GRID 2024
12. INTERNATIONAL SYMPOSIUM ON GRAPHIC ENGINEERING AND DESIGN
14-16. NOVEMBER 2024

12th GRID SYMPOSIUM

Bookbinding Operational Planning and Scheduling Optimization with Deep Learning Algorithms

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Introduction

In modern book production, optimizing softcover binding processes is crucial for increasing efficiency and reducing costs. The growing demand for flexibility, smaller batch sizes, and adaptability to dynamic market conditions requires advanced technological solutions like artificial neural networks (ANN) for resource management and process optimization. This study analyzes four different production scenarios in bookbinding, evaluating their efficiency and exploring how ANN models can enhance production by predicting bottlenecks and suggesting optimal machine layouts and resource utilization.

Modelling Framework

Input data for the model

To successfully optimize the softcover binding process, the ANN model uses the following key input parameters that define the capacity and operating cycle of each machine:

- N_s - number of sheets per book
- T_{cu} - time for cutting the sheets per unit (in sec)
- t_s - time for folding the sheets per unit (in sec)
- t_{co} - time for collating (in sec)
- t_b - time for binding (in sec)
- t_t - time for trimming (in sec)
- R - labour force (number of employees)
- P - number of units to be produced (in pieces)

These parameters are crucial for optimization, and the ANN uses their combination to make predictions about optimal production configurations.

Output data

The aim of the model is to predict the following output parameters:

- T_{opt} - optimal cycle time for each machine
- S_{opt} - optimal machine configuration
- W_{opt} - optimal work configuration for each segment of production
- Q_{opt} - maximum number of units produced within a given time frame

The optimized production cycle can be expressed as follows:

$$T_{total} = P \cdot (t_{co} + t_s + t_{cu} + t_b + t_t)$$

Where is:

- T_{total} - total time required for production
- P - number of units produced

Activation Functions

The ReLU (Rectified Linear Unit) activation function:

$$f(x) = \max(0, x)$$

Learning Algorithm

The ANN uses the backpropagation algorithm to learn from data:

$$E = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where is:

- y_i - the actual output value
- $\hat{y}_i$ - predicted output value
- n - the number of data samples

The error or loss function to be optimized can also be written as follows:

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

The mathematical model of the neural network is based on the approximation of a function that maps the input values X to the target values y and can be expressed as follows:

$$y = f(W_2 \cdot f(W_1 \cdot X + b_1) + b_2)$$

Where is:

- X - input data (N_A, t_s, t_c, t_b, t_t, R, P)
- W_1, W_2 - weighting factors between the layers
- b_1, b_2 - biases
- f - activation function (ReLU)
- y - model output (predicted value for optimization)
- n - number of data samples

Based on the ANN predictions, the optimization of bookbinding production can be expressed by an optimization function that minimizes the total production time T_{total}, which can be expressed mathematically as follows:

$$MinT_{total} = P \cdot \left(\sum_{i=1}^{n} t_i \cdot x_i\right)$$

Where is:

- t_i - time for each machine i
- x_i - number of units processed by machine i
- P - number of units produced

Using this mathematical model and ANN optimization, a simulation of four scenarios is performed:

- **Scenario A (SS_A):** a multi-stage plant with material transportation problems between machines, resulting in longer cycle times.
- **Scenario B (SS_B):** A single-level plant with a flexible arrangement of machines and labor in which cycle speed is improved.
- **Scenario C (SS_C)**: A seamless binding line where machine integration is most efficient and allows for shorter production cycles.
- **Scenario D (SS_D)**: A standard line with a typical layout, but with optimized planning and manpower distribution.

Optimization Code

Generating Simulated Data

The original data for four case studies is provided, including input parameters such as the number of sheets, cutting, folding, gathering, binding and trimming times, as well as the number of employees and order sizes. To enhance the data set for training the model, synthetic data is generated using a script that generates random values for these input parameters related to the bookbinding process.

Data Preparation and Splitting

The data is scaled and split into a training data set and a test data set so that the model can learn from part of the data and be tested on unseen data. The data is scaled to ensure that all input parameters are on the same scale and then split into training (75%) and test (25%) data to evaluate the performance of the model.

Building the Artificial Neural Network (ANN)

An artificial neural network (ANN) is created and trained to predict time based on input parameters. TensorFlow is used to define, compile and create a multi-layer neural network model. The model is then trained on the simulated data to improve its prediction accuracy.

