International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Integrating Artificial Intelligence in Polymer Extrusion: Trends, Challenges, and Future Directions

Sri Charan Yarlagadda

Submitted :11/05/2024 **Revised:** 23/06/2024 **Accepted:** 03/07/2024

Abstract: Polymer extrusion, a fundamental method in plastics production, is seeing great benefits from the adoption of AI technologies. This review looks at current trends and challenges, as well as where we might be headed in the future, with the use of AI to improve polymer extrusion processes. Techniques driven by AI such as machine learning, deep learning, and even reinforcement learning bring many clear advantages when it comes to dealing with complex process parameters. They offer a way to handle the nonlinearity and high dimensionality that are intrinsic to many aspects of extrusion. In addition, these same techniques allow for fault detection and process monitoring in "smart" extrusion systems. One significant advantage of using AI is its predictive capability. For example, neural networks can be trained to act as predictive models for how an extrusion process will behave given certain input conditions (e.g., material properties, temperatures, pressures). These models can replace or supplement the highly simplified mathematical models that have traditionally been used to describe extrusion processes. Nonetheless, the application of AI in polymer extrusion encounters hurdles like insufficient data, a lack of domain specific expertise, and the requirement for clear models. This review examines how these challenges can be overcome to use AI for advancing sustainable practices in polymer extrusion. Overall, this article fills a few gaps in the current research and provides a thorough understanding of how AI is beginning to "revolutionize" polymer extrusion.

Keywords; *revolutionize, AI, practices, requirement, encounters*

1. Introduction

Polymer extrusion is fundamental to contemporary manufacturing, enabling the production of a vast range of plastic products essential for various critical industries. It is especially vital in sectors such as food packaging, where polymers are crucial for extending shelf life and ensuring safety (Tajeddin et al., 2020); healthcare, where they are used in medical devices and drug delivery systems (Maitz, 2015); automotive, where advanced polymers enhance vehicle performance and fuel efficiency (Zhang et al., 2022); and aerospace, where they are essential for lightweight and high-performance materials (Parveez et al., 2022)—areas that significantly impact human well-being.

In agriculture, extrusion technology is used to create strong yet flexible films for greenhouse covers and crop protection, helping to shield plants from harsh weather and pests (Sikder et al., 2021). These films also serve as row covers in organic farming, deterring insects while allowing sunlight to nourish the plants. In the construction industry, extruded plastics are essential for producing pipes, window frames, and insulation materials, all of which enhance building energy efficiency and sustainability (Shen et al., 2020). Polymer extrusion is a versatile technique that is vital not only for industrial applications but also for the creation of everyday consumer goods, such as films, bottles, and various household items (Namazi, 2017).

Since the 1950s, plastic production has surged, with estimates forecasting that between 2016 and 2030 alone, an annual output of 260 to 460 million metric tons of plastic waste will be generated (Borrelle et al., 2020). Further projections suggest that by midcentury, cumulative global plastic production will have surpassed half a billion metric tons—more than 33 times the amount produced in the entire decade of the 1960s (Sardon et al., 2018). Figure 1 presents data on total global plastic production from 2018 to 2021, alongside more detailed breakdowns of the output of certain types of plastics and figures for overall plastic

PhD, Chemical & Biomolecular Engineering,
Georgia Institute of Technology,
St Louis, Missouri,
ysricharanacads@gmail.com

usage across different applications in 2021 (Malik et al., 2024).

Although emerging materials are being developed as alternatives to traditional polymers, it is unlikely that they will entirely replace plastics. The polymer extrusion process offers unmatched advantages in producing items at scale with consistent quality and cost-effectiveness. As there is an increasing emphasis on sustainability, extrusion technology offers the potential to incorporate recycled materials into production processes, thus supporting circular economy goals (Kassab et al., 2023).

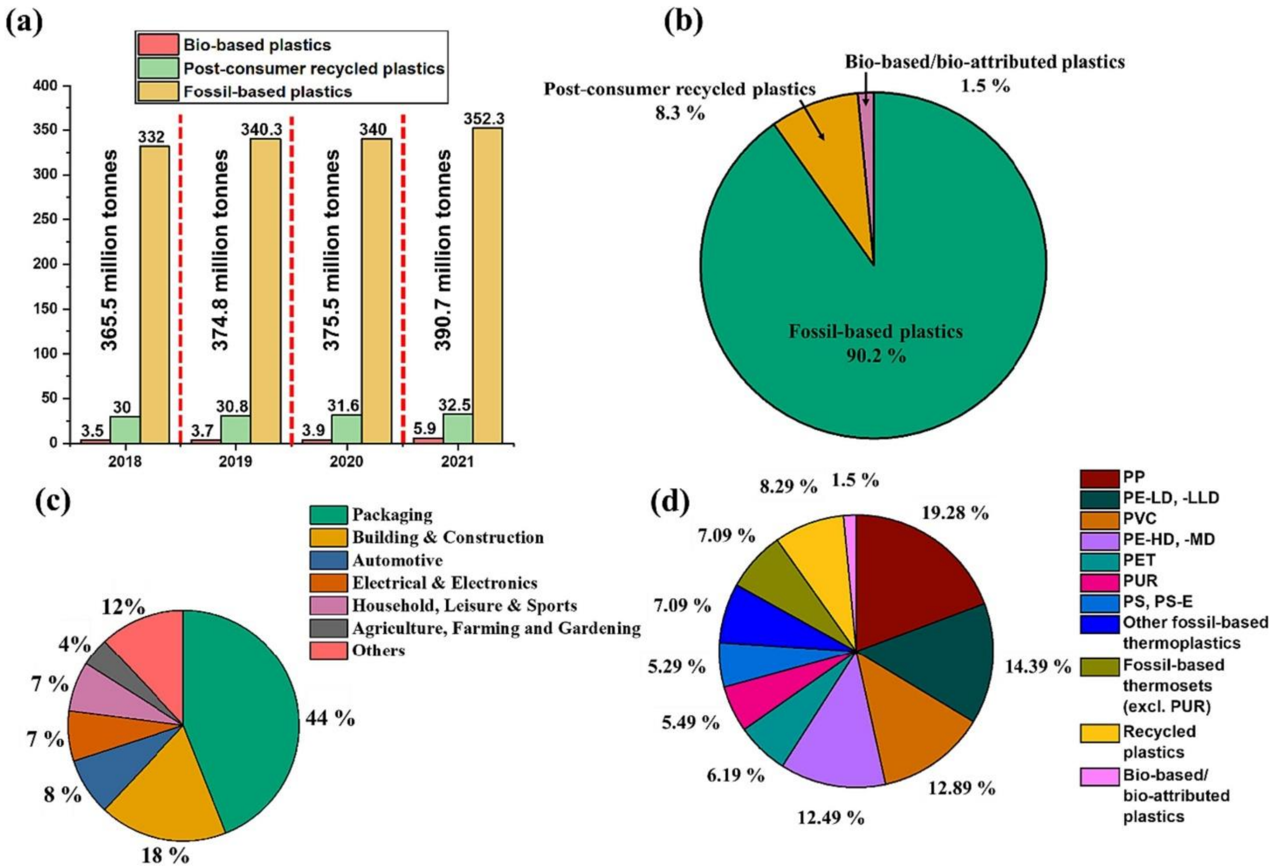

Figure 1(a) Global plastic production trends from 2018 to 2021. (b) Composition of global plastics production in 2021. (c) Breakdown of Global Plastics Use by Application in 2021. (d) Plastic-type breakdown in 2021. (Malik et al., 2024)

