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Manufacturing Process Parameter Optimization: A Comprehensive Review and Research Directions

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Abstract
Manufacturing industries face significant challenges in minimizing the scrap generated during production processes. Any measurable input element in the manufacturing process, such as temperature, raw material quality, or wire feed rate, along with any transformation activity within the process that affects the output, is considered a process parameter. Optimizing these process parameters through various techniques can reduce scrap rates and enhance product quality. This paper reviews and synthesizes the available literature on manufacturing process parameter optimization. The survey emphasizes key manufacturing processes, including shaping, forming, machining, joining, finishing, and chemical processing. It categorizes process parameter optimization approaches into online and offline methods, revealing that online optimization currently accounts for only 6–7% of the research focus. A retrospective analysis underscores the need for further research in online optimization for dynamically changing environments. The previous review from Weichert et al. (2019) focused narrowly on machine learning methods (2008–2018) for quality improvement. Likewise, Panzer & Bender (2022) examined only deep reinforcement learning in production. In contrast, this review covers a broader algorithmic map across all major manufacturing processes (shaping, forming, machining, etc.). It uniquely quantifies the split between offline and online studies. The paper concludes by discussing the challenges in implementing solutions for process parameter optimization and calls for additional academic and industrial research, particularly through advanced machine learning techniques, to optimize manufacturing process parameters.

Keywords
Modeling for control optimization; Process control; Industrial process control; Manufacturing systems; Machine learning; Parameter estimation.

Introduction

The manufacturing industry has been a cornerstone of progress for centuries, driving advancements from the printing press to the automobile industry (Checkland, 1970). These innovations have consistently boosted productivity and minimized waste. Over the last century, mathematical and statistical analysis has significantly enhanced manufacturing processes. In the past two decades, the manufacturing industries have produced unprecedented volumes of data, propelled by the rise of data-driven statistical methods and artificial intelligence (Rüssmann, 2015).

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As its name suggests, data collection is foundational for the application of data-driven methods. This forms the basis for data aggregation. Well-established ERP software platforms, such as SAP, have long facilitated processes of data collection, aggregation, and manipulation (Snijders, Matzat & Reips, 2012).

In any manufacturing industry, enhancing quality and reducing costs are essential objectives. These goals can be achieved through various methods, such as mass production, intelligent scheduling, feedback from mathematical simulations, and process parameter optimization. In this work, the authors have investigated optimization techniques aimed at improving manufacturing processes by refining process parameters, drawing insights from over 200 research articles published in the past two decades. While Weichert et al. (2019) reviewed machine learning methods for optimizing manufacturing processes, this paper provides a broader overview, highlighting established optimization techniques, implementation challenges, and directions for future research. The goal is to offer a systematic review of the literature, assisting researchers with existing work and identifying new avenues for exploration.

According to Groover (2021), manufacturing processes are primarily categorized into shaping, forming, machining, joining, and finishing processes. This research systematically surveys the literature related to these processes, targeting specific keywords and techniques relevant to optimization. At its core, the concept of "manufacturing process parameter optimization" seeks to enhance overall productivity and reduce costs by refining parameters across various stages of production. The term "manufacturing" is often used interchangeably with "production". However, "production" may also refer to intangible services, such as an analyst producing financial solutions; therefore, the term "manufacturing" is exclusively used here to avoid ambiguity (Khan, 2025). The authors attempt to answer the research questions (RQs) mentioned below in the best possible manner with the help of a comprehensive literature survey:

RQ1: What algorithms are used to optimize process parameters across various manufacturing processes?

RQ2: How has machine learning contributed to the optimization of manufacturing process parameters?

RQ3: What challenges and opportunities are associated with process parameter optimization implementation?

