Chapter 8

Improving Production with Artificial Neural Networks and Integration into ERP Systems: An Approach within the Scope of Industry 4.0

Gizem Şara Onay[1]

Mehmet Çakmakçı[2]

Abstract

This study aims to digitize production planning by utilizing prediction models based on production data and reducing human intervention to increase efficiency. Production data obtained from a real manufacturing system through the Manufacturing Execution System (MES) interface was analyzed using an artificial neural network (ANN) algorithm, and future production quantities were predicted. By integrating the production forecast results into the Enterprise Resource Planning (ERP) system, it was aimed to automatically direct the production processes. Thus, production decisions can be automatically made by the system based on past data. As a result of the implementation, dynamic and data-driven decision-making processes in production management were facilitated through the forecast outputs integrated into the ERP system. This prediction-based approach is more flexible compared to traditional production planning methods and enables quicker responses from the production system. Consequently, this study presents an innovative approach that contributes to digital transformation within the scope of Industry 4.0 and serves as an example for decision support systems in production management. With this study, the development of predictive systems that operate with real-time data flow is aimed for the future.

1 Dokuz Eylül University, Institute of Science, İzmir / Turkey

2 Dokuz Eylül University, Faculty of Engineering, İzmir / Turkey

https://doi.org/10.58830/ozgur.pub865.c3499

INTRODUCTION

The concept of Industry 4.0 encompasses digitalization, automation, and data-driven decision support infrastructures in production systems. This study enables businesses to utilize their resources more efficiently, adopt a flexible production structure, and respond more quickly to customer expectations. However, many manufacturing facilities still operate with manual data processing procedures and traditional planning methods. This leads to several operational challenges, including excess inventory, material shortages, shipment errors, and production losses.

In this study, the losses caused by the improper planning of SMD (Surface Mount Device) type materials in the production line of a company manufacturing television mainboards were examined. Since material requests are reported to the production site as a total quantity, the need on a reel basis is not fully reflected, and an excessive number of reels are sent to production. This leads to both stock inflation and layout inefficiency on the production line.

To prevent this problem, production data was collected from the past and analyzed using an artificial neural network model; future production quantities were predicted. These predictions were integrated into the ERP system, and stock control and supply planning were automated, thereby eliminating manual errors.

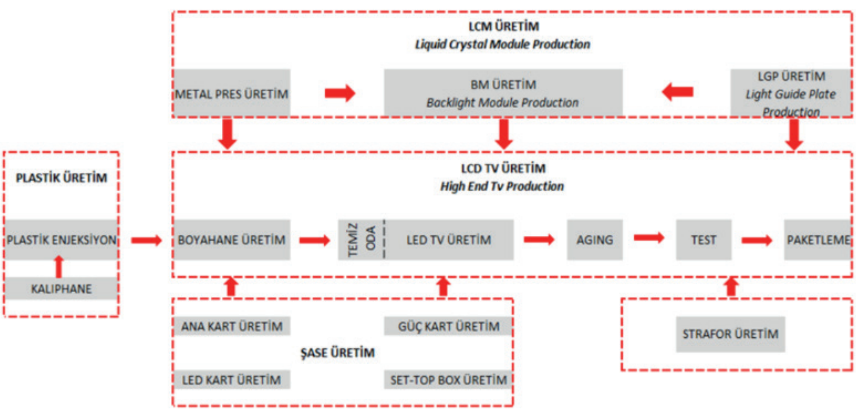

Figure 1. TV mainboard production

MATERIAL AND METHODS

Material

The mainboard production line of an electronics manufacturing facility operating in the Aegean Region was selected as the application area. The SMD materials (resistors, capacitors, etc.) used on this line are supplied in reels and automatically placed by the machines on the production line. Since the required number of reels is manually calculated based on the production quantity, over- or under-supply frequently occurs.

Theoretical Framework

In the past decade, numerous publications have been made on the concepts of Industry 4.0, MES, and ERP. The diversity of methods found in the literature stems from various approaches ranging from forecasting algorithms to system integration.

