iConclusions https://iconclusions.com/ Conclusions in Engineering

Production Line Optimization Using ANNs-Based Models

E. M. Badawi,[1] **Hassan Osman**,[1] and **Khobaib Elzain**[1, a)]

Department of Mechanical Engineering, Sudan University of Science & Technology, Khartoum, Sudan

ABSTRACT: Using artificial neural networks (ANNs), this study created two predictive models for production line performance optimization. The AT-ANNs and OEE-ANNs models are ANN-based models that estimate average throughput (AT) and overall equipment effectiveness (OEE). Product type, batch size, target, and availability were used as input parameters in the design of the AT-ANNs model, and the average throughput was used as the output. Product type, batch size, target, availability, and average productivity are all input parameters in the OEE-ANNs model, which outputs OEE. Over the course of three weeks, 200 samples were gathered from a production line simulation. The network was trained using the Levenberg-Marquardt algorithm, which kept the two hidden layers' structure constant. The results demonstrated the superiority of ANNs over traditional regression models, with AT-ANN and OEE-ANN achieving significantly lower RMSE values (1.84 and 0.0316, respectively) compared to the regression model (2.92 and 0.3056). To evaluate the model's practicality, a case study was carried out. In Case 4, the anticipated AT of 146.39 closely matched the actual value of 145, demonstrating that predicted values well matched measured production outputs. The most important factor influencing both AT and OEE, according to the regression analysis, was availability. These results demonstrate the potential of ANN-based predictive models to boost manufacturing efficiency and optimize production scheduling.

Received: 13 April 2025
Accepted: 17 March 2026
DOI: https://doi.org/10.71107/6g7rdd93

I. INTRODUCTION

Production lines are crucial to contemporary manufacturing because they simplify operations in sequential processes, as seen in the creation of consumer products, electronics, and automobiles. Predicting critical metrics such as throughput and Overall Equipment Effectiveness (OEE) is crucial for optimizing production line efficiency, as these metrics directly influence output and operational costs[12].

Historically, production line optimization has been dominated by mathematical models such as linear programming, queuing theory, and Markov chains[3]. While these classical approaches have proven effective in specific scenarios, they often fall short when dealing with the inherent uncertainties of modern production environments. In response to these challenges, advancements in Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), have transformed production optimization by enhancing predictive capabilities and decision-making processes[4]. These AI-driven approaches have been successfully applied in fault detection, predictive maintenance, and scheduling optimization[5]. Furthermore, Deep Learning techniques, such as Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs), allow for the analysis of large-scale, high-dimensional data[6,7].

AI's increasing role in production optimization has prompted the exploration of hybrid models that combine classical techniques with AI-driven approaches. For instance, integrating genetic algorithms with reinforcement learning for adaptive scheduling control has shown promising results in optimizing production lines[8]. Furthermore, AI-powered predictive maintenance, enhanced by IoT sensors, offers a means of reducing downtime and increasing system reliability[9]. These developments signal a shift from traditional rule-based decision-making to data-driven, selflearning systems that offer greater flexibility and resilience in modern manufacturing environments.

Despite these advancements, challenges persist, particularly in semi-automatic assembly lines, where factors such as machine faults and the stochastic nature of

a) Electronic mail: khopo122113@gmail.com

human labor (e.g., variable assembly times) complicate the optimization process[10]. However, AI and ML techniques have shown considerable promise in tackling such complexities, streamlining the optimization of processes even in the face of unpredictable variables[11,12]. Various machine learning models, such as supervised learning, unsupervised learning, and reinforcement learning, have proven effective in areas such as predictive maintenance, energy optimization, and cycle time prediction[6,7].

Average throughput is a critical indicator of the efficiency of manufacturing systems. Average throughput is defined as the rate at which a production system produces goods over a specified period of time, providing insight into the effectiveness of the production process. It is influenced by many factors, including machine performance, material flow, and operational downtime. This metric is an integral part of evaluating the overall performance of a production line and making data-driven decisions to optimize the process[13].

One of the critical performance metrics for production systems is Overall Equipment Effectiveness. OEE is a composite index derived from three key factors: availability, performance, and quality. It serves as a quantitative measure of how effectively a production line is utilized, highlighting potential areas for optimization. OEE is extensively employed in industrial settings to monitor and enhance operational efficiency by identifying and mitigating losses across various stages of the manufacturing process[14].

