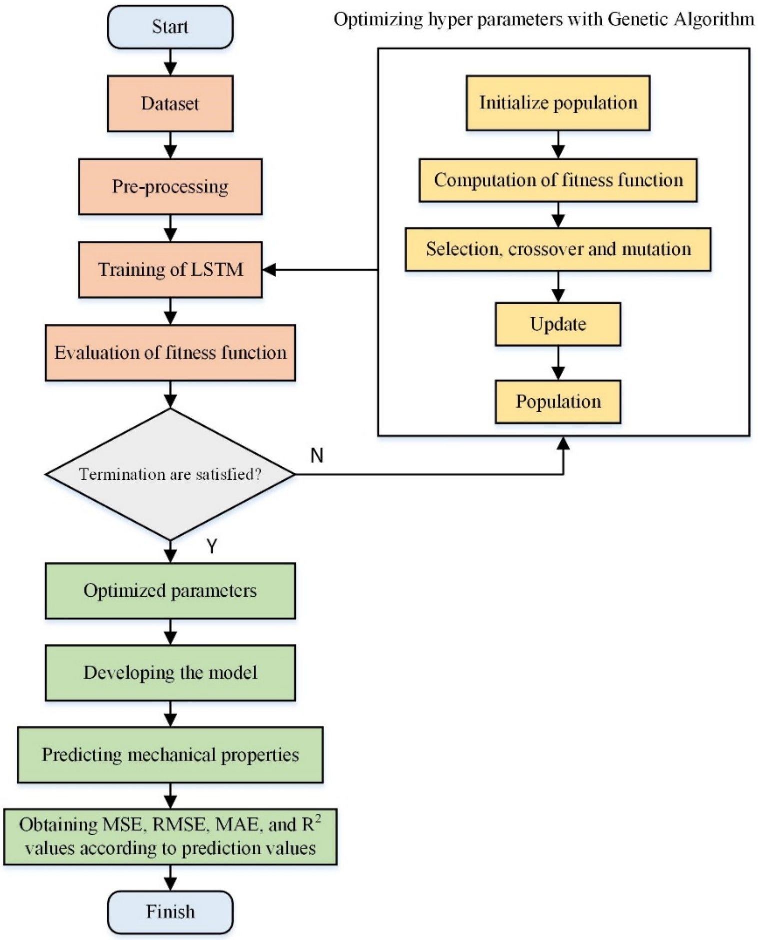

Figure 5. Flowchart of the developed model

EXPERIMENTAL RESULTS

In order to determine the error between the predictions and the actual values, MSE, MAE, RMSE, and R^2 results are given below for each thermoplastic separately and together.

Mechanical Predictions of LDPE-HDPE

This study evaluated the mechanical test results of LDPE and HDPE specimens in the data set. In addition, the tensile, bending, and izod test results of LDPE-HDPE obtained with the developed hybrid GA-LSTM model were given.
Table 3 shows the variations among the actual and predicted values of the tensile test results of LDPE and HDPE processed together. If R^2 is examined from these changes, it is seen that it is above 0.9 for all models. Therefore, when this value approaches 1, the difference in standard deviation among the actual and predicted values is nearly negligible. and the accuracy is high. A convergence to zero is sought if the MSE, RMSE, and MAE metrics are examined. When we look at the developed GA-LSTM-based deep learning method, it is seen that the R^2 value is 0.992 and the margin of error is minimum, and the other metrics are the closest values to 0 in the GA-LSTM-based model. If the R^2 value moves away from 1, it is understood that the standard deviation range increases and the difference between the actual and predicted values widen.

Table 3. Tensile strength results

Model	MSE	RMSE	MAE	R^2
LR	2.718	1.649	1.271	0.925
RF	1.724	1.313	1.007	0.953
SVM	2.607	1.615	1.176	0.928
MLP	1.482	1.218	0.938	0.959
RNN	1.192	1.092	0.899	0.967
LSTM	0.748	0.865	0.759	0.979
GA-LSTM	**0.444**	**0.666**	**0.585**	**0.992**

Table 4. Three Point Bending strength results

Model	MSE	RMSE	MAE	R^2
LR	1.813	1.347	1.077	0.869
RF	1.780	1.334	0.987	0.871
SVM	3.416	1.848	1.314	0.753

MLP	1.744	1.320	1.096	0.874
RNN	1.569	1.253	1.036	0.886
LSTM	0.800	0.894	0.682	0.942
GA-LSTM	**0.771**	**0.878**	**0.670**	**0.958**

Table 5. Izod impact strength results

Model	MSE	RMSE	MAE	R^2
LR	9.612	3.100	2.451	0.501
RF	4.393	2.096	1.765	0.772
SVM	8.194	2.862	1.858	0.575
MLP	7.346	2.710	2.195	0.619
RNN	6.062	2.462	1.848	0.686
LSTM	1.441	1.200	0.854	0.925
GA-LSTM	**1.396**	**1.181**	**0.841**	**0.939**

Tables 4 and 5 analysis reveals that GA-LSTM is the most effective model. The minimal standard deviation R^2 in Table 4 is 0.958, whereas the minimum distinction among the actual and predicted values in Table 5 is 0.939. In addition, if all three tables are examined, it is seen that the LSTM deep learning method gives the second-best results, apart from GA-LSTM.