The extrusion process encompasses several different methods, such as single-screw and twin-screw extrusion, as well as film, sheet, and profile extrusion, each offering specific advantages tailored to specific applications. Each of these extrusion processes, may appear straightforward, but are highly efficient and effective. Broadly, they all start out with heating raw polymer materials until they reach a molten state. This molten polymer is then forced through a die, a specialized tool that shapes the material using pressure generated from a screw or piston. As the polymer emerges from the die, it takes on the desired form, such as a film, sheet, pipe, or profile. Once out of the die, the material cools and solidifies into its final shape. Below, we briefly describe the different extrusion methods that are currently being utilized across all industries.

- ***Single screw extrusion*** is the most widely used method for continuous production. In this process, a rotating screw pushes molten polymer through a die, forming a specific shape. Pipes, tubes, and various films are frequently made using this technique.
    - ***Twin screw extrusion*** employs two intermeshing screws that provide superior

mixing and processing capabilities. This method is often used for compounding and blending operations in high performance applications such as reinforced plastics.

- ***Blown Film Extrusion*** process is used to create flexible films by extruding a polymer into a tubular form and then expanding it into a bubble. This method is suitable for thin, uniform films and finds its greatest application in the production of packaging materials, agricultural films, and various types of bags.
- ***Sheet Extrusion***, molten polymer is flattened into sheets. These sheets are later thermoformed into different products, such as packaging materials, panels used in construction, or signage.
- ***Profile Extrusion*** produces shapes that have continuous lengths but relatively complex cross sections. Window frames, seals, and weatherstrips are good examples of what this process can do.

These extrusion processes require precise control over material properties and dimensions—an outcome heavily influenced by temperature, pressure, screw speed, and material feed rates. Operators have traditionally used manual tweaks and their own know how to fine tune the variables of polymer extrusion. This has often led to process inefficiencies, wasted material, and products of uneven quality. In recent years, however, the demands for more productive and sustainable extrusion operations that also yield better quality products have prompted many in the industry to turn to artificial intelligence as a potentially transformative tool for optimizing polymer extrusion.

1.1 How AI is Transforming Polymer Extrusion

The polymer extrusion industry is reaping substantial rewards from the AI revolution, especially in the fields of machine learning and deep learning. These technologies are now being used to solve many of the sector's perennial problems and to push it toward new frontiers of efficiency and innovation.

- ***Process Optimization:*** The exact fine tuning of process parameters such as temperature, pressure, and screw speed is now possible with AI. This powerful tool sifts through enormous quantities of historical and real time data to find the optimal extrusion conditions for various polymers. Manual adjustments are reduced to a minimum, and the outdated trial and error method is nearly being eliminated from production. We are more efficient; we produce less waste; and, as Park et al. (2022) observe, machine learning "holds great promise" for predicting polymer properties.

- ***Real-Time Process Control:*** Munir et al. (2021) demonstrated that AI driven real time monitoring systems could enhance the control of extrusion processes, specifically in optimizing film thickness. These systems use real time data to make adjustments and maintain the quality of products being extruded. By employing these new methods, manufacturers can expect to see not only a reduction in the number of defective products but also a decrease in the amount of material used during production runs. A study conducted by Munir et al. (2023) focused on the real time monitoring of polylactic acid (PLA) degradation during extrusion. The researchers used data from sensors and machine settings to create understandable models that forecast the polymer's molecular weight and mechanical properties. They found that combining Recursive Feature Elimination (RFE) with Random Forest (RF) yielded the most accurate, straightforward, and computationally efficient results among the methods tested. Their work highlighted pressure and temperature—especially at the extrusion exit—as crucial factors for determining both the PLA's mechanical properties and its degradation rate. Thus, they recommended their RFE RF approach for quality control of thermally sensitive polymers like PLA.

- ***Predictive Maintenance:*** According to Cinar et al. (2020), machine learning can be applied to predictive maintenance towards sustainable smart manufacturing in several industries. This very well can be applicable for polymer extrusion, and this application can help avert expensive equipment failures. It relies on sensor data from the machinery and a set of algorithms that "extract meaningful patterns" from the data. The patterns then provide a kind of forecast of when the failure of the extrusion equipment is likely to occur. These failure forecasts provide enough lead time for personnel to carry out timely maintenance and prevent actual failures from occurring.

- ***Quality Assurance:*** AI powered systems, such as deep learning in machine vision, can perform product inspections and identifications in real time. They can detect surface defects, dimensional inaccuracies, and material inconsistencies. This guarantees a higher level of quality control and minimizes material wastage. These applications are especially critical in the packaging and medical device industries, where even minor deviations from product specifications can have serious consequences.

- ***Sustainability and Energy Efficiency:*** Polymer extrusion can also be made more environmentally friendly with the help of AI. More than a third of energy used in the materials processing sector is accounted for by the polymer processing (Abeykoon et al., 2021). This technology can cut energy consumption and material waste by a significant amount. Because extrusion involves melting solid polymer pellets and pushing them through a die, it is very energy intensive. Abeykoon et al. (2021) studied how AI could be applied to reduce energy use in extrusion without compromising product quality. Their work provides a thorough assessment of energy utilization, identifies where and why energy losses occur, and advocates strategies for boosting process efficiency.

- ***Advanced Materials and Customization:*** The development of new polymer formulations and customization of products is accelerating due to artificial intelligence. By predicting the behavior of new materials during extrusion, AI allows industries like automotive and aerospace to push the limits of high-performance polymers. AI is beginning to have a profound effect on both the speed and nature of innovations in polymers. It allows these companies to work much faster, but it also permits them to be far more creative and flexible than they could have imagined even a few years ago. Researchers like Park et al. (2022) have shown how this can happen by applying AI not only to the design of new materials but also to their processing, which is crucial when working with advanced polymers and composites that must be formed into intricate shapes during extrusion or other operations.

