Smart tire manufacturing

AI-driven rubber compound evaluation in the era of Industry 4.0

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In the contemporary digital era, the strategic adoption of advanced technologies to enhance industrial efficiency and product quality has become increasingly critical. Digital transformation provides a robust framework to address multifaceted challenges by enabling the seamless integration of digital solutions across all sectors of industry. Moreover, emerging technologies have significantly reshaped consumer behavior, redefining the pathways through which individuals access information, and influencing their preferences and decision-making processes regarding specific products and services. This evolving landscape underscores the imperative for industries to embrace digital innovation as a means of maintaining competitiveness and meeting dynamic market demands.[1]

The Fourth Industrial Revolution (Industry 4.0) represents the foundation of digital transformation, aiming to convert traditional manufacturing systems into intelligent, interconnected environments. By integrating physical assets into cyber-physical systems, Industry 4.0 enables the creation of smart factories and adaptive manufacturing networks.[2] Disruptive technologies, including advanced sensors, artificial intelligence and IoT platforms, serve as the primary enablers for implementing Industry 4.0 principles, offering significant opportunities to optimize processes, enhance operational efficiency and drive industrial modernization. However, successful adoption necessitates overcoming challenges such as limited data infrastructure and regulatory uncertainties. Overall, digital transformation under Industry 4.0 enhances business integration, competitiveness and customer engagement while improving reliability, reducing human error and increasing overall equipment effectiveness (OEE).

For manufacturing leaders, it is crucial to gain a deep understanding of how operations technologies (OT: encompassing factory control and manufacturing execution systems) and information technologies (IT: integrating enterprise-wide functions) can be strategically optimized through the adoption of disruptive innovations. Technologies such as the Industrial Internet of Things (IIoT), artificial intelligence (AI), augmented and virtual reality (AR/VR) and digital twin platforms offer transformative potential, enabling enhanced process control, real-time decision-making and the creation of intelligent, adaptive manufacturing environments.[3] Mastery of these technologies is essential for driving operational efficiency, improving product quality and maintaining competitive advantage in the rapidly evolving industrial landscape.

Integrating digital and Industry 4.0 solutions

Industry 4.0 has emerged as the leading paradigm of the new industrial revolution, surpassing the traditional concept of industrial automation by integrating cyber-physical systems, data analytics and interconnected smart technologies. Within this context, the tire industry faces the imperative to implement substantial transformations across its production, design and supply chain processes to meet rapidly evolving customer expectations and maintain long-term competitiveness. Key technologies, including the IIoT, AI, machine learning, digital twin platforms and advanced robotics, are enabling tire manufacturers to optimize compound formulation, automate tire building and vulcanization, enhance quality control and streamline logistics operations. By strategically adopting these innovations, leading tire companies are not only improving operational efficiency but also positioning themselves to respond proactively to market dynamics and sustainability requirements in an increasingly technology-driven environment.

A variety of approaches, technologies and methodological frameworks have been demonstrated to enhance product quality while concurrently contributing to environmental sustainability.[4] Within these emerging paradigms, automated manufacturing processes, underpinned by advanced intelligent digital applications, constitute a principal catalyst for innovation. Such integration facilitates the production of superior-quality tires in highly connected and fully automated industrial settings, addressing the dual challenges of escalating product variant complexity and increasingly stringent quality standards.

Building upon disruptive technologies, a comprehensive suite of process-specific solutions has been systematically developed to address each phase of tire manufacturing.[5] This encompasses the formulation and production of rubber compounds and individual components, tire assembly, vulcanization and final finishing, while also extending to the management and recycling of end-of-life tires. Such an integrated approach enables both optimization of product quality and alignment with sustainable lifecycle practices. A further dimension of digital transformation within the tire industry involves the strategic implementation of production-oriented technologies, with a dual focus on interrelated objectives: first, the deployment of advanced methodologies and tools to optimize manufacturing processes across the production chain; and second, the integration of dedicated technologies aimed at promoting sustainable production practices throughout the product lifecycle.