In the literature review conducted, 32 studies were examined. Some of these studies focused solely on production data forecasting and did not include ERP integration. For example, El Madany et al. (2022) proposed a hybrid time series model for supply forecasting; however, ERP integration was not included. Similarly, the ARIMA-based forecasting model developed by IFS Applications was used for demand prediction but did not support real-time MES integration.

The unique aspect of this study is the combination of ANN-based production forecasting with ERP-MES system integration. While MES systems monitor the production process, ERP systems handle corporate planning. The coordinated operation of these two systems will enhance production efficiency and the quality of decision-making.

Methods

Material tracking problems were analyzed using a fishbone diagram under the categories of material, method, human, and process:

- **Material**: Small-sized components → confusion and loss
- **Method**: Total quantity → excess reels → stock inflation
- **Human**: Inconsistency between the system and the production floor
- **Process**: Too many feeding points → irregular distribution

Consequently, this structure results in unnecessary inventory and production disruptions.

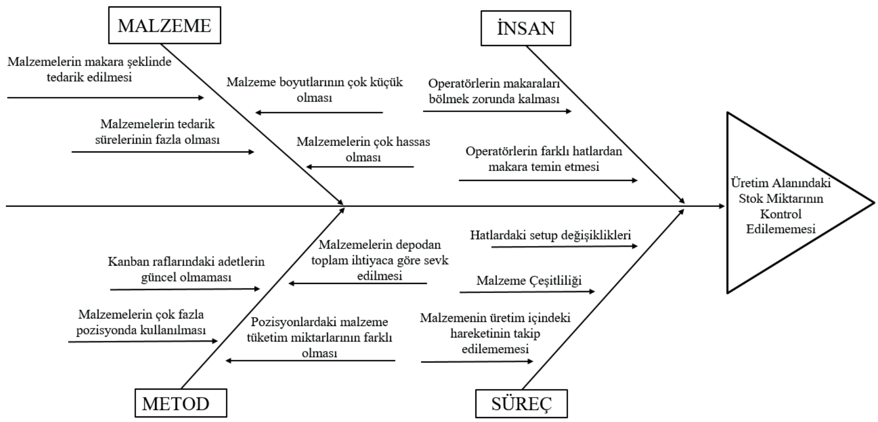

Figure 2. Fishbone Diagram

Data Collection Process

Production data, material usage records, and order information were collected through the factory's Manufacturing Execution System (MES). A Pareto analysis was applied to identify critical materials. According to the analysis, 24 out of 72 materials accounted for 80% of the total inventory. These 24 materials were selected as critical input data for the model.

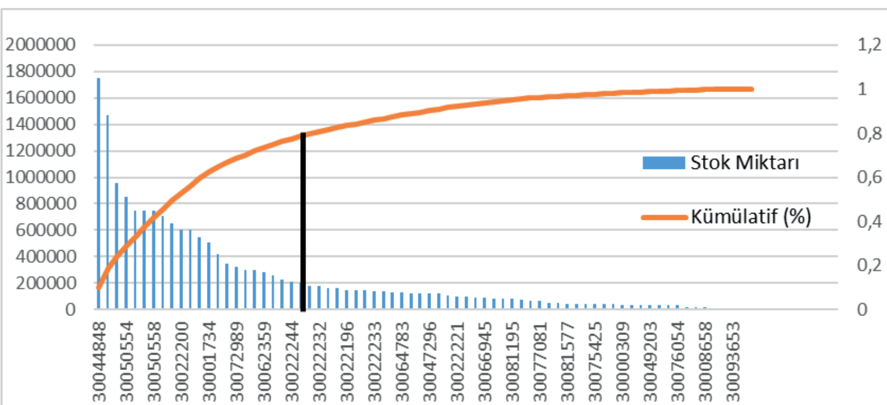

Figure 3. Distribution of the 24 most used materials according to the Pareto analysis

Artificial Neural Network Model

The modeling process was carried out in the MATLAB environment. A multilayer feedforward artificial neural network model was chosen, and historical production quantities were used as input variables. The output was the predicted production quantity for the next 10 days. 70% of the data was used for training and 30% for testing. The performance of the model was evaluated based on MSE (Mean Squared Error) and R^2 criteria.