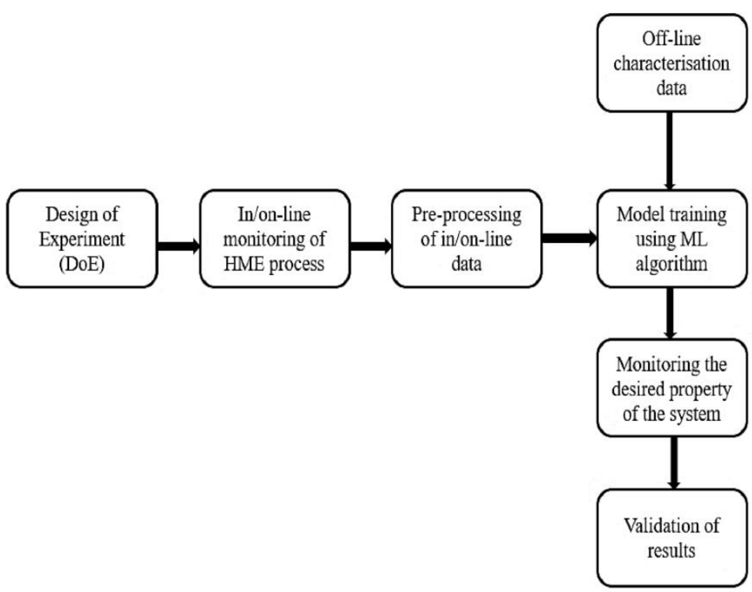

Figure 2 Schematic representation of in/on-line monitoring of the extrusion process with machine learning (Munir et al., 2021)

2. Previous literature

As technological advancements reshape industrial processes, the integration of artificial intelligence (AI) into polymer extrusion is unlocking new opportunities for innovation, optimization, and sustainability. Below is an overview of recent research contributions that highlight key developments in this area.

- **Traditional Process Optimization and Limitations**

  Polymer extrusion has traditionally depended on the expertise of operators and manual fine tuning to set and control key process parameters. Temperature, pressure, screw speed, and material feed rate all had to be adjusted using a combination of simple mathematical models, empirical methods, and—most importantly—the kind of intuition that comes only with years of experience. Yet even with this "best practices" approach, precision in polymer extrusion remained elusive. Namazi (2017) noted that despite improvements in extrusion technology, controlling the process precisely enough to avoid waste and achieve consistent quality products was still a major hurdle.

- **Early Applications of AI in Polymer Processing**

  Weichert et al. (2019) analyzed how machine learning and optimization methods are being integrated into manufacturing, thanks to digitalization and data availability. Interest is clearly growing in employing these tools to boost production efficiency, save resources, and cut waste. The authors reviewed literature from 2008 to 2018 that examined different machine learning algorithms and optimization techniques applied to product quality and process improvement. Yet this body of work showed only limited connections among the types and amounts of data, the kinds of algorithms used, and the optimization methods applied to tackle specific production problems. Nevertheless, progress is being made, even if some key challenges remain unresolved.

  AI's ability to manage the nonlinearities and high dimensionality of extrusion processes has made it a valuable tool for process control and optimization. Park et al. (2022) demonstrated that machine learning models could predict the properties of polymers with an accuracy surpassing that of conventional techniques. This improved predictive capability stands to benefit both process control and material quality. A next generation smart extrusion system that uses AI promises even greater advances in this regard. Munir et al. (2021) has shown how AI powered systems could detect deviations in blown film extrusion, like thickness variations. This capability helps keep product quality consistent and reduces the downtime of machines.

- **Advancements in Predictive Modeling and Real-Time Control**

  One of the main advantages of using AI in polymer extrusion is its ability to predict outcomes. For instance, neural networks can understand and replicate the intricate relationships that exist between various input parameters (like material properties, temperatures, and pressures) and the results they produce (such as the dimensions and quality of the extruded product). These predictive models are far more accurate than the traditional mathematical models we have used in the past. By relying on them, we can avoid a lot of the guesswork that has historically been associated with extrusion processes. Additionally, Cinar et al. (2020) highlighted the use of ML in predictive maintenance. By examining sensor data from extrusion equipment, AI can predict when the machinery is likely to wear out or fail. This allows for maintenance to be performed just in time, avoiding the kind of unplanned downtime that can really cost a company.

- **AI's Role in Enhancing Sustainability**

  The polymer processing industry is under increasing pressure to reduce its environmental impact, particularly with respect to energy consumption and material waste. Abeykoon et al. (2021) examined how artificial intelligence could be employed to optimize energy use in extrusion processes. They identified where energy was being lost and proposed AI based solutions for reducing those losses. Their study showed that AI can assist in making plastic production more sustainable without compromising the quality of the end product. Material efficiency is another area where AI can contribute to sustainability goals, especially as the industry intensifies its focus on those goals. The role of artificial intelligence in enhancing the use of recycled materials in extrusion processes was investigated by Kassab et al. (2023). They found that AI can forecast the performance of recycled polymers, allowing manufacturers to fine tune their operations for peak efficiency. This capability holds great promise for advancing a circular economy in plastics production.

2.1 Gaps in Current Research and Opportunities for AI in Polymer Extrusion

Even with substantial progress, fully achieving AI's potential in polymer extrusion remains elusive. A major hurdle is the absence of high quality, domain specific data needed to train AI models. Without strong datasets, the models have difficulty generalizing to the wide variety of polymers and extrusion techniques. Yet another significant challenge is developing interpretable AI models that can offer clear explanations of why they make the decisions or predictions they do. Munir et al. (2021) emphasized the importance of interdisciplinary collaboration between materials scientists, data scientists, and engineers to overcome these obstacles and maximize AI's impact in polymer extrusion. This kind of collaboration can help remove the roadblocks currently preventing AI from having its full effect on polymer extrusion.

To sum up, even though AI has already shown how it can improve polymer extrusion, there is still a lot of room for new ideas and innovations. This review extends earlier studies by filling in some current gaps and offering solutions to several present-day problems. The main thrust of this work is on three areas: sustainability, process optimization, and interdisciplinary collaboration.

2.2 Uniqueness and Contributions of This Review

This review offers a comprehensive examination of the intersection between artificial intelligence (AI) and polymer extrusion, with a unique focus on the following areas:

- **Challenges and Solutions**
  - **Detailed Challenges**: Unlike current reviews that offer only broad perspectives, this one provides a detailed look at the specific difficulties of getting AI into the many extrusion methods. The first and perhaps biggest challenge to solving any machine learning problem is to determine if the right kind of data is available. That is particularly true for extrusion, which involves many different variables. Despite the complexity of these problems, we remain optimistic about AI's potential to make extrusion more sustainable and efficient—especially with regard to reductions in material waste and energy consumption (Abeykoon et al., 2021).
  - **Innovative Solutions**: In addition to identifying challenges, this review proposes innovative solutions, building on Munir et al. (2021), who offered practical approaches to making AI effective in industrial settings. These include securing high-quality data, ensuring model interpretability, and fostering interdisciplinary collaboration.
- **Future Directions and Emerging Trends**
  - **Future Prospects**: The review adopts a forward-looking perspective on the future of polymer extrusion, highlighting current trends and possible breakthroughs that could mold this sector of the plastics industry. We emphasize how artificial intelligence (AI) can help drive advances in process optimization, sustainability, and energy efficiency - three areas ripe for improvement in polymer extrusion.

- **Research Roadmap**: A comprehensive research roadmap specifies the principal questions and areas that need further exploration. This guide for future research accentuates pivotal gaps and opportunities for innovation in AI driven polymer extrusion, allowing the systematic development of this nascent field.