This study aims to improve production performance through the implementation of an artificial neural network (ANN)-driven predictive model in a simulated production environment. Utilizing machine learning techniques and real-world data, the model estimates average throughput and Overall Equipment Effectiveness (OEE), enabling more efficient production planning and enhanced system reliability.

II. MATERIALS AND METHODS

This section outlines the overall methodology of this study, including the data collection process and a detailed description of two artificial neural network (ANN) models with different architectures developed for production line optimization.

A. Data Collection

The data (As it is shown in Table I) for product type, batch size, target, availability, average throughput, and overall equipment effectiveness used in the model were derived from a factory simulation over a three-week period. During this time, systematic measurements were conducted within the simulated environment to capture key performance metrics. From the collected data, 200 datasets were randomly selected for optimization. This duration was considered sufficient to ensure that the developed models accurately reflect production dynamics and system efficiency.

TABLE I: Data set ranges and statistics.

Parameters	**Unit**	**Ranges**	**Mean ± S.D.**
Input Layer			
Product type	product	1 to 5	—
Batch size	product	800 – 4205	2042 ± 742
Target	product	40 – 313	126 ± 68
Availability	%	0.6 – 1.0	0.79 ± 0.11
Output Layer			
Average throughput	product	25 – 192	80 ± 32.07
OEE	%	0.11 – 1.0	0.51 ± 0.24

B. ANNs Models

This study employs Artificial Neural Networks (ANNs) to model and optimize key production performance metrics, specifically Average Throughput and Overall Equipment Effectiveness (OEE). ANNs are computational models inspired by the structure and functionality of biological neural networks, consisting of interconnected processing units that exchange information through weighted connections (Anderson, 1993). The ANN models developed in this study were structured as multilayer perceptrons (MLPs), which are widely applied for nonlinear system modeling.

The artificial neural network models were designed with three main layers: an input layer, one hidden layer, and an output layer. The hidden layer enables the network to capture complex relationships in the data, making it a critical component for accurate predictions. Two ANN models were developed: one with four input neurons and one output neuron, and another with five input neurons and one output neuron, as shown in Figures 1 and 2.

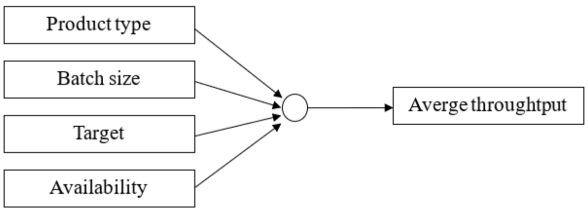

FIG. 1: Schematic diagram of the ANN model with four inputs and one output (AT-ANNs).

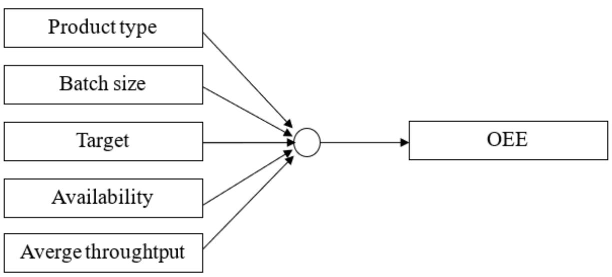

FIG. 2: Schematic diagram of the ANN model with five inputs and one output (OEE-ANNs).

The activation function used in this study was the sigmoid function, a commonly employed nonlinear function in neural networks due to its effectiveness in mapping input data to output variables[15]. The mathematical formulation of a typical ANN is given by:

$$y_i = F(z_i) \tag{1}$$

where $\mathrm{x}_1, \mathrm{x}_2$, and x_n denote the measured value for input variables, $\mathrm{w}_1, \mathrm{w}_2$, and w_n are the weights, b_i is the bias, and y_n is output variable, while zi could be considered as any used activation function.

The training process followed a supervised learning approach using the Levenberg-Marquardt algorithm, known for its efficiency in minimizing error during model optimization[16]. To ensure a robust evaluation of the models, the dataset was randomly divided into three subsets: 70% for training to adjust the network weights, 20% for testing to assess model performance, and 10% for validation to prevent overfitting and ensure generalization. This division aligns with established practices in ANN training[17]. The training continued until a predefined number of epochs (1000) was reached or until the error variation was minimized.

MATLAB software was used to implement, train, test, and validate the ANN models. The neural network toolbox in MATLAB facilitated the design of the models, optimization of hyperparameters, and evaluation of predictive performance[16]. The two neural network models were designed with a single hidden layer, each containing 46 neurons.