Mechanical Predictions of LDPE-HDPE-PP

The results for the LDPE-HDPE and PP co-processed values are given in the tables below. Table 6 shows the success of the tensile test results obtained by machine learning and deep learning methods. These results show that LSTM and GA-LSTM deep learning models give the most accurate convergence, similar to the analysis performed for LDPE and HDPE. However, the difference here is that the standard deviation range, i.e., the difference between the actual and predicted values, is higher than the LDPE-HDPE results. This is because although polypropylene is a commercial thermoplastic in the polyolefin group, it is a different material with different properties than polyethylene.

Table 6. Tensile strength results

Model	MSE	RMSE	MAE	R^2
LR	17.254	4.154	3.380	0.756
RF	16.180	4.022	2.615	0.771
SVM	18.816	4.338	2.803	0.734
MLP	17.297	4.159	3.472	0.755
RNN	8.067	2.840	2.483	0.886
LSTM	7.608	2.758	2.263	0.892
GA-LSTM	**7.287**	**2.699**	**2.215**	**0.911**

PP and PE have a crystalline/semi-crystalline structure, but PP is synthesized from propene monomer instead of ethylene and has unique properties. LDPE and HDPE are both PE-based; that is, they are more similar in structure since the polymerization of ethylene monomer produces them. The most apparent difference between them is their density. In addition, PP is a brittle material, while PE is ductile. This makes PP more brittle and therefore causes variability from production parameters to test results.

Table 7. Three Point Bending strength results

Model	MSE	RMSE	MAE	R^2
LR	40.777	6.386	5.128	0.810
RF	29.076	5.392	4.048	0.864
SVM	45.741	6.763	4.814	0.786
MLP	38.241	6.184	4.498	0.821
RNN	24.095	4.909	3.525	0.888
LSTM	14.927	3.864	2.210	0.930
GA-LSTM	**14.236**	**3.773**	**2.158**	**0.952**

Table 8. Izod impact strength results

Model	MSE	RMSE	MAE	R^2
LR	14.587	3.819	2.962	0.224
RF	5.698	2.387	2.006	0.697
SVM	14.707	3.835	2.326	0.218
MLP	3.068	1.751	1.316	0.837
RNN	1.960	1.400	1.081	0.896
LSTM	1.605	1.267	0.968	0.915
GA-LSTM	**1.559**	**1.248**	**0.954**	**0.928**

The outputs of the models used to predict the bending test results are shown in Table 7. Similar to earlier studies, it is clear from these data that GA-LSTM and LSTM deep learning models produce the most outstanding outcomes. However, the difference between the actual and predicted results has increased since the results for PP are included in addition to LDPE and HDPE. For example, while the R^2 value obtained only for LDPE-HDPE was 0.958, here it was 0.952, slightly more than 1.
Table 8 shows the models' outputs depending on the Izod impact test results obtained by working with LDPE-HDPE-PP. Looking at these results, it is seen that the best models are GA-LSTM and LSTM, deep learning models. The following compares the predicted values obtained for tensile, three-point bending, and izod tests with the actual values. As shown in Figure 6, the mechanical results obtained from the original experimental results were successfully predicted. Graphically, it is seen that the actual results and the predicted results coincide.