- **Interdisciplinary Approach**
    - **Cross-Disciplinary Insights**: This multidisciplinary review encompasses materials science, data science, and engineering to assess AI's potential and challenges in polymer extrusion. Insights from these disciplines underscore the critical role of collaboration in advancing AI applications.
    - **Collaboration**: To advance AI technologies for extrusion, interdisciplinary teamwork is essential. The problems we face are too intricate to be solved without the imaginative input of different disciplines working together.

This review stands apart from the current body of work by concentrating on several key aspects, making it a useful tool for researchers and industry experts aiming to realize the full potential of AI in polymer extrusion. We have structured this paper into four main parts: an examination of the data types generated during manufacturing; a detailed look at how machine learning can improve quality control; a thorough discussion connecting data, machine learning, and optimization; and, finally, a set of conclusions that also serve to highlight some intriguing open questions for further research.

3. Data: The Foundation of AI Integration

The initial and most crucial phase in using AI for polymer extrusion is to secure appropriate data. Data forms the basis upon which machine learning models build, allowing AI to discern patterns, make forecasts, and fine tune processes. Yet, finding and collecting suitable data is often a daunting task. Extrusion involves numerous sensors and machine parameters that together yield a plethora of data—too much, in fact, for human minds to process easily. But not all of this data is useful or relevant for AI applications. To guide AI toward meaningful results, we must identify key process variables like temperature, pressure, screw speed, etc., the system can then use as inputs for its learned model.

According to Weichert et al. (2019), to effectively utilize AI, data must be first carefully structured and categorized into several types:

- **Qualitative vs. Quantitative Data**:
    - **Qualitative Data**: This is non numerical information, like what a process operator might observe, that makes up the context of the system being studied. Because it is less straightforward to analyze with traditional methods, some researchers might consider it to be of less value than quantitative data. Yet, "what" and "how much" a system does are not the same questions. These two kinds of data come together in a good study to provide a richer understanding of the system's context. Guetterman et al. (2015) put it well when they say, "Qualitative data can provide insights and context that make analyses of quantitative data more meaningful."
    - **Quantitative Data**: This is numerical information, like what a process operator might measure with a handheld device. It is what you would see plotted on a graph. Quantitative data are essential for training machine learning models because you cannot train a model on the "what" alone without the numerical expressions that define it. Al Kharusi et al. (2022) note that what you measure in the field and how you measure it make up this important component of a study.

- **Controllable vs. Uncontrollable Data**:
    - **Controllable Data**: Operators or automated systems can adjust certain variables, like temperature

settings, screw speed, and material feed rates. These are what we call controllable data. They are crucial for optimization because they directly affect the extrusion process and can be tuned to yield desired results.

- **Uncontrollable Data**: On the other hand, there are variables that cannot be easily adjusted, like ambient temperature, humidity, or the properties of raw materials. These fall into the category of uncontrollable data. Although this kind of data is not directly modifiable, understanding its impact on the process is important for developing robust AI models (Gupta et al., 2014).

- **Time Series vs. Work-Piece Related Data**:
  - **Time Series Data**: This data is gathered continuously over time and includes details like temperature changes, pressure shifts, and energy use. It is critical for understanding the operation of dynamic systems. For instance, if we want to know whether a system is trending toward failure or understand what "normal" looks like for a system, we need to look at time series data. Analyzing it allows us to detect trends and anomalies and make real time adjustments (Colosimo et al., 2014).
  - **Work-Piece Related Data**: This pertains to specific characteristics of the final product, such as its dimensions, surface finish, and mechanical properties. When evaluating the quality of an extruded part, this is the kind of data that gets looked at. It tells us whether or not the extrusion process produced a satisfactory piece. Sometimes this can also be time series data if we are looking at dynamic processes that affect work piece attributes (Al Kharusi et al., 2022).

- **Present vs. Historical Data**:
  - **Present Data**: This is real time data gathered from extrusion processes that are happening during ongoing extrusion processes. Present data is indispensable for not only maintaining a real time understanding of the state of the system but also for using that understanding to perform control actions. If something starts to go awry, the present data will show it, and this can be used to figure out what adjustments need to be made, either automatically by the system or manually by an operator to maintain optimal line conditions (Gupta et al., 2014).
  - **Historical Data**: This refers to data taken from past extrusion runs or historical records. Historical data is useful for looking at trends over time, performing retrospective analyses, and training AI models. It offers a wider perspective on how process variations influence results over time. But the way we collect data can, and often does, change over time. So, when we are using historical data to train models, we may need to clean it up first or we might just opt not to use it at all, to ensure we are not working with faulty data (Colosimo et al., 2014).

- **Measured vs. Simulated Data**:
  - **Measured Data**: Directly obtained from physical sensors and instruments, the measured data reflects the true state and performance of the extrusion system. Because of this, it is absolutely indispensable for accurate modeling and for ensuring that any computational work, be it simulation or something else and has real world applicability (Al Kharusi et al., 2022).

- **Simulated Data**: In contrast, simulated data are generated through computational models or simulations based on either theoretical or empirical equations. This data can be useful in situations where real measurements are not available or feasible but do not necessarily capture all the complexities of a process in the same way that measured data does. There are times when both measured and simulated data need to be used together to improve a machine learning model's predictive capability (Colosimo et al., 2014).

- **Observable Quantities vs. Process State Variables**:
  - **Observable Quantities**: These are parameters that can be directly measured and observed, such as temperature, pressure, and screw speed. They give immediate feedback and are often used as inputs to AI models (Gupta et al., 2014). Process State Variables:
  - **Process State Variables**: These represent variables internal or latent to the process that influence it but are not directly gauged, such as molecular weight or polymer degradation. Understanding these variables often requires deep modeling or estimation techniques. They are crucial not only for good process control and supervision but also for gaining insights into the behavior of the process (Guetterman et al., 2015).

Understanding the production data structure is vital for selecting appropriate machine learning models. Most sensor derived data from production systems, like those used in manufacturing, are considered structured and thus more straightforward to process than unstructured data. However, a key challenge remains: ensuring quality and consistency in the data. When data are incomplete, noisy, or poorly labeled, they can yield flawed models and unreliable predictions. This issue is compounded by the complexity of extrusion systems, which involve many interacting variables that change dynamically during production. For AI models to work effectively, they need diverse and comprehensive datasets that reflect the many nuances of the systems they are meant to emulate. In the case of polymers and extrusion setups, these datasets must capture a wide range of process conditions. If they do not, there is a real risk that the machine learning algorithms will overfit—that is, learn too well from a limited dataset—making them ineffective when asked to predict the behavior of fundamentally different systems.

To gather relevant, high quality production data for refining machine learning models, several essential strategies must be followed. The first is to design data collection systems that capture a full spectrum of process variables—temperature, pressure, flow rates, and material properties—with precision and accuracy. It is equally important to ensure these variables are correctly correlated with production outcomes.

Advanced sensors and real time monitoring technologies can boost the resolution and trustworthiness of the data collected. However, they cannot make up for poor system design or sloppy instrument calibration. When all these elements come together properly, what remains is to manage the data well: cleaning it, normalizing it, and validating it so that inconsistencies and noise are eliminated before the data enters the machine learning pipeline. In addition, using a blend of measured and simulated data can compensate for the absence of real measurements. Data fusion techniques can integrate experimental and numerical data to create a more comprehensive dataset. It is also essential to collaborate with domain experts when selecting relevant features and assembling datasets to ensure that the data collection process serves the specific aims of the machine learning model. By employing these strategies, manufacturers can obtain high quality production data that will greatly improve the performance of machine learning models used to optimize manufacturing processes and increase efficiency.