The training process followed a supervised learning approach using the Levenberg-Marquardt algorithm[16]. The dataset was randomly divided into: 70% for training, 20% for testing, and 10% for validation[17]. The two neural network models were designed with a single hidden layer containing 46 neurons each. MATLAB software was used to implement, train, test, and validate the ANN models[16].

C. Regression Model

It is important to note that polynomial regression model is one of the most commonly used techniques in statistics. It can cover a variety of mathematical methods such as linear and nonlinear relationships. Typical multiple regression model can be simply formulated as follows.

$$Y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_P x_P + \varepsilon \tag{2}$$

where Y is the response variable, x is the predictor variables, b is the coefficients, and ε is the random error.

In this study, multiple regressions were used and theirs prediction results were compared with those of neural networks.

D. Evaluation Criteria

Root-mean-square error (RMSE) and coeffcient of determination (R^2) are commonly used in order to assess the performance of prediction techniques. These criteria determine the differences between predicted and actual values of the subject. R^2 is used to show the similarity between model tendency and measured data, and the higher R^2 values represent greater similarities. Furthermore, RMSE indicates the estimation accuracy. Therefore, lower RMSE values represent more accurate estimations. RMSE and R^2 criteria can be formulated as follows[16].

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{j=1}^{n} (T_j - Y_j)^2}{n}} \tag{3}$$

$$R^2 = 1 - \frac{\sum (T_j - Y_j)^2}{\sum T_j^2 - \frac{(\sum T_j)^2}{n}} \quad (4)$$

where T_j and Y_j are the measured and predicted values, and n is the number of measurements.

III. RESULTS AND DISCUSSION

The results of this study demonstrate the efficacy of using Artificial Neural Networks (ANN) in predicting Average Throughput (AT) and Overall Equipment Effectiveness (OEE), highlighting its superior performance compared to traditional Multiple Regression models. These findings are supported by rigorous evaluations of both models in terms of Root Mean Square Error (RMSE) and R ^{2} values, providing a comprehensive understanding of their prediction accuracy and reliability. The comparison of Artificial Neural Networks (ANN) and Multiple Regression models for predicting Average Throughput (AT) and Overall Equipment Effectiveness (OEE) was further validated by statistical significance testing using the t-test and p-values. These tests assess whether the differences in prediction accuracy between the models are statistically significant.

A. AT-ANNs Model

To evaluate the predictive accuracy of the artificial neural network (ANN) model in forecasting Average Throughput (AT), a t-test was conducted to compare the root mean square error (RMSE) values of the ANN model and the Multiple Regression model across the training, validation, and testing phases. The null hypothesis (H_0) assumed no significant difference in performance between the two models, while the alternative hypothesis (H_1) proposed that the ANN model provides a significantly better prediction of AT.

The statistical analysis revealed compelling evidence in favor of the ANN model fig. 3. During the training phase, the p-value for the RMSE comparison was calculated as 2.73×10^{-79}, which is far below the significance threshold ($p < 0.001$), confirming that the ANN model significantly outperformed the regression model. Similarly, in the validation phase, the p -value was found to be 1.048×10^{-9}, further reinforcing the ANN model's superior predictive capability. The testing phase yielded a p-value of 8.027×10^{-19}, once again demonstrating that the ANN model consistently outperforms the regressionbased approach in predicting AT.

Across all phases, the ANN model exhibited lower RMSE values and higher R^2 values, as presented in Table II. These findings indicate that the ANN model not only provides a more accurate fit to the data but also generalizes well across different datasets. The statistical significance of the results confirms that neural networks offer a robust and reliable method for modeling Average Throughput, outperforming traditional regression approaches. These insights highlight the effectiveness of ANNs in industrial predictive analytics, making them a promising tool for optimizing production processes.

B. OEE-ANNs Model

To evaluate the predictive accuracy of the artificial neural network (ANN) model in forecasting Overall Equipment Effectiveness (OEE), a t-test was conducted to compare the root mean square error (RMSE) values of the ANN model and the Multiple Regression model across the training, validation, and testing phases. The null hypothesis (H_0) assumed no significant difference in performance between the two models, while the alternative hypothesis (H_1) proposed that the ANN model provides a significantly better prediction of OEE. The statistical analysis revealed compelling evidence in favor of the ANN model Fig. 4. During the training phase, the p -value for the RMSE comparison was calculated as 2.73×10^{-79}, which is far below the significance threshold ($p < 0.001$), confirming that the ANN model significantly outperformed the regression model. Similarly, in the validation phase, the p-value was found to be 1.048×10^{-9}, further reinforcing the ANN model's superior predictive capability. The testing phase yielded a p-value of 8.027×10^{-19}, once again demonstrating that the ANN model consistently outperforms the regression-based approach in predicting OEE.