In the tire industry, digital transformation increasingly leverages production-focused technologies, serving as a driver for enhancing manufacturing efficiency across the production chain and advancing sustainable practices throughout the tire lifecycle. This integrated approach not only streamlines process performance but also aligns product development with contemporary environmental and quality standards. Digitalization presents significant opportunities for enhancing the efficiency and responsiveness of the tire manufacturing supply chain. By systematically collecting, integrating and analyzing data related to orders, suppliers and customers, digital technologies enable real-time visibility across the entire supply chain. This comprehensive approach facilitates more precise tracking of orders and deliveries, minimizes delays and optimizes the allocation of resources. As a result, operational costs are reduced, production planning is improved and customer satisfaction is enhanced through faster order fulfillment and increased reliability of delivery schedules. Moreover, the integration of predictive analytics and digital monitoring tools can support proactive decision-making, enabling manufacturers to anticipate disruptions, adapt to demand fluctuations and maintain high standards of service quality.[6] Finally, digitalization can also be used to increase the innovation and efficiency of tire manufacturing. By using digital tools such as analytics, predictive modeling and machine learning, tire manufacturers can gain valuable insights into customer preferences and behavior, and forecast future trends. This knowledge can be used strategically to design and optimize more efficient workflows and manufacturing processes, thereby enabling the production of high-quality tires that effectively align with evolving customer demand.

Leveraging AI for smart manufacturing

Comprehensive global assessments indicate that, among emerging technologies, artificial intelligence demonstrates the highest level of integration within the tire industry. AI-driven applications provide substantial benefits, including predictive maintenance, process optimization, real-time quality assurance and enhanced ability to anticipate evolving customer preferences and market trends.[7] Effective deployment of these technologies necessitates robust digital infrastructure, high-fidelity data acquisition systems and a workforce proficient in AI methodologies and data interpretation. These factors not only elevate operational efficiency and product quality, but also catalyze innovation across the entire tire manufacturing value chain.

In light of these findings, the next section of this paper delves into the specific AI-based frameworks and tools that are currently driving transformative improvements in tire production processes. To this end, the current deployment and impact of artificial intelligence technologies across tire manufacturing processes are systematically analyzed, providing a comprehensive understanding of their capabilities, benefits and transformative potential.

- Rubber compound optimization: AI models analyze vast datasets to predict the optimal combination of materials, enhancing tire performance and durability. During vulcanization, predictive modeling enables accurate control of temperature and pressure profiles, reducing material waste and energy consumption.
- Defect detection: Advanced image recognition techniques, such as convolutional neural networks (CNNs), are used to identify defects in tire surfaces during production, ensuring high quality standards.
- Predictive maintenance: AI-driven predictive analytics forecasts equipment failures, enabling timely maintenance, reducing downtime and enhancing the reliability and efficiency of production machinery, minimizing operational costs.
- Process optimization: AI algorithms analyze production data to identify inefficiencies and recommend adjustments, leading to streamlined operations.

Collectively, these applications contribute to superior tire quality, higher production throughput and adaptive manufacturing capabilities, allowing companies to respond swiftly to evolving market demands while maintaining stringent quality standards.

AI-based assessment of rubber compounds

In the tire manufacturing industry, the evaluation and decision-making process regarding the release of non-conforming compounds into the production line, based on laboratory mixing test results, represents a critical and highly sensitive stage of quality assurance. To achieve this objective, Barez Kurdistan Tire factory has adopted the implementation and advancement of an AI-based model, aimed at minimizing errors, standardizing status determination in comparable cases, and ensuring the rapid and accurate identification of non-conforming compounds. In alignment with global trends toward digital transformation and the integration of Industry 4.0 principles into tire manufacturing, the implementation of this AI-based model extends