This review underscores the significance of data as a major challenge, yet one brimming with promise. By concentrating on amassing high quality, domain specific data, manufacturers can realize AI's true potential to boost process control, minimize material waste, and heighten energy efficiency in polymer extrusion. Solving this data problem is the necessary first step toward integrating AI successfully into extrusion processes. The following section outlines various approaches to production optimization using machine learning.

4. Model Training using ML algorithm

After gathering and organizing the essential high quality production data, the next pivotal move in using artificial intelligence for polymer extrusion is to train models with machine learning (ML) algorithms. This phase aims to create models that can precisely forecast results, refine processes, and boost total production efficiency using the organized data.

4.1. Selection of Machine Learning Algorithms

Choosing the right machine learning algorithms is crucial for training models. The data's characteristics and the application's goals guide the selection of various algorithms. Some widely used options are:

- **Linear Regression and Logistic Regression**: These basic predictive modeling techniques are quite useful for tasks with linear relationships, like predicting the polymer melt viscosity during extrusion (James et al., 2013). They become problematic, however, when trying to handle more complex nonlinear relationships. Moreover, they lack interpretability in some cases, especially when dealing with logistic regression for classification problems.

- **Decision Trees and Random Forests**: Decision trees excel at making straightforward "if then" decisions and can handle both numerical and categorical data. They provide a clear path from input features to a final decision or prediction. However, their performance can be unstable because they tend to overfit the training data when used alone. Random forests mitigate this problem by using multiple decision trees in parallel (Breiman, 2001). Random Forests are particularly effective for handling intricate decision making tasks, such as fine tuning extrusion parameters. They improve upon simple decision trees by using an ensemble of trees, which boosts accuracy and allows the method to handle high dimensional data with ease. This makes Random Forests a good choice for robustly modeling the complex, multi factor environments found in many extrusion processes (Breiman, 2001).

- **Support Vector Machines (SVM)**: SVMs are classification powerhouses. They work especially well when the number of features far exceeds the number of samples—i.e., in high dimensional spaces. SVMs are valuable tools for identifying tasks like optimal operating conditions and classifying products based on multifactor quality assessments (Cortes et al., 1995).

- **Neural Networks**: Neural networks, especially deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), excel at capturing complex, nonlinear patterns in large datasets. Convolutional Neural Networks (CNNs) are great for examining image-based datasets, like those containing surface defects. Meanwhile, Recurrent Neural Networks (RNNs) are better suited for time series data. This makes them ideal for analyzing how changes in extrusion conditions affect a process over time (LeCun et al., 2015).

- **Gradient Boosting Machines (GBM)**: GBMs such as XGBoost and LightGBM, take predictive performance to the next level by using a boosting framework to combine the predictions of multiple models. They handle complex datasets with ease and are known for their efficiency and accuracy across a range of tasks. In our context, they work quite well for optimizing extrusion parameters and predicting when maintenance will be needed (Chen et al., 2016).

4.2 Model Training Process

The model training process involves several key steps:

- **Data Splitting**: The gathered data is split into three parts: training, validation, and test sets. The training set is used to train the model, while the validation set helps in tuning hyperparameters and selecting the best model. Finally, the test set evaluates the model's performance on new data (Al Kharusi et al., 2022).

- **Feature Selection and Engineering**: When performing feature selection, we choose relevant variables from our dataset that we believe will improve model performance. Feature engineering is more creative and involves making new features or modifying existing ones to help our models learn better from the data (Colosimo et al., 2014).

- **Training the Model**: Using the training data, we teach an ML algorithm to find patterns and relationships in the data by minimizing a loss function that quantifies how much the predicted outcomes differ from what actually happened. Iterating over the data during training adjusts the model's parameters to enhance accuracy (Goodfellow et al., 2016).

- **Validation and Hyperparameter Tuning**: We use the validation set to check how well the model generalizes to unseen data. Although we refer to it as a "set," the validation data can be used in several different ways depending on the specific technique being applied (e.g., k fold cross validation). The primary role of this step is to ensure that our model has not merely memorized the training data but instead learned an underlying pattern. While performing these checks, we also adjust hyperparameters—those parameters of the learning algorithm that are external to the model and cannot be learned from the training data. These need to be set before training begins and include things like learning rate, batch size, and number of layers if using a neural network. The choice of hyperparameters significantly impacts model performance. To find good values for them, we might use techniques such as grid search or random search (Bergstra et al., 2012).

- **Evaluation**: In this final step, we assess how well our model performs by applying it to a test set—a collection of examples kept aside and never shown to the model during either its initial parameter tuning phase or any subsequent retraining phases. Model effectiveness in outcome prediction and decision-making is evaluated using various metrics. These include accuracy, precision, recall, F1 score, and mean squared error (Powers, 2011).

4.3 Challenges and Considerations

Training ML models for polymer extrusion presents several challenges:

- **Overfitting and Underfitting**: These are two sides of the same coin when it comes to balancing model complexity. Overfitting occurs when a model is too complex, capturing noise in the training data as if it were true signals (Goodfellow et al., 2016). As a result, the model performs well on the training data but poorly on new, unseen data. In contrast, underfitting happens when the model is too simple and unable to capture the underlying patterns in the data. Both situations lead to unreliable models.

- **Data Quality**: The saying "garbage in, garbage out" applies here. If the training data are inaccurate, noisy, or incomplete, one cannot expect to obtain reliable models with good performance (Al Kharusi et al., 2022).

- **Computational Resources**: Particularly for deep learning models, significant computational resources and time are required to train complex models. Balancing these aspects is crucial for achieving robust ML model performance for polymer extrusion applications. Efficient algorithms and high-performance computing can alleviate these difficulties (LeCun et al., 2015).

After training, the machine learning model can be deployed in the production environment for real time control and optimization. It is capable of forecasting key performance indicators, suggesting process modifications, and assisting in decisions that improve overall efficiency, reduce variability, and enhance product quality. By adopting a systematic approach to model training, manufacturers can realize the full potential of machine learning to revolutionize polymer extrusion processes, achieving major gains in both performance and sustainability.

5. Application of machine learning for optimization of production

5.1 Integration of a machine learning model into an extrusion process

Once a machine learning (ML) model has been properly trained and validated, the next crucial step is to integrate it into the extrusion process for optimization. This means deploying the model in a real-world production setting where it can impact decision making, process control, and performance improvement. If done correctly, an integrated ML model can boost the efficiency, quality, and even the sustainability of an extrusion process. This section describes, in five steps, how to integrate an ML model into an extrusion process. It also provides references to relevant literature for those interested in more detail about any of the steps or considerations described here.