These research questions are addressed throughout the article. The *Foundation of Process Parameter Optimization* section demonstrates the foundation of manufacturing process parameters as an optimization problem as well as differentiates between offline and online optimization approaches. The research methodology, including the collection process of the research material, is described in the *Research methodology section.* An extensive review of the literature categorized into different manufacturing processes is described in section *Literature review* while also answering RQ1. Section *Survey retrospective* reflects on the review of the literature and answers RQ2. It also addresses various challenges that come across from the literature review for the implementation of process parameter optimization into the industry (RQ3). Finally, a conclusion is provided in the last section. The overall paper serves as a guide for future research in the field of manufacturing process parameter optimization.

Novelty and contribution of this review

Unlike previous surveys, this paper integrates both offline and online manufacturing process parameter optimization methods. Weichert et al. (2019) focused narrowly on machine learning (2008–2018) for quality and process improvement, and Panzer & Bender (2022) reviewed only deep reinforcement learning (RL) in production settings. In contrast, this review explicitly spans the full spectrum of algorithms. For example, it is found that evolutionary approaches dominate offline manufacturing process parameter optimization studies whereas real-time RL controllers are relatively rare (only $\sim 6-7\%$ of papers). The review also emphasizes aspects largely missing from prior surveys, such as improving process capability (Cpk) via adaptive control and embedding optimization into live factories. In summary, the contributions of this work are: (a) a unified conceptual framework combining modeling, batch and online optimization, and deployment; (b) a broad literature synthesis across manufacturing processes and methods; and (c) highlighting underexplored areas such as online and RL methods, as well as integration challenges that earlier reviews did not cover.

Foundation of Process Parameters Optimization

Manufacturing process parameter optimization is defined as the process of identifying optimal parameters within a defined parameter space that adhere to user-specified boundary limits and enhance the quality of the produced part. These parameters may span over multiple stages of the manufacturing process and may exert either direct or indirect influence on the final part quality. As noted by Oh, Han, and Cho (2001), process parameters can be classified based on their controllability. Controllable parameters are those that can be adjusted either manually or automatically, for instance, the roll gap trim in the rolling process. Conversely, uncontrollable parameters cannot be modified, examples of which include environmental temperature, material properties, and other inherent factors.

Let X_c represent the set of controllable parameters and X_u the set of uncontrollable parameters. The complete process parameter set X can be expressed as:

$$X = X_c \cup X_u \tag{1}$$

The optimization of process parameters can be categorized into two main types: offline optimization and online optimization. This categorization is based on whether the requirements for optimization are static (offline) or dynamic (online). The terminology is inspired by the work of Dagge et al. (2009), which discusses these concepts in the context of cement production analysis. The distinction between these categories is elaborated below with illustrative examples.

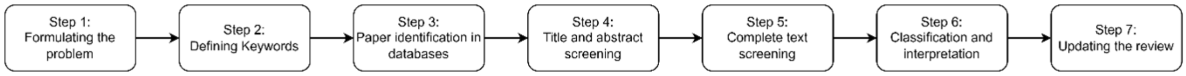

Fig. 1. Step by step approach for a comprehensive review for manufacturing process parameter optimization

Offline optimization: Offline optimization involves adjusting process parameters before actual production begins. This approach allows for the determination of an optimized configuration that serves as a baseline during the production phase. For example, in a food processing plant that produces products in series, presetting oven parameters – such as temperature and baking time – during the pre-production stage can enhance product texture and minimize defects, such as burnt loaves. This preparatory optimization is crucial for ensuring consistent quality from the onset, without considering any dynamic changes during manufacturing.

Online optimization: In contrast, online optimization refers to the adjustment of process parameters in a dynamically changing environment. This technique continuously refines control parameters in response to fluctuating conditions, such as variations in ambient temperature, oven settings, or sheet thickness requirements in rolling processes. Unlike the pre-production settings used in offline optimization, these adjustments are made dynamically during production cycles to address real-time operational needs. Here, "real-time" indicates the time frame available for making specific adjustments, such as trimming the roll gap in a flexible rolling process.