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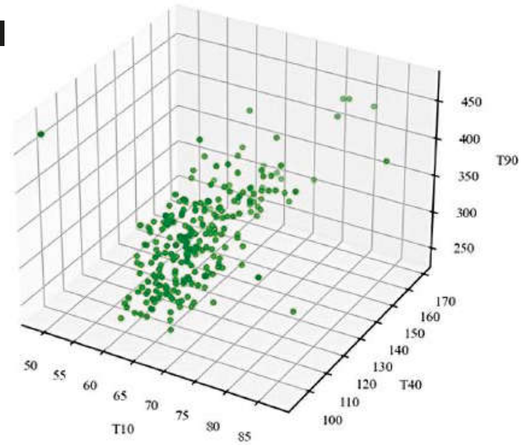
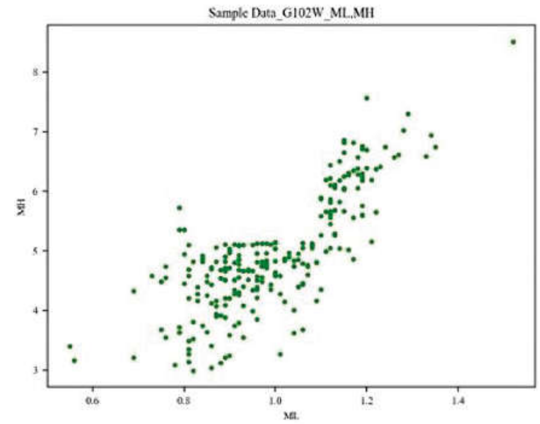
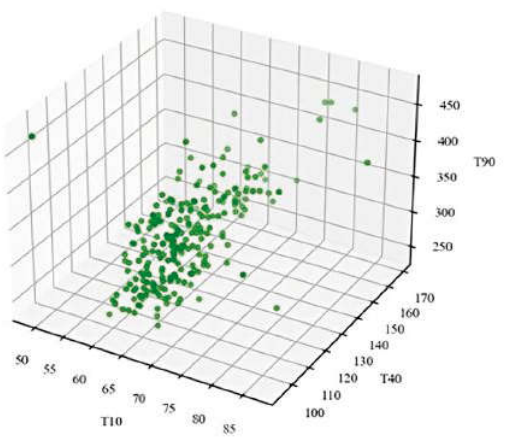


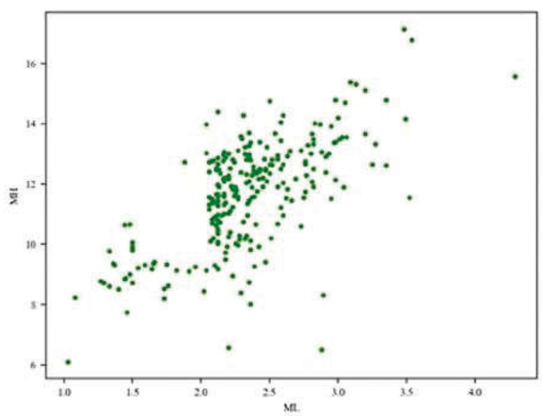
a) Scatter plot of T938 compound measurements by curing time



b) Scatter plot of G102W compound measurements by curing time



c) T938 data distribution by mechanical properties



d) G102W data distribution by mechanical properties

Figure 1: Distribution of G102W and T938 compounds data

beyond the simple classification of compounds into conforming or non-conforming categories. By systematically analyzing physicochemical property data derived from laboratory testing, the model ensures that only compounds meeting the required standards are introduced into the production line, while defective batches are promptly excluded. This functionality not only strengthens quality assurance practices but also reduces production errors, material waste and operational costs.

Furthermore, the integration of AI-driven decision-support systems into the manufacturing process enhances workflow efficiency, supports data-driven process standardization and enables greater responsiveness to market and customer demands. Consequently, such advances position tire manufacturers at the forefront of innovation, reinforcing competitiveness and sustainability in an increasingly digitalized industrial landscape.