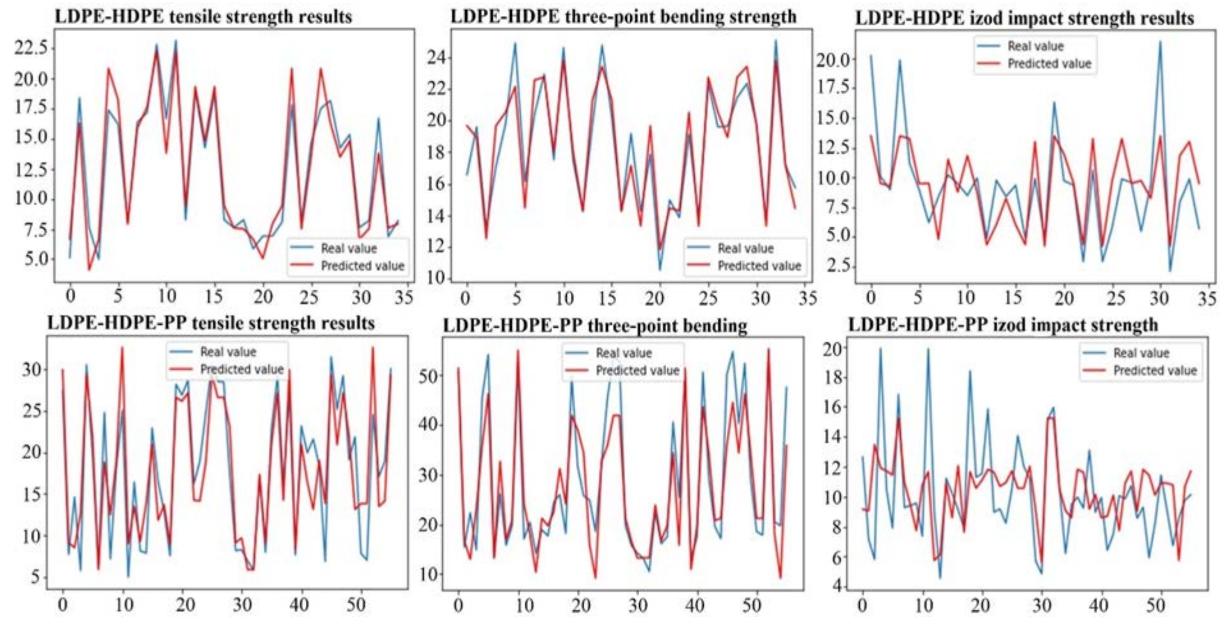

Figure 6. The comparison of original experimental values and GA-LSTM predicted values

The LDPE-HDPE-PP izod impact strength results overlap less than the others, as shown in the graph above. Within a limited range, the hybrid model gave mechanical results comparable to the actual experimental results.

DISCUSSION

GA-LSTM has achieved quite successful results in the training and testing phases, but the model's performance with completely new data that is not in the original dataset may have some difficulties. LSTM models are strong at learning long-term dependencies in time series data, but when faced with new untrained data patterns, performance may decrease. This situation can occur especially when structural changes or different distributions in the dataset are not fully reflected in the model.

LSTM optimized with GA may be prone to learning data-specific features. In this way, although the model achieves successful results on training data, it may lead to overfitting problems on new data. Although cross-validation techniques have been used to prevent overfitting, this risk exists when faced with a completely new dataset.

The GA-LSTM model used in this study has shown superior performance in the injection molding processes of polyolefin matrix thermoplastics when compared to other machine learning and deep learning methods frequently used in the literature.

Ahmed et al. [16] used Random Forest and Gradient Boosting models to predict the bending properties of PVC in injection molding processes, providing over 85% accuracy. However, the GA-LSTM model used in this study achieved a superior performance in modeling complex process parameters, achieving over 0.95 in R^2 value.

Schulze Struchtrup et al. [17] used ANN and SVM methods for quality prediction in injection molding, and R^2 values were generally below 0.90 in their studies. Our GA-LSTM model, on the other hand, showed that it better models complex and nonlinear relationships, providing results up to 0.95 in R^2 value, especially in flexural strength and impact strength predictions.

The ability of the LSTM model presented by Hochreiter and Schmidhuber [35] to process time series data was also verified in this study. However, the GA-LSTM model optimized with genetic algorithms clearly demonstrated the effect of parameter optimization by achieving lower error rates in predictions compared to the pure LSTM.

Comparisons with studies in the literature support that the proposed model offers higher accuracy and consistency for the prediction of mechanical properties, especially in polymer-based injection molding processes, compared to the methods in the literature. When compared with the data obtained from other studies in the literature, it was concluded that the hybrid model used can accurately model the effects of different parameters and has a significant potential for improving product quality.

CONCLUSION

This study investigated the effect of production parameters on product quality in the injection molding of LDPE, HDPE, and PP thermoplastics with particle filler reinforcement. In plastic injection molding production, the part must be easy to separate from the mold, burr formation is prevented, and the part surface must be smooth. All these are also among the factors affecting the mechanical properties of the produced parts. In this study, the optimum production parameters of the parts produced by plastic injection molding were processed with the developed GA-LSTM-based deep learning model, and the forecasted values were studied using the actual values of the mechanical analysis results of both LDPE-HDPE and LDPE-HDPE-PP. Especially in the LSTM learning model used, it was determined that the R^2 value was close to 1, and the MAE value was close to 0. These results indicate that the standard deviation range is decreasing, and the actual and predicted values are close to each other. Therefore, it is supported that these parameters, which are used primarily in producing synthetic particle filler-reinforced LDPE, HDPE, and PP, can also be used in similar productions.

Nowadays, items that directly affect production, such as material and labor costs, especially energy costs, are essential for companies to be sustainable. As a result of the outcomes obtained in this study, energy, labor, and material costs for companies producing with plastic injection molding machines can be reduced, and time losses can be minimized by supporting mass production. Predicting the production parameters that directly affect the product quality, such as temperature, pressure, receiving amount, and cooling time in advance, will allow production to start without trial and error. As a result, material, energy, and time spent on production can be saved. Consequently, the quality of the parts produced and production efficiency will increase positively.

In future work, we aim to expand the use of GA-LSTM in different industrial applications and apply it to more complex data sets. In addition, it is planned to apply it to different areas such as other manufacturing processes, biomedical data analysis and time series prediction, in addition to the mechanical properties of the polymer materials used in this study.

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