5.1.1 Deployment of the ML Model

Model Deployment in a production environment can be achieved through several methods**:**

- **Real-Time Monitoring Systems:** One effective approach is to integrate the ML model with real time monitoring systems. These systems are continuously fed data from sensors attached to the extrusion equipment and other critical components of the process being monitored (Charalampous et al., 2021). The model processes this data in real time and provides feedback that operators can use to keep the process within specified limits.

- **Control Systems Integration:** Another method involves integrating the model with existing process control systems. In this approach, which requires very close collaboration between humans and machines, the ML model makes predictions that are used to adjust control variables like temperature, pressure, or screw speed (Munir et al., 2021).

- **Cloud-Based Solutions:** If more complex models need to be deployed or if computational resources are limited, cloud-based solutions can also be utilized for deploying the ML model. In this method, the model operates on high-capacity servers and communicates control signals or suggestions to the extrusion process via networked systems (Babu et al., 2022).

5.1.2 Continuous Data Flow and Model Updates

Maintaining the precision and relevance of the ML model requires a steady stream of data. The following components make up this continuous data flow:

- **Real-Time Data Collection:** It is crucial that all relevant extrusion process data, such as temperature, pressure, and material properties, are continuously collected and fed into the ML model.

- **Model Retraining and Updating:** New data necessitate changes to the model. The ML model must be regularly retrained with new data so it can adapt to changes in either the extrusion process or material characteristics (Rasmussen et al., 2006). This retraining can happen in an "online" fashion with single instances or small batches of data, or it can occur more conservatively with larger batches of data over time.

- **Feedback Loops:** The predictions made by the ML model should be compared with actual outcomes to provide a closed loop system for improving model performance. Predicted and actual outcomes do not align often, so we tweak the model or its parameters to make it better and fix the discrepancies (Sutton et al., 2018).

5.1.3 Process Optimization and Control

Process optimization uses an ML model to improve different facets of the extrusion process:

- **Parameter Tuning:** The ML model identifies the best settings for process parameters to maximize efficiency and product quality. For example, it may recommend optimal screw speed or temperature settings based on the desired properties of the materials being extruded.

- **Anomaly Detection and Predictive Maintenance:** The ML model is also used for anomaly detection in the extrusion process. It finds potential problems that might occur and gives a warning before they actually happen. In addition, predictive maintenance algorithms reduce downtime by forecasting when equipment will need attention long before it reaches a critical state (Zope et al., 2019).

- **Quality Control:** Deploying the model to provide real time monitoring and control of product quality. The model forecasts defects or deviations from quality standards and recommends adjustments to maintain consistent product quality.

5.1.4 User Interface and Decision Support

User Interface Development is essential for ensuring smooth interaction between operators and the ML model. Key components include

- **Visualization Tools:** Dashboards and visualization tools need to be developed to present model predictions, recommendations, and process metrics in an accessible and actionable format. It is critical that these formats be operator friendly so that informed decisions can be made quickly (Rawat et al., 2021).

- **Decision Support Systems:** The ML model needs to be integrated with decision support systems so that operators can receive actionable insights and recommendations based on the model's outputs. This integration enhances overall decision making in process management (González Rodríguez et al., 2019).

5.1.5 Validation and Continuous Improvement

It is crucial to validate the integrated ML model in the production environment to confirm its effectiveness and reliability. This validation involves two primary activities:

- **Performance Monitoring:** After the ML model has been put into operation, its performance needs to be monitored continuously to ensure it is achieving the desired results. This monitoring process tracks several key performance indicators (KPIs) that reflect different aspects of the model's effect on production. The most relevant KPIs for our context are related to product quality, production efficiency, and operational costs (Surucu et al., 2023). If any of these indicators start trending unfavorably, immediate corrective actions need to be taken, which usually involve either adjusting the model itself or making changes to how it is being used.

- **Continuous Improvement:** The same insights gained from ongoing performance monitoring can also be used in a more long-term sense to drive continuous improvement of the ML model and the overall extrusion process. In this context, "improvement" can mean refining the ML model itself—making it better at whatever task it was assigned—adjusting process parameters based on new insights provided by the model, or implementing entirely new strategies suggested by the model (Weichert et al., 2019).

5.2 Process Optimization Topics

Process optimization with machine learning can be organized into two primary areas, differentiated by whether production parameters are modified during manufacturing:

- **Optimization Without Changing Production Parameters**

This method enhances product quality without directly changing the production parameters during manufacturing. It is mainly used when it is not feasible or desirable to alter the production process in real time. Some examples of this approach include:

  - **Root Cause Analysis:** This is a systematic method used to identify and address the fundamental causes of recurrent quality issues that affect production.
  - **Early Prediction of Manufacturing Outcomes:** This involves forecasting potential problems or deviations in product quality well before they occur.
  - **Diagnostic Methods:** Detecting and diagnosing erroneous behavior in products or processing units.

The methods described enhance comprehension of process behavior and potential problems. However, they stop short of making real time adjustments to production parameters.

- **Optimization With Changing Production Parameters**

Key aspects include: In contrast, the approach I am about to describe does involve such real time adjustments. Key aspects of this method are:

  - **Parameter Optimization**: We determine settings for production parameters that yield better than average quality.
  - **Self-Optimizing Control Systems:** We automate adjustments to certain production parameters based on real time data and process models.
  - **Machine Learning Approaches with Optimization Modules:** Using ML in conjunction with traditional optimization techniques to refine processes.

The objective for optimization can be product specific (e.g., surface roughness, shrinkage) or process specific (e.g., energy consumption, tool wear) or sometimes both. Both approaches described above yield improved product quality and process efficiency in terms of cost, time, resource consumption, and specific optimization goals.

6. Discussion, Analysis and Future Directions

In this paper, we present a detailed review and analysis of how machine learning (ML) models are being integrated into the polymer extrusion process. We focus on two main areas: process parameter optimization and overall production efficiency improvements. Our discussion highlights the use of ML for several key tasks—real time monitoring, process control, and continuous improvement—in extrusion processes. We cover in detail the training, deployment, and integration of models for these tasks. We also discuss in depth the effect that ML is having on both process optimization and quality control in extrusion operations.

The paper examined a range of machine learning algorithms and how well they fit various aspects of polymer extrusion. We talked about linear regression, decision trees, support vector machines (Cortes et al., 1995), neural networks (Goodfellow et al., 2016), and gradient boosting machines (Chen et al., 2016) and noted their particular strengths and applications. We assessed each algorithm's ability to handle numerical and categorical data, predict outcomes, and optimize parameters based on recent literature (James et al., 2013; Breiman, 2001). We also analyzed the model training process, which includes splitting the data, selecting features, and tuning hyperparameters (Bergstra et al., 2012). We placed special emphasis on techniques like online learning and periodic batch retraining to maintain models that are accurate and relevant. We discussed how to enhance model performance and adaptability using feedback loops. These loops involve comparing model predictions with real world results to fine tune the model, essentially employing a basic control system to keep the model in check and on track.