Dataset description and AI model development

As an initial step, rheometer datasets obtained at two processing temperatures (180°C and 160°C) were examined, encompassing key parameters such as maximum torque (MH), minimum torque (ML), T10 (scorch time), T40 (intermediate cure time) and T90 (optimum cure time) – as seen in Figure 1. The analysis focused on two representative compounds, T938 and G102W, produced in 2022, for which a total of 36,473 and 9,131 batch measurements at 180°C, as well as 117 and 64 batch measurements at 160°C, respectively, were systematically investigated. Furthermore, experimentally validated status datasets were compiled for compounds T938 and G102W, consisting of 565 and 251 individual records, respectively.

To establish a reliable ground truth for model training and evaluation, the associated rheometer measurements were systematically annotated with binary classification labels, denoting either ‘approved’ or ‘rejected’ status. This structured labeling approach not only facilitated the accurate identification of conformity outcomes but also ensured data consistency, thereby improving the robustness, generalizability and predictive precision of the proposed AI-based classification model.

Model analysis and prediction results

Advanced machine learning methodologies, including artificial neural networks, semi-supervised learning via the label spreading algorithm, and unsupervised learning

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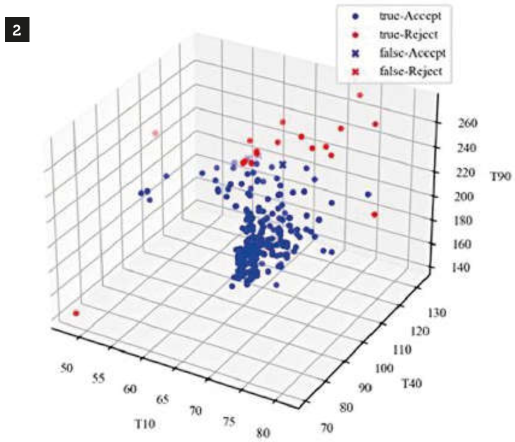
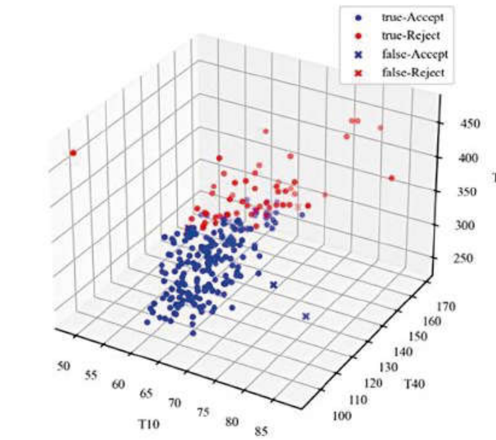
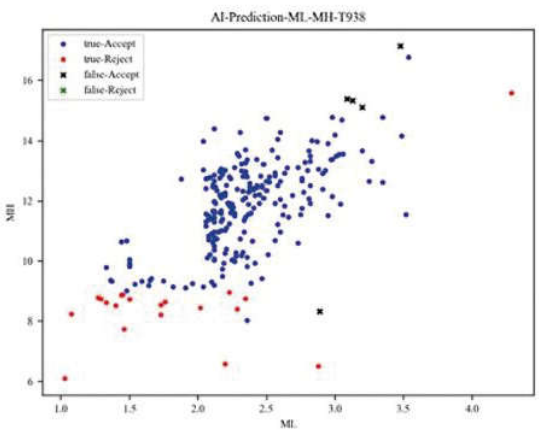