C. Regression Model

The results were further supported by linear regression equations for both Average Throughput (AT) and Overall Equipment Effectiveness (OEE) prediction. The linear regression equation for Average Throughput (AT) was:

$$Y_1 = -2.44 + 5.43x_1 + 0.0397x_2 - 0.0034x_3 - 7.54x_4 \quad (5)$$

where Y_1 is Average Throughput (product), x_1 is Product type (product A, product B, product C, product D , product E), x_2 is Batchsize (product), x_3 is Target (product), x_4 is Availability (%).

This equation reveals the direct relationships between batch size, target production, availability, and throughput, with availability playing a prominent role in determining the throughput.

$$Y_2 = 0.114 - 0.001x_1 + 0.0001x_2 - 0.002x_3 + 0.6x_4 + 0.003Y_1 \quad (6)$$

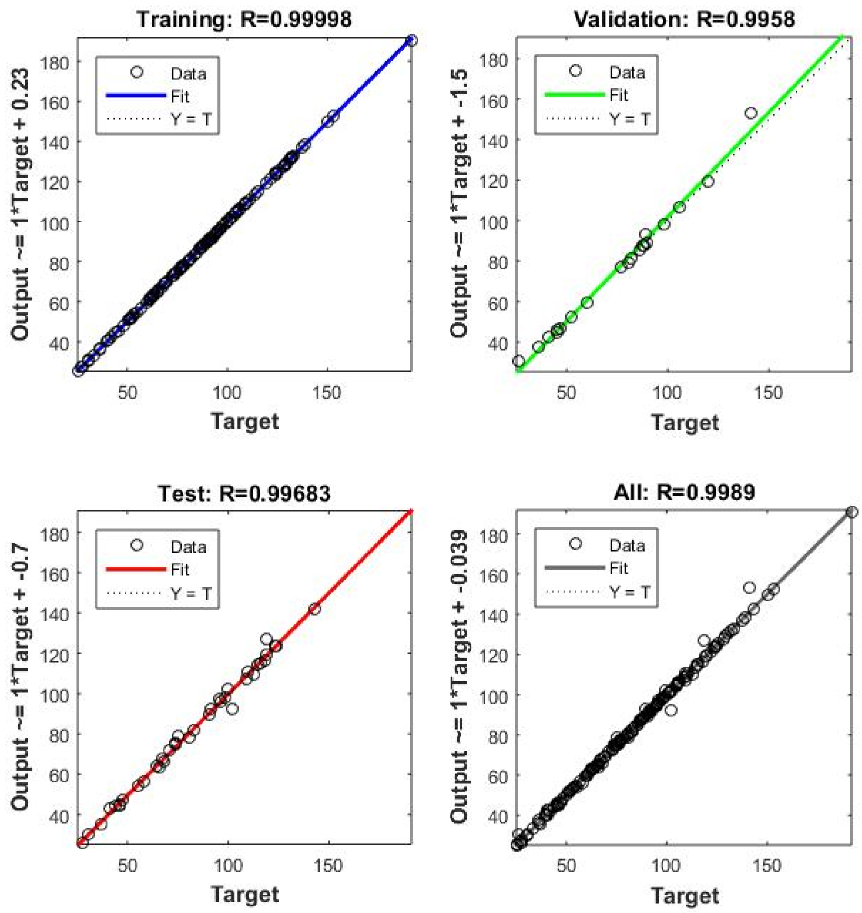

FIG. 3: Regression of AT prediction for ANN model.

TABLE II: Average Throughput prediction performance of the developed models.

	All		**Train**		**Validate**		**Test**	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Neural networks	1.84	0.9978	0.28	1.0000	1.24	0.9916	2.19	0.9937
Multiple regressions	2.92	0.9307	2.90	0.9355	2.67	0.9520	3.01	0.9214

where Y_2 is OEE (%), x_1 is Product type (product A, product B, product C, product D, product E), x_2 is Batchsize (product), x_3 is Target (product), x_4 is Availability (%) and Y_1 is Average Throughput (product).