ERP Integration

The forecasting results were transferred to the ERP system, which was developed on a PostgreSQL basis, via a REST API. The production, inventory, and order modules within the ERP system read this data to provide real-time suggestions to managers. The system provides the purchasing team with future production forecasts based on historical data.

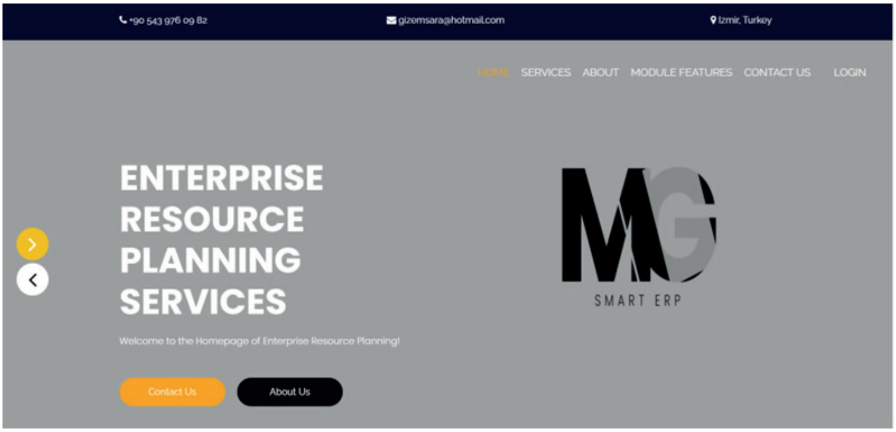

Figure 4. ERP Login Screen

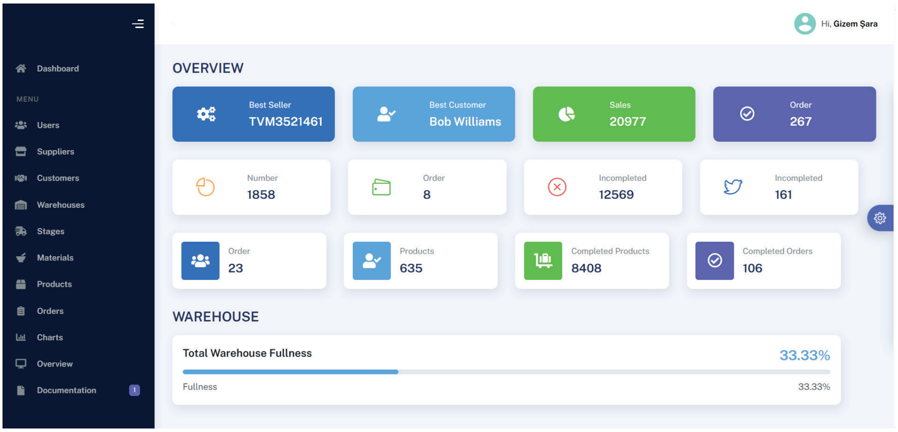

Figure 5. ERP Screen

RESULTS

This study aimed to address the problems encountered in the most critical areas of production processes such as production planning and inventory management through artificial intelligence and digital system integration. The artificial neural network model developed based on field observations and system data made highly accurate production forecasts using historical production data; these forecasts were integrated with the PostgreSQL-based ERP system, contributing to the digitalization of decision support processes.

As a result of the analyses, it was found that a large portion of production inventory consisted of a small number of critical materials, and it was understood that planning processes should be optimized around these materials. In this context, Pareto analysis and fishbone diagrams were effective both in identifying the problem and in generating solution strategies.

A high correlation coefficient was obtained for the artificial neural network model. This indicates that the model has a strong forecasting capacity and can make reliable predictions regarding production quantities. Through integration with the ERP system, these predictions were systematically transferred to the production, procurement, and inventory modules; thus, manual planning errors, time losses, and waste were significantly reduced.