The model consists of an input layer and several hidden layers with 256, 128 and 64 neurons. The ReLU activation function is used for all layers except the output layer. The Adam optimizer and the Mean Squared Error (MSE) loss function are used to train the network. The model is trained for 300 epochs with the training data.

Model Evaluation

The calculated Mean Squared Error (MSE) after successful training of the artificial neural network (ANN) is 25.86, indicating that there is a significant difference between the actual and predicted values, indicating the need for further optimization to improve prediction accuracy.

The model's accuracy is illustrated by comparing actual and predicted values in a graph (Figure 1), allowing quick assessment and identification of any discrepancies.

Simulation of various input values shows how changes affect production time, highlighting key factors influencing efficiency. The SciPy library's minimize function is used to optimize parameters, reducing predicted time and enhancing production efficiency.

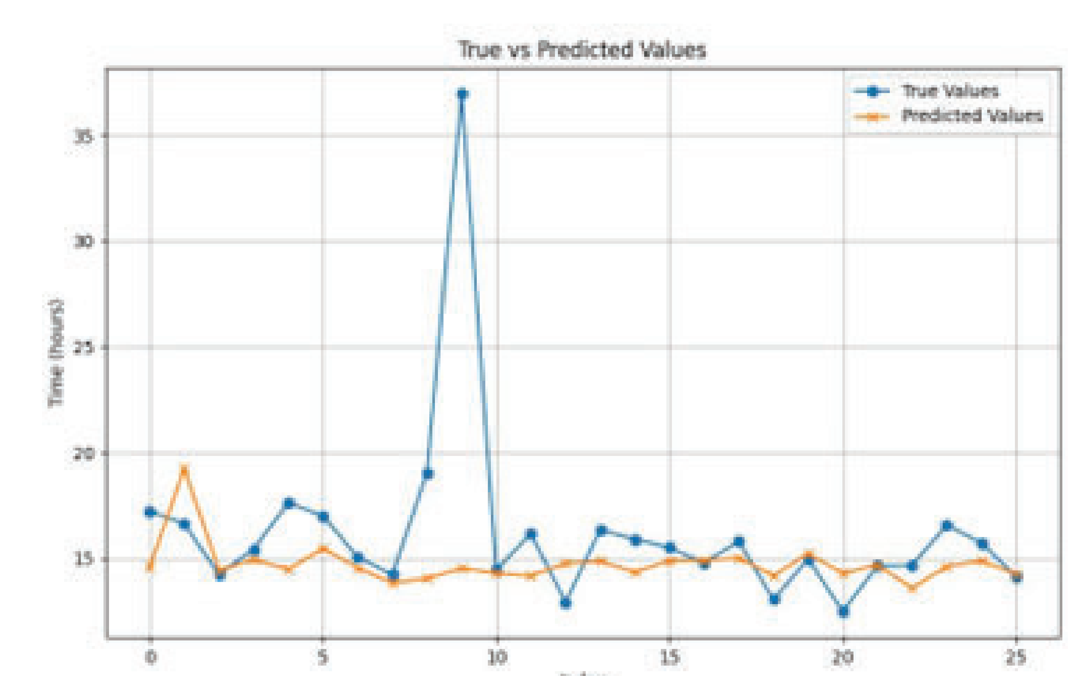

Figure 1

Comparison of true and predicted values

The analysis compares predicted and actual production times for four production lines (SS_A, SS_B, SS_C, and SS_D), showing high accuracy for standardized lines (SS_B, SS_C, SS_D) and larger deviations for complex lines like SS_A due to factors like transportation delays. Adjusting hyperparameters and collecting additional data could improve model accuracy, especially for complex processes. These insights support production optimization, highlighting the need for continuous model refinement to adapt to specific operational challenges and maximize efficiency in various production contexts.

Conclusion

The use of artificial neural networks (ANN) improves production efficiency, reduces costs, and enhances flexibility. Despite initial high Mean Squared Error (MSE) indicating the need for a larger dataset and hyperparameter tuning, the model shows potential for real-time optimization and adaptation to specific production needs. Future developments could incorporate advanced models like RNN or LSTM and optimization techniques to further enhance performance in the bookbinding industry.