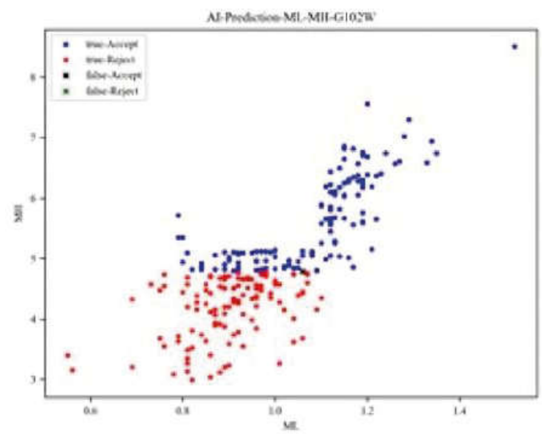
a) AI model predictions for T938 compound



b) AI model predictions for G102W compound



c) AI model predictions for T938 compound



d) AI model predictions for G102W compound

Figure 2: AI-based evaluation of G102W and T938 compounds

techniques, were employed to classify rubber compound datasets. This study primarily focused on rheometric measurements recorded at 180°C for both T938 and G102W compounds. The models were trained on the curated and labeled datasets, with scatter plots and other visualization techniques employed for exploratory data analysis and to assess data distribution patterns.

Model performance was rigorously validated using cross-validation protocols, achieving predictive accuracies exceeding 94% (Figure 2). Furthermore, feature importance analysis and interpretability assessments were conducted to elucidate the influence of specific rheometric parameters on conformity outcomes, thereby providing not only robust predictive capability but also actionable insights for process optimization in tire manufacturing.

The model outcomes revealed that T10 and T90 possessed the highest discriminatory power for differentiating between approved and rejected compound batches. Analysis of the predictive patterns demonstrated that lower T90 values were predominantly associated with accepted compounds, indicating optimal curing characteristics, whereas higher T90 values were mainly linked to rejected batches, reflecting suboptimal cure behavior. Similarly, variations in T10 contributed to early-stage differentiation, providing additional resolution in identifying borderline cases. These findings underscore the critical role of rheometric parameters in accurately predicting compound conformity, highlighting their potential as key indicators for real-time quality control and process optimization in tire manufacturing. Analysis of the ML and MH parameters revealed a positive correlation between these rheometric characteristics and their influence on curing outcomes. The predictive model accurately classified the majority of samples, with misclassifications primarily observed in the transitional regions between accepted and rejected batches, corresponding

Table 1: Accuracy of the AI model considering different parameters

Compound	Curing time	Mechanical properties	All parameters
T938	98.8%	96.66%	96.66%
G102W	97.2%	99.6%	94%

to curing conditions near the approval/rejection thresholds. This observation highlights the model's sensitivity to borderline cases and underscores the critical importance of these parameters in determining compound conformity.

Finally, parameters – including T10, T40, T90, ML and MH – were concurrently used as input features for model training, allowing the algorithm to capture potential interactions and combined effects among the rheometric variables. This integrative approach enhanced the model's discriminatory capability, improving classification accuracy across borderline cases. The results of this comprehensive training procedure are summarized in Table 1, highlighting the importance of multiparameter consideration for robust and reliable prediction of compound conformity.

For the rheometric measurements conducted at 160°C for both T938 and G102W compounds, the decision tree algorithm was employed due to the limited volume of available data (Figure 3). In this framework, three key features – T10, T90 and MH – were selected as input variables for the T938 compound, whereas two features – T90 and MH – were used for the G102W compound. This feature selection strategy was implemented to optimize model efficiency while preserving high classification accuracy.

The described model predicts the acceptance or rejection of samples based on rheometric data and three primary parameters: MH, T90 and T10. Among these, MH serves as the most critical indicator, with all samples exhibiting MH ≤11.01 automatically classified as rejected. For samples with higher MH values, T90 functions as the secondary criterion, whereby values exceeding 628.65 result in rejection. Within the lower T90 range, T10 contributes to rejection in only a single exceptional instance, while all remaining samples are accepted. Evaluation of the Gini index at each decision node, which quantifies classification purity, reveals consistently low values at the terminal nodes, indicating a high level of confidence in the model's predictions. **tire**