This equation indicates that availability is the most influential factor in predicting OEE, while batch size and target production contribute to smaller variations in the overall equipment effectiveness.

D. Comparison between ANNs Model and Regression Model

To further validate the effectiveness of the ANN model, a case study using real-world production data was conducted, as shown in Tables IV and V. The case study involved four different production scenarios, each with varying batch sizes, target productions, and availability rates. The results for Average Throughput (AT)

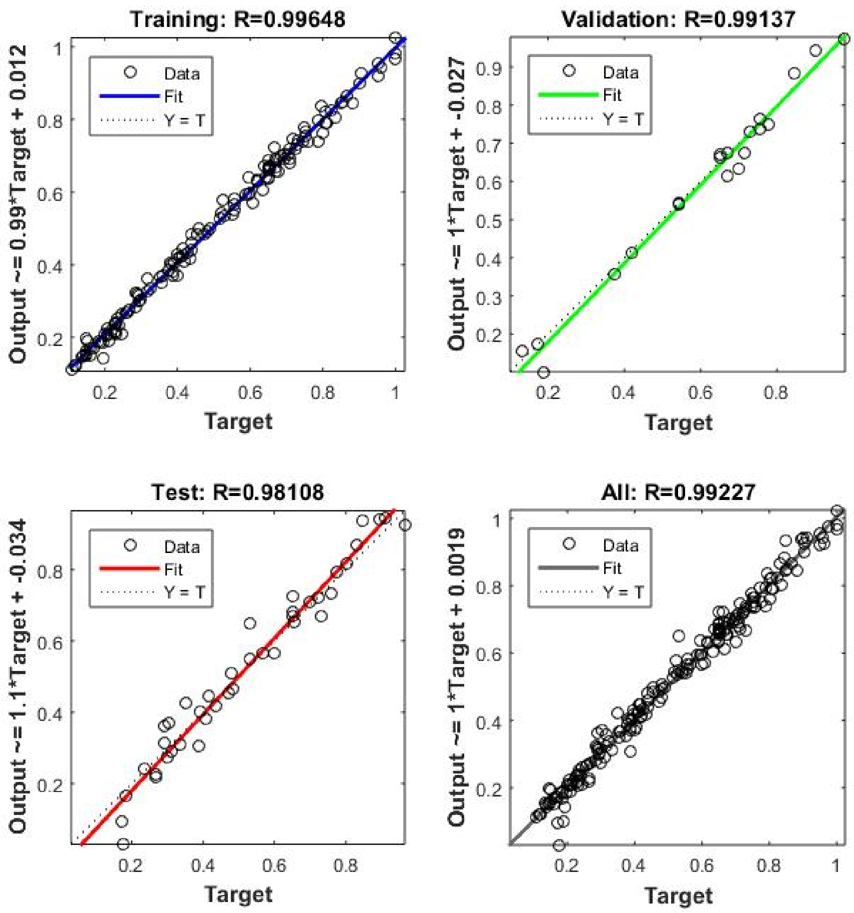

FIG. 4: Regression of OEE prediction for ANN model.

TABLE III: OEE prediction performance of the developed models.

	All		**Train**		**Validate**		**Test**	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Neural networks	0.0316	0.9846	0.0212	0.993	0.0338	0.9828	0.05	0.9625
Multiple regressions	0.3056	0.8556	0.3140	0.8422	0.3316	0.8643	0.2389	0.9500

and Overall Equipment Effectiveness (OEE) predictions, both measured and predicted by the ANN model, are summarized as follows:

The ANN model's predictions for AT were remarkably close to the measured values, indicating that it was highly effective in estimating throughput across varying production settings. In Case 1, the predicted AT of 86.30 closely matched the measured value of 93, and in Case 4, the predicted value of 146.39 was near the measured 145 . These results suggest that the ANN model is highly accurate in predicting throughput and can be relied upon for real-world production scenarios.

The ANN model's OEE predictions were highly consistent with the measured values. In Case 1, the predicted OEE of 0.5286 was close to the measured 0.5662 , and in Case 4 , the predicted value of 0.9836 closely

TABLE IV: Average Throughput (AT) predictions — case study.