Integrating machine learning (ML) models into the extrusion process is vital for enhancing production efficiency and product quality. We outlined strategies for deploying ML models, such as using real time monitoring and control systems, and cloud-based solutions. To keep the models accurate, we ensure a steady flow of data and use it to retrain the models when necessary. For reliability, we are focusing on anomaly detection and predictive maintenance—two areas where we believe ML can add significant value. By using these techniques, we aim to forecast failures in the extrusion equipment before they happen and suggest maintenance actions that will keep the equipment running smoothly (Çınar et al., 2020; Zope et al., 2019).

The review emphasized how machine learning can optimize manufacturing processes, especially when it comes to fine tuning parameters to enhance product quality and efficiency. We explained that ML models can suggest the best settings for various process parameters—like screw speed and temperature—to obtain the desired material characteristics. We also looked at how ML can be used for real time quality control and defect prediction, showing its value in keeping product quality consistent (Munir et al., 2021; Munir et al., 2023).

The significance of user interfaces and decision support systems in maximizing the value of ML models was highlighted. It is crucial to create dashboards and visualization tools that display model forecasts and suggestions in a way that is clear and actionable for operators. They must be able to see what the model is saying and use that information to make decisions swiftly. When ML models are integrated with decision support systems, they improve process control and enhance overall decision making (González Rodríguez et al., 2019).

Ensuring ML models remain effective in production requires continuous performance monitoring. It is especially important to track certain key performance indicators (KPIs) that directly reflect model performance. For example, product quality and production efficiency are two KPIs that are critical for evaluating the performance of many types of ML models. Insights from these evaluations can be used to drive what some refer to as "continuous process improvement" or "ongoing process optimization." This essentially means using the insights gained from understanding why a model is underperforming (or has stopped performing altogether) to refine processes and implement new strategies (Surucu et al., 2023; Weichert et al., 2019).

Integrating machine learning models into polymer extrusion has shown great promise for making production more efficient, improving the quality of products, and aiding in real time decisions. The literature and methods reviewed highlight the transformative effect that ML can have on extrusion processes, offering useful perspectives on how best to apply these technologies.

Despite recent advancements, there are still some persistent problems, such as those concerning the quality of data, available computational power, and the necessity for models that can be easily adjusted (Rawat et al., 2021). Solving these problems is essential if we are to wring every last benefit from machine learning in extrusion processes and ensure its smooth operation on the factory floor.

Future research in the field of ML for polymer extrusion is likely to focus on several key areas:

- **Advanced Algorithms and Techniques**: The continued evolution of advanced ML algorithms, like deep learning (LeCun et al., 2015) and reinforcement learning (Sutton et al., 2018), could further boost the capability of ML models to handle complex extrusion processes and improve their predictive accuracy. Generative AI techniques, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) (Goodfellow et al., 2016), hold significant promise for the field of polymer extrusion. They could be used to generate new designs for polymer materials or optimize the parameters of the extrusion process. By creating novel compositions of materials or honing in on process parameters, generative AI can drive innovation and enhance the efficiency of polymer production.

- **Real-Time Data Integration and Processing**: Ensuring model precision and relevance calls for more efficient methods of real time data collection, integration, and processing. Sensor technologies and data management systems will likely provide innovations that can be applied to these tasks (Babu et al., 2022).

- **Scalability and Computational Efficiency**: Another crucial aspect is computational efficiency. We must overcome the training and deployment challenges associated with modern complex ML models if we are to maintain their scalability and keep costs under control. Future research may investigate more scalable and efficient computing solutions, like edge computing and distributed systems (Gupta et al., 2014), to support large scale extrusion processes

- **Adaptability and Robustness**: Another key future research area is developing models that are more adaptable and robust. This especially means models that can handle the changing process conditions and material characteristics that are inevitable in extrusion. Transfer learning, meta learning, and other advanced techniques could play a big role here (Rasmussen et al., 2006).

- **Integration with Emerging Technologies**: Integrating machine learning models with emerging technologies like the Internet of Things (IoT) and digital twins can open up new avenues for improving process optimization and real time monitoring. According to Zhang et al. (2022), this kind of collaboration between different technological layers can lead to even greater opportunities for innovation and efficiency in various applications.

To sum up, the integration of machine learning models into polymer extrusion offers great potential for improving production efficiency and quality control. This nascent field requires more research to overcome current challenges and realize new opportunities for process optimization and innovation.

But as artificial intelligence becomes more common in manufacturing, it is also necessary to think about ethics. We cannot ignore issues like job displacement or data privacy. If we are going to automate tasks with AI, we need to have strategies in place that ensure displaced workers are reskilled and transitioned into new roles. Moreover, the gathering and utilization of data bring up issues of privacy and data security. To address these concerns, it is vital to have strong data protection measures in place and clear, honest practices with the collected data.

In regard to using AI for automating tasks, the expertise of humans still holds primacy in making decisions and solving problems. AI should be considered a means of amplifying human abilities rather than a direct substitute for them. In a productive collaboration between humans and AI, the "H" in "human" still represents an essential component. The future of AI development will center on how it can bolster human abilities and improve teamwork.

References:

[1] Tajeddin, B., & Arabkhedri, M. (2020). Polymers and food packaging. In M. A. AlMaadeed, D. Ponnamma, & M. A. Carignano (Eds.), *Polymer Science and Innovative Applications* (pp. 525-543). Elsevier. https://doi.org/10.1016/B978-0-12-816808-0.00016-0

[2] Maitz, M. F. (2015). Applications of synthetic polymers in clinical medicine. *Biosurface and Biotribology, 1*(3), 161-176. https://doi.org/10.1016/j.bsbt.2015.08.002

[3] Shen, J., Liang, J., Lin, X., Lin, H., Yu, J., & Yang, Z. (2020). Recent progress in polymer-based building materials. *International Journal of Polymer Science, 2020*, 1-15. https://doi.org/10.1155/2020/8838160

[4] Zhang, W., & Xu, J. (2022). Advanced lightweight materials for automobiles: A review. *Materials & Design, 221*, 110994. https://doi.org/10.1016/j.matdes.2022.110994

[5] Parveez, B., Kittur, M. I., Badruddin, I. A., Kamangar, S., Hussien, M., & Umarfarooq, M. A. (2022). Scientific advancements in composite materials for aircraft applications: A review. *Polymers, 14*(22), 5007. https://doi.org/10.3390/polym14225007

[6] Sikder, A., Pearce, A. K., Parkinson, S. J., Napier, R., & O'Reilly, R. K. (2021). Recent trends in advanced polymer materials in agriculture-related applications. *ACS Applied Polymer Materials, 3*(3), 1203-1217. https://doi.org/10.1021/acsapm.0c00982

[7] Martin, T. B., & Audus, D. J. (2023). Emerging trends in machine learning: A polymer perspective. *ACS Polymers Au, 3*(3), 239-258. https://doi.org/10.1021/acspolymersau.2c00053

[8] Namazi, H. (2017). Polymers in our daily life. *Bioimpacts, 7*(2), 73-74. https://doi.org/10.15171/bi.2017.09

[9] Kassab, A., Al Nabhani, D., Mohanty, P., Pannier, C., & Ayoub, G. Y. (2023). Advancing plastic recycling: Challenges and opportunities in the integration of 3D printing and distributed recycling for a circular economy. *Polymers, 15*(19), 3881. https://doi.org/10.3390/polym15193881