To express the statement mathematically, let X_c denotes the set of optimized control parameters and F_{opt} denotes an optimization model. The set of optimized parameters can then be calculated using the equation:

$$X_c = F_{\text{opt}}\left(X_o, M_{\text{process}}\right) \tag{2}$$

In this equation, X_o denotes the initial set of process parameters or random initialization and M_{process} refers to the process model. The process model represents any statistical, analytical, simulation, rule-based model or machine learning based model. The process model is a substitute for the real process. M_{process} can be represented by a real process; however, this is often impractical due to the high costs and resource waste involved in training the optimization model, as highlighted in section *Literature review*.

Research Methodology

This section outlines the basic methodology employed for the literature review on process parameter optimization. The systematic approach adopted for this review is inspired by the work of Panzer and Bender (2022). A seven-step methodology, as illustrated in Figure 1, was utilized to ensure a comprehensive and structured review. The reviewed research has been categorized based on different types of manufacturing processes, with detailed discussions provided in section *Literature review*.

Collection of research papers

Research papers published in journals and conferences over the past two decades were collected (Fig. 2). Keywords used for filtering these articles include 'process optimization,' 'process parameter optimization,' and 'quality control' in abstract and at least 'optimization' in the article's title. This keyword search procedure was applied to databases such as, but not limited to, ScienceDirect, Taylor and Francis Online, and IEEE Explore. A comprehensive literature review was undertaken from the year 2000. Publications predating 2000

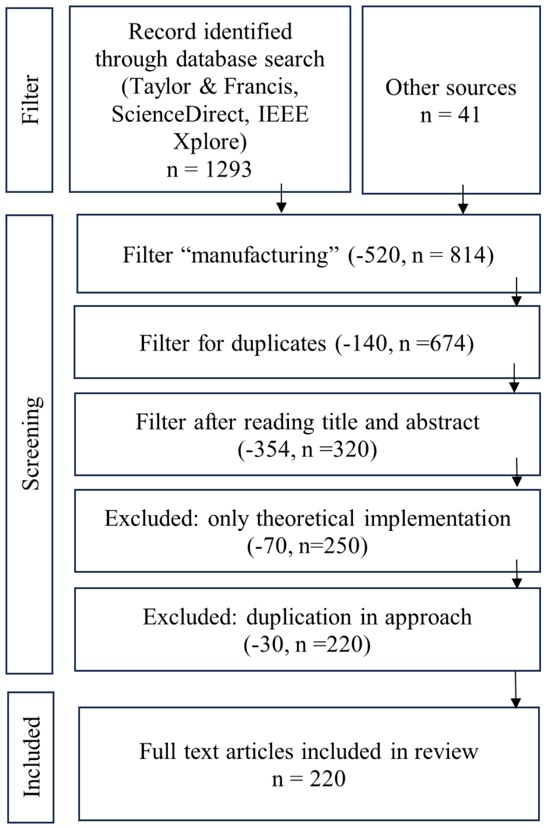

Fig. 2. PRISMA flow diagram illustrating the literature selection process

exhibit a limited number of instances related to the optimization of process parameters. An overview of the number of publications for manufacturing process parameters per year is illustrated in Figure 3. The papers from the database search results were examined by their title, keywords, and abstract to ensure relevance to manufacturing process parameter selection and optimization. The survey intentionally avoided the problem of process scheduling and dispatching, as it is a relatively older optimization problem with significant research already conducted. Considering the practical focus of the optimization problem under review, papers emphasizing methodology, theory, or algorithm development without application to a manufacturing use case were given less importance. Any duplicates or papers addressing the same manufacturing problems, process simulations, and optimization processes without any new and relevant conclusions were filtered out. This process is summarized in the PRISMA flow diagram shown in Fig. 2, resulting in the collection of approximately 220 papers from the last two decades. The next section summarizes the work, focusing primarily on techniques used for optimization.