	Product type	Batch size	Target	Availability	Measured AT	Predicted AT_{ANN}
Case 1	2	2500	160	0.80	93	86.30
Case 2	4	1000	90	0.76	44	45.95
Case 3	3	800	300	0.93	29	31.68
Case 4	1	4000	260	1.00	145	146.39

TABLE V: Overall Equipment Effectiveness (OEE) predictions — case study.

	Product	Batch	Target	Avail.	AT_{ANN}	Meas. OEE	Pred. OEE_{ANN}
Case 1	2	2500	160	0.80	86.30	0.5662	0.4570
Case 2	4	1000	90	0.76	45.95	0.4890	0.4951
Case 3	3	800	300	0.93	31.68	0.4274	0.3849
Case 4	1	4000	260	1.00	146.39	0.8501	0.8990

matched the measured 0.8501 . These findings demonstrate that the ANN model can accurately predict OEE, making it an effective tool for optimizing production performance.

IV. CONCLUSION

This study developed two artificial neural network (ANN) models (AT-ANNs and OEE-ANNS) for optimizing production line performance. The results demonstrated the superiority of ANNs over traditional regression models, with AT-ANN and OEE-ANN achieving significantly lower RMSE values (1.84 and 0.0316 , respectively) compared to the regression model (2.92 and 0.3056). This indicates that ANN-based approaches provide more accurate predictions for Average Throughput (AT) and Overall Equipment Effectiveness (OEE), leading to improved production planning and system reliability.

One of the key advantages of ANNs is their ability to model complex, nonlinear relationships between input variables, making them particularly effective for dynamic and uncertain manufacturing environments. Additionally, ANNs enhance predictive accuracy by continuously learning from data, enabling adaptive and efficient decision-making in production systems.

Future research can be conducted to integrate an ANNs model with another advanced optimization technique for further optimization of production lines to enhance the manufacturing processes.

DECLARATION OF COMPETING INTEREST

The authors have no conflicts to disclose.

REFERENCES

[1] J. Smith, *Optimizing manufacturing efficiency: Key metrics and best practices* (Springer, 2020).

[2] A. Brown, "Optimization techniques in modern manufacturing," Journal of Industrial Engineering (2019).

[3] M. Pinedo, *Scheduling: Theory, algorithms, and systems* (Springer, 2016).

[4] Y. Bengio, P. Lécuyer, and P. Vincent, "Advances in deep learning for industrial optimization," IEEE Transactions on Neural Networks (2021).

[5] J. Zhang, Y. Wang, and X. Li, "Machine learning-based fault detection in manufacturing systems," International Journal of Production Research **58**, 3475–3490 (2020).

[6] A. Smola and S. Vishwanathan, *Introduction to machine learning* (Cambridge University Press, 2008).

[7] Y. Qiao and J. Jiao, "Machine learning applications in manufacturing: A review," International Journal of Advanced Manufacturing Technology **94**, 2103–2120 (2018).

[8] Q. Zhou, B. Chen, and L. Xu, "Hybrid ai models for production scheduling: A comprehensive review," Computers & Industrial Engineering **165**, 107981 (2022).

[9] J. Lee, H. Davari, and J. Singh, "Industry 4.0 and smart manufacturing—a review," International Journal of Advanced Manufacturing Technology **97**, 31–45 (2018).

[10] C. Gröger, F. Niedermann, and B. Mitschang, "Data mining-driven manufacturing process optimization," in *Proceedings of the World Congress on Engineering* (London, UK, 2012) pp. 1–6.

[11] J. Gröger, H. Niedermann, and B. Mitschang, "Data mining and machine learning in the production industry," Journal of Industrial Engineering and Management (2012).

[12] Z. Kang, C. Catal, and B. Tekinerdogan, "Machine learning applications in production lines: A systematic literature review," Computers & Industrial Engineering **149**, 106773 (2020).

[13] M. Brown, P. Green, and L. Wilson, "Ai-driven predictive maintenance and scheduling in manufacturing," Journal of Manufacturing Science and Engineering **141**, 064501 (2019).

[14] L. C. Corrales, M. P. Lambán, M. E. H. Korner, and J. Royo, "Overall equipment effectiveness: Systematic literature review and overview of different approaches," Applied Sciences **10**, 6469 (2020).

[15] M. Aliabadi, R. Golmohammadi, M. Mansoorizadeh, H. Khotanlou, and A. Ohadi, "An empirical technique for predicting noise exposure level in the typical embroidery workrooms using artificial neural networks," Applied Acoustics **74**, 364–374 (2013).