References

1) *Elyashiv T, Technology life cycles, waves, and Darwinism. In Investing in revolutions: Creating wealth from transformational technology waves (pp. 121-142). Berkeley: Apress, 2025*
2) *Queiroz M M, Fosso Wamba S, Chiappetta Jabbour C J, Lopes de Sousa Jabbour A B and Machado M C, Adoption of Industry 4.0 technologies by organizations: A maturity levels perspective. Annals of Operations Research, 348(3), pp. 1989-2015, 2025*
3) *Rotolo D, Hicks D and Martin B R, What is an emerging technology? Research policy, 44(10), pp. 1827-1843, 2015*
4) *Shahdadi A, Digital transformation in the tire industry, Tire Technology International Annual Review 2024*
5) *Borcan I, Particularities of digitalization in the tire industry. Annals of the University of Craiova, Economic Sciences, 1(48), 2020*
6) *Temel A and Ayaz M, Digital transformation design of the Banbury mixing unit in tire manufacturing. In the 2019 International Conference on Applied Automation and Industrial Diagnostics (ICAAID) (Vol. 1, pp. 1-6). IEEE, September, 2019*
7) *Zakrajsek A J and Mall S, The development and use of a digital twin model for tire touchdown health monitoring. In 58th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference (p. 0863), 2017*

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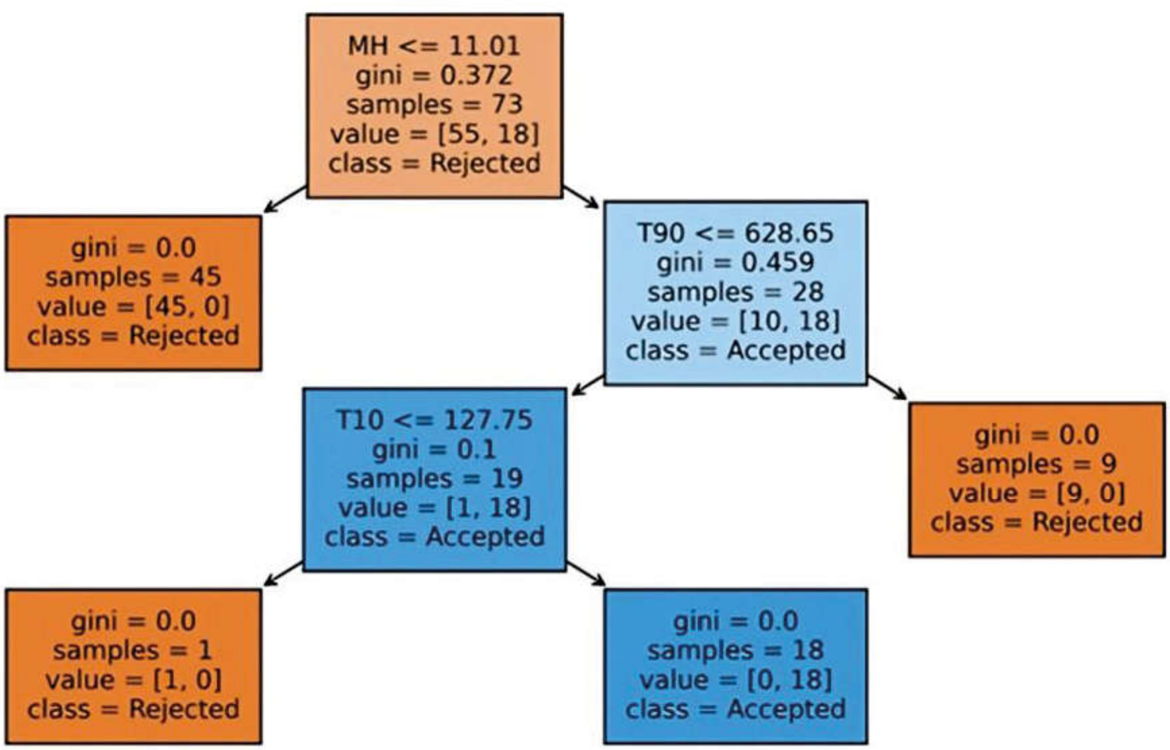

Figure 3: Decision tree for the G102W compound