Moreover, the developed system's ability to provide real-time data flow between ERP and MES not only enhances planning but also improves operational efficiency. This situation can provide transparency in the production process and allow decision-makers to intervene quickly in the field. Problems such as material surplus, misdirection, and operator confusion on the production line will be significantly reduced through this system.

This study also demonstrated that:

- Artificial intelligence models integrated into the production process provide not only efficiency but also strategic flexibility.
- The harmonious operation of ERP and MES systems is a cornerstone in the journey of digital transformation.
- With data-driven forecasting, businesses can optimize their resources not only based on the past but also for the future.

As a result, the proposed method of this study is a low-cost, sustainable digitalization example that can be easily applied in small and medium-sized manufacturing enterprises. The method is not merely a forecasting algorithm but also a digital transformation strategy that shapes decision-making processes.

DISCUSSION AND CONCLUSION

The implementation of production forecasting using the artificial neural network model developed in this study, and the integration of the forecast results into the ERP system, provided accuracy, speed, and efficiency in production planning. The high R^2 value of the model represents a significant achievement compared to similar studies. For instance, El Madany et al. (2022) used time series analysis methods for supply chain forecasting but did not integrate model accuracy with ERP systems. From this perspective, the proposed model is innovative not only in terms of forecasting performance but also in system integration.

Studies based on deep learning models, such as those by Bengio (2009), also emphasize that neural networks perform excellently in nonlinear and complex systems. In this study, the dynamic structure of the production system was successfully modeled using an artificial neural network. However, the number of data points and the sampling period used for training the system were limited. This may affect the model's generalization capacity.

The findings supported by Pareto analysis and fishbone diagrams enabled the basic problems on the production floor to be identified within a broader framework. It was understood that the core problems encountered in material planning stem not only from technical issues but also from organizational and procedural deficiencies. In this regard, the socio-technical integration requirement frequently emphasized in literature supports the findings of this study.

In addition, the integration of predictions into the ERP system provided a significant advantage to managers in real-time decision-making processes. As emphasized by Ghadge et al. (2022) in the context of the green supply chain, digitalization positively affects not only production but also sustainability and resource efficiency.

In conclusion, this study offers a practical example of digital transformation through AI-assisted planning and ERP integration, while also contributing original insights to fill existing gaps in literature.

Future Work and Practical Implications

This study demonstrates the applicability of real-time data-driven forecasting systems integrated with ERP and MES in small and medium-sized enterprises (SMEs) in the manufacturing sector. Expanding the model to different production lines or multi-product systems may further optimize resource planning. In addition, a fully integrated MES-ERP infrastructure can be extended to include other functional modules such as supply chain management, maintenance planning, and workforce allocation, thereby evolving into a holistic digital transformation system.

References

Abacı SH, Tahtalı Y, Şekeroğlu A, 2020. Comparison of some different clustering methods in double dendrogram heat maps. 1st International Applied Statistics Conference, 1-4 October 2020, Page: 270, Tokat, Turkey.

Aires, S., et al., "Requirements Elicitation in ERP Implementation Process," 2022.

Alaskari, O., et al. "Framework for Implementation of Enterprise Resource Planning (ERP) Systems in Small and Medium Enterprises (SMEs): A Case Study." 2021.

Arı A. ve Önder, H. (2013). Farklı Veri Yapılarında Kullanılabilecek Regresyon Yöntemler, Anadolu Tarım Bilim. Derg.,28(3):168-174

Aydın, S. E. ve Küçükyaşar, M. (2017). "Bir Elektronik Fabrikasında Malzeme Sipariş Miktarlarının Optimizasyonu ve Kanban Uygulaması" (Lisans Tezi) Dokuz Eylül Üniversitesi.

Bengio, Y. (2009). Learning deep architectures for AI. Foundations and trends® in Machine Learning, 2(1), 1-127.