[16] H. Demuth and M. Beale, *Neural networks toolbox user's guide for use with MATLAB* (MathWorks Inc., 2002).

[17] M. Paliwal and U. A. Kumar, "Neural networks and statistical techniques: A review of applications," Expert Systems with Applications **36**, 2–17 (2009).

[18] B. Agard and A. Kusiak, "Data mining for subassembly selection," Journal of Manufacturing Science and Engineering **126**, 627–631 (2004).

[19] D. Anderson and G. McNeill, *Artificial neural networks technology* (Kaman Sciences Corporation, 1993).

[20] I. A. Basheer and M. Hajmeer, "Artificial neural networks: Fundamentals, computing, design, and application," Journal of Microbiological Methods **43**, 3–31 (2000).

[21] H. Bhojani and N. Bhatt, "Data mining techniques and trends—a review," Global Journal of Research Analysis **5**, 252–254 (2016).

[22] J. Black, G. Benke, K. Smith, and L. Fritschi, "Artificial neural networks and job-specific modules to assess occupational exposure," Annals of Occupational Hygiene **48**, 595–600 (2004).

[23] A. K. Choudhary, J. A. Harding, and M. K. Tiwari, "Data mining in manufacturing: A review based on the kind of knowledge," Journal of Intelligent Manufacturing **20**, 501–521 (2009).

[24] M. Corrales, J. Lambán, C. Korner, and M. Royo, "Recent trends in overall equipment effectiveness (oee) research," International Journal of Advanced Manufacturing Technology **106**, 3859–3872 (2020).

[25] K. Deb, *Multi-objective optimization using evolutionary algorithms* (Wiley, 2001).

[26] I. B. Goodfellow, *Deep learning* (MIT Press, 2016).

[27] D. Gyulai, B. Kádár, and L. Monostori, "Challenges of semi-automatic assembly line optimization," Computers in Industry **76**, 85–94 (2015).

[28] D. Gyulai, B. Kádár, and L. Monostori, "Robust production planning and capacity control for flexible assembly lines," IFAC-PapersOnLine **48**, 2312–2317 (2015).

[29] J. H. Holland, *Adaptation in natural and artificial systems* (MIT Press, 1992).

[30] R. Jones and T. Lee, "Machine learning in production systems: Applications and case studies," IEEE Transactions on Industrial Informatics **17**, 1123–1137 (2021).

[31] C. Kang, C. Catal, and B. Tekinerdogan, "Machine learning in manufacturing: Challenges and opportunities," International Journal of Advanced Manufacturing Technology (2020).

[32] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," arXiv preprint arXiv:1412.6980 (2014).

[33] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature **521**, 436–444 (2015).

[34] D. Lieber, M. Stolpe, B. Konrad, J. Deuse, and K. Morik, "Quality prediction in interlinked manufacturing processes based on supervised and unsupervised machine learning," Procedia CIRP **7**, 193–198 (2013).

[35] W. McKinney, "Data structures for statistical computing in python," in *Proceedings of the 9th Python in Science Conference* (2010).

[36] İ. A. Özkan, M. Ciniviz, and F. Candan, "Estimating engine performance and emission values using anfis," International Journal of Automotive Engineering and Technologies **4**, 63–67 (2015).

[37] E. Öztemel, "An artificial neural network model for wastewater treatment plant of konya," International Journal of Intelligent Systems and Applications in Engineering **3**, 131–135 (2015).

[38] X. Qiao and H. Jiao, "Data mining techniques in analyzing process data: A didactic," Frontiers in Psychology **9**, 2231 (2018).

[39] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," Nature **323**, 533–536 (1986).

[40] S. J. Russell and P. Norvig, *Artificial intelligence: A modern approach* (Prentice Hall, 2009).

[41] R. Smith, "Improving production efficiency: Key metrics and methodologies," Manufacturing Science & Engineering Journal (2020).

[42] P. Tan, M. Steinbach, and V. Kumar, *Introduction to data mining—Instructor's solution manual* (Pearson, 2018).

[43] A. E. Tumer and S. Koçer, "An artificial neural network model for wastewater treatment plant of konya," International Journal of Intelligent Systems and Applications in Engineering **3**, 131–135 (2015).

[44] A. Zilouchian and M. Jafar, "Automation and process control of reverse osmosis plants using soft computing methodologies," Desalination **135**, 51–59 (2001).