[10] Borrelle, S. B., et al. (2020). Predicted growth in plastic waste exceeds efforts to mitigate plastic pollution. *Science, 369*(6509), 1515-1518. https://doi.org/10.1126/science.aba3656

[11] Sardon, H., & Dove, A. P. (2018). Plastics recycling with a difference. *Science, 360*(6387), 380-381. https://doi.org/10.1126/science.aat4997

[12] Malik, H., Mohanty, A. K., & Misra, M. (2024). 3D printing in upcycling plastic and biomass waste to sustainable polymer blends and composites: A review. *Materials & Design, 237*, 112558. https://doi.org/10.1016/j.matdes.2023.112558

[13] Park, J., Shim, Y., Lee, F., Rammohan, A., Goyal, S., Shim, M., Jeong, C., & Kim, D. S. (2022). Prediction and interpretation of polymer properties using the graph convolutional network. *ACS Polymers Au, 2*(4), 213-222. https://doi.org/10.1021/acspolymersau.1c00050

[14] Munir, N., Nugent, M., Whitaker, D., & McAfee, M. (2021). Machine learning for process monitoring and control of hot-melt extrusion: Current state of the art and future directions. *Pharmaceutics, 13*(9), 1432. https://doi.org/10.3390/pharmaceutics13091432

[15] Munir, N., McMorrow, R., Mulrennan, K., Whitaker, D., McLoone, S., Kellomäki, M., Talvitie, E., Lyyra, I., & McAfee, M. (2023). Interpretable machine learning methods for monitoring polymer degradation in extrusion of polylactic acid. *Polymers (Basel), 15*(17), 3566. https://doi.org/10.3390/polym15173566

[16] Park, J., Shim, Y., Lee, F., Rammohan, A., Goyal, S., Shim, M., Jeong, C., & Kim, D. S. (2022). Prediction and interpretation of polymer properties using the graph convolutional network. *ACS Polymers Au, 2*(4), 213-222. https://doi.org/10.1021/acspolymersau.1c00050

[17] Weichert, D., Link, P., & Stoll, A. (2019). A review of machine learning for the optimization of production processes. *International Journal of Advanced Manufacturing Technology, 104*(5), 1889-1902. https://doi.org/10.1007/s00170-019-03988-5

[18] Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in Industry 4.0. *Sustainability, 12*(19), 8211. https://doi.org/10.3390/su12198211

[19] Abeykoon, C., McMillan, A., & Nguyen, B. K. (2021). Energy efficiency in extrusion-related polymer processing: A review of state of the art and potential efficiency improvements. *Renewable and Sustainable Energy Reviews, 147*, 111219. https://doi.org/10.1016/j.rser.2021.111219

[20] Guetterman, T. C., Fetters, M. D., & Creswell, J. W. (2015). Integrating quantitative and qualitative results in health science mixed methods research through joint displays. *Annals of Family Medicine, 13*(6), 554-561. https://doi.org/10.1370/afm.1865

[21] Al-Kharusi, G., Dunne, N. J., Little, S., & Levingstone, T. J. (2022). The role of machine learning and design of experiments in the advancement of biomaterial and tissue engineering research. *Bioengineering (Basel), 9*(10), 561. https://doi.org/10.3390/bioengineering9100561

[22] Colosimo, B., Pagani, L., & Strano, M. (2014). Reduction of calibration effort in FEM-based optimization via numerical and experimental data fusion. *Structural and Multidisciplinary Optimization, 51*, 1193-1205. https://doi.org/10.1007/s00158-014-1149-0

[23] Gupta, A., Guntuku, S. C., Desu, R., & Balu, A. (2014). Optimisation of turning parameters by integrating genetic algorithm with support vector regression and artificial neural networks. *The International Journal of Advanced Manufacturing Technology, 77*, 1-9. https://doi.org/10.1007/s00170-014-6282-9

[24] Bergstra, J., & Bengio, Y. (2012). Random Search for Hyper-Parameter Optimization. *Journal of Machine Learning Research, 13*, 281-305.

[25] Breiman, L. (2001). Random Forests. *Machine Learning, 45*(1), 5-32. https://doi.org/10.1023/A:1010933404324

[26] Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785-794). https://doi.org/10.1145/2939672.2939785

[27] Cortes, C., & Vapnik, V. (1995). Support-Vector Networks. *Machine Learning, 20*(3), 273-297. https://doi.org/10.1007/BF00994018

[28] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

[29] James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An Introduction to Statistical Learning: With Applications in R*. Springer.

[30] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep Learning. *Nature, 521*, 436-444. https://doi.org/10.1038/nature14539

[31] Powers, D. M. W. (2011). Evaluation: From Precision, Recall and F-Factor to ROC, Informedness, Markedness & Correlation. *Journal of Machine Learning Technologies, 2*, 37-63.

[32] Charalampous, P., Kostavelis, I., Kopsacheilis, C., et al. (2021). Vision-based real-time monitoring of extrusion additive manufacturing processes for automatic manufacturing error detection. *International Journal of Advanced Manufacturing Technology, 115*, 3859-3872. https://doi.org/10.1007/s00170-021-07419-2

[33] Babu, S. S., Mourad, A. H. I., Harib, K. H., & Vijayavenkataraman, S. (2022). Recent developments in the application of machine-learning towards accelerated predictive multiscale design and additive manufacturing. *Virtual and Physical Prototyping, 18*(1). https://doi.org/10.1080/17452759.2022.2141653

[34] Rasmussen, C. E., & Williams, C. K. I. (2006). *Gaussian Processes for Machine Learning*. The MIT Press.

[35] Sutton, R. S., & Barto, A. G. (2018). *Reinforcement Learning: An Introduction* (2nd ed.). The MIT Press.

[36] Zope, K., Singh, K., Nistala, S. H., Basak, A., Rathore, P., & Runkana, V. (2019). Anomaly Detection and Diagnosis In Manufacturing Systems: A Comparative Study Of Statistical,

Machine Learning And Deep Learning Techniques. *Annual Conference of the PHM Society, 11*(1). https://doi.org/10.36001/phmconf.2019.v11i1.815

[37] Rawat, S., Rawat, A., Kumar, D., & Sai Sabitha, A. (2021). Application of machine learning and data visualization techniques for decision support in the insurance sector. *International Journal of Information Management Data Insights, 1*(2), 100012. https://doi.org/10.1016/j.jjimei.2021.100012

[38] González Rodríguez, G., Gonzalez-Cava, J. M., & Méndez Pérez, J. A. (2019). An intelligent decision support system for production planning based on machine learning. *Journal of Intelligent Manufacturing, 30*, 2381-2394. https://doi.org/10.1007/s10845-019-01420-6

[39] Surucu, O., Gadsden, S. A., & Yawney, J. (2023). Condition Monitoring using Machine Learning: A Review of Theory, Applications, and Recent Advances. *Expert Systems with Applications, 221*, 119738. https://doi.org/10.1016/j.eswa.2023.119738