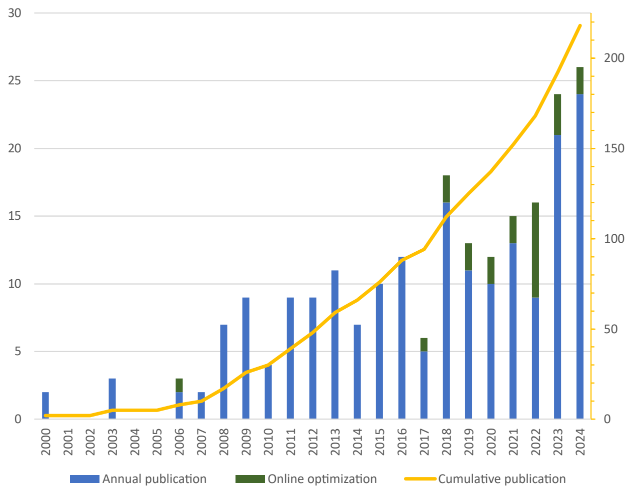

Fig. 3. Number of online and offline optimization publications per year from 2000

Classification of research papers

The collected research papers have been classified according to their process type, as shown in Figure 4 This classification of process is inspired by the work of Groover (2021) and various use cases encountered during the survey. The chemical process has been included in the review due to the substantial number of research papers addressing the optimization of chemical processes. Additive manufacturing has been categorized under shaping processes, as defined by Gibson, Rosen, and Stucker (2014). Most of the published research focuses on various types of machining processes, encompassing both conventional methods, such as milling, turning, and drilling, and non-traditional methods, including electric discharge machining and abrasive jet machining.

Process model and optimization model

The optimization of manufacturing process parameters typically involves two main steps. The first step is the development of an appropriate process model, which serves as a surrogate for the actual manufacturing process. This model can take the form of a simulation, predictive surrogate and is used to emulate the behavior of the real process under various parameter settings. In the second step, an optimization model or algorithm is applied to the process model to determine the optimal set of process parameters. The objective of the optimization model is to identify the global or local minima within the parameter space, ensuring improved performance or quality outcomes.

Directly training optimization algorithms on live manufacturing processes is generally avoided due to the associated risks of production halts and waste generation. Instead, process simulations or predictive models, trained using orthogonal experimental data, Design of Experiment (DoE) data, or historical data are widely employed. These models are capable of predicting target quality based on process parameters and provide a controlled environment for validating optimization algorithms. In this research, such models are collectively referred to as the process model.

A straightforward method for parameter optimization involves grid search across an n-dimensional parameter space to locate the global minimum. However, advanced optimization techniques offer more efficient alternatives. The focus of this survey is on the optimization algorithms applied to various manufacturing processes. The literature review section specifically examines these algorithms, and the findings are summarized in a pie chart highlighting the prevalence of different techniques.

Literature review

To address the research questions, the collected papers were analyzed and interpreted according to their categorization as shown in Figure 4. The depth and extent of the content of the subsections are influenced by the number of publications for the respective process type.