Bircan, H. (2004). Lojistik Regresyon Analizi: Tıp Verileri Üzerine Bir Uygulama. Kocaeli Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 2004 / 2: 185-208.

Brandes P, Das D, 2006. Locating behaviour cynicism at work: Construct issues and performance implications. Employee Health, Coping and Methodologies. (Editors: Pamela L. Perrewe, Daniel C. Ganster), JAI Press, pp.233-266, New York.

Brecher, C., et al. "Viable System Model for Manufacturing Execution Systems." 2013. MES, Endüstri 4.0.

Can, M.B., Eren, Ç., Koru, M., Özkan, Ö. ve Rzayeva, Z. (2012). "Veri Kümelerinden Bilgi Keşfi: Veri Madenciliği", Başkent Üniversitesi Tıp Fakültesi XIV. Öğrenci Sempozyumu, Ankara.

Coşlu, E. (2013). "Veri madenciliği." Akademik bilişim.

D'Antonio, G., et al. "A Novel Methodology to Integrate Manufacturing Execution Systems with the Lean Manufacturing Approach." 2017.

Deniz, Ö. (2005). Poısson Regresyon Analizi. İstanbul Ticaret Üniversitesi Fen Bilimleri Dergisi Yıl:4 Sayı:7 Bahar 2005/1 S. 59-72.

E. Kabalcı, Esnek Hesaplama Yöntemleri- II: Yapay Sinir Ağları. Jeoloji Mühendisliği ABD, ders notları.

EDUCBA, Pyria Pedamkar (2018). "Introduction To Data Mining" https://www.educba.com/data-mining-techniques-for-business/

Fayyad, U. M. (1996). Piatetsky-Shapiro, G., Smyth, P. and Uthurusamy, R. "Advances in Knowledge Discovery and Data Mining", USA: MIT Press.

Freese, J. ve Long, J. S. (2006). Regression Models for Categorical Dependent Variables Using Stata. College Station: Stata Press.

Ghadge, A., et al., "Link Between Industry 4.0 and Green Supply Chain Management: Evidence from the Automotive Industry," 2022.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT press.

Guliyev, N. J. ve Ismailov, V. E. (2016). A single hidden layer feedforward network with only one neuron in the hidden layer can approximate any univariate function. Ithaca: Cornell University Library, arXiv.org.

Güçle, G. (2010). Veri ambarı ve veri madenciliği teknikleri kullanılarak öğrenci karar destek sistemi oluşturma. Yayınlanmamış yüksek lisans tezi. Denizli, Pamukkale Üniversitesi Fen Bilimleri Enstitüsü.

Hinton, G. (2012). Improving neural networks by preventing co-adaptation of feature detectors. arXiv preprint arXiv:1207.0580.

Holsheimer, M. ve Siebes, A. (1994). "Data Mining: The Search for Knowledge in Databases", CWI Technical Report, Amsterdam, s. 2.

Hung, S., Yen, D. C. ve Wang, H. (2005). "Applying Data Mining to Telecom Churn Management", Expert Systems with Applications, s. 1-10.

Hyndman, R. J. (2004). 'The interaction between trend and seasonality', International Journal of Forecasting, 20(4), 561–563.

Jaskó, M., et al. "Development of Manufacturing Execution Systems in Accordance with Industry 4.0 Requirements: A Review of Standard- and Ontology-Based Methodologies and Tools." 2020.

Acknowledgment

I would like to thank Prof. Dr. Mehmet Çakmakçı for his academic support and guidance throughout the execution and direction of this study. I am also grateful to the officials of the manufacturing company for facilitating field observations and data access.

Conflict of Interest

The authors declare that there is no conflict of interest regarding this study.

Author Contributions

Gizem Şara Onay:

Conceptual framework of the study, data collection, execution of analyses, development of the artificial neural network model, ERP integration, and manuscript writing.

Mehmet Çakmakçı:

Academic supervision, methodological guidance, evaluation of the modeling process, interpretation of results, and revision of the manuscript.