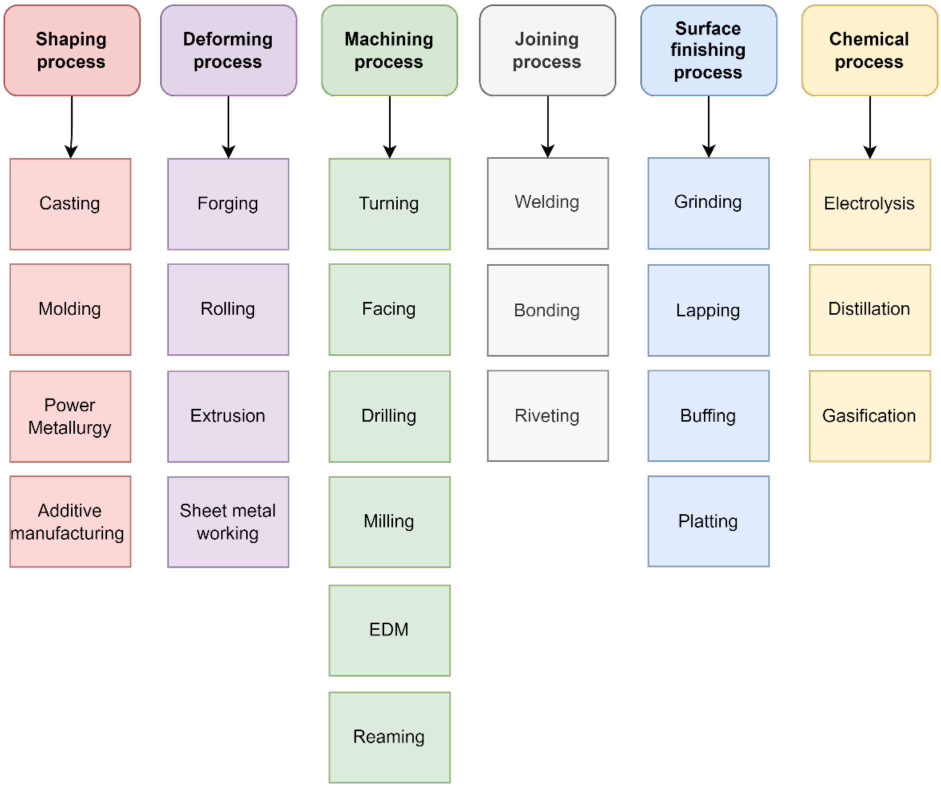

Fig. 4. Classification of the production processes into various categories

Shaping process

Shaping processes involve removing material to create specific shapes, with complexity varying based on the material, geometry, and precision required. Process parameter optimization techniques are widely applied in shaping processes like casting, injection molding, and additive manufacturing to enhance performance.

In Low-Pressure Die Casting (LPDC), Zhang et al. (2007) used the Taguchi DoE method, neural networks, and genetic algorithms (GA) to optimize temperature parameters, reducing porosity in automotive wheels. Chandrasekaran et al. (2019) combined simulation software, Taguchi DoE, and ANOVA to optimize filling time and shrinkage porosity, lowering scrap rates from 14% to 9%. Li et al. (2021) employed XGBoost and GA for improved quality in casting processes. Kaushik and Singhal (2018) optimized wear resistance in metal matrix composites using a hybrid Taguchi-GRA-PCA approach.

Injection molding studies applied ANNs for process simulation and optimization techniques like PSO and GCA (Grey Correlation analysis) to minimize defects in parameters like shrinkage and edge thickness. Guo et al. (2019) demonstrated real-time optimization with RL, enhancing precision and improving the process capability index for optical lens manufacturing. This is an example of online optimization.

Additive manufacturing involves printing three-dimensional object layer by layer using digital design data. Considered to be one of the expensive processes, most of the process optimization work focuses on finding the right process parameters with limited amount of experimental data. Miyanaji et al. (2016) used DoE and ANOVA to find optimal process parameter for 3D printing of porcelain structures. Ahsan, Habib and Khoda (2016) used GA to determine optimum build orientation and tool path deposition direction to minimize fabrication complexity for parts in AM processes. Dharmadhikari, Menon and Basak (2022) discuss on-the-fly (online) optimization framework with RL for metal AM system. An off-policy reinforcement learning framework, based on Q-learning, is proposed to identify the optimal combinations of laser power and scan velocity with the goal of maintaining a steady-state melt pool depth.

Deforming process

The deforming process, also known as the forming process, involves altering the shape of a material by applying mechanical forces. While primary shaping processes encompass a broader range of techniques to create initial forms and shapes, deforming is mainly focused on altering the shapes with forces of bending, stretching, compression, or rolling. Various deforming processes tend to demonstrate process parameter optimization with evolutionary algorithms mainly GA and PSO. For optimization of the roll-forming process, Park and Binh (2012) integrate a knowledge-based neural network with genetic and hill-climbing algorithms. Shi, Yin, and Yang (2014) applied PSO to rolling mills and demonstrated about 2% reduction in energy consumption by optimized rolling reduction parameters. A similar optimization analysis with PSO is carried out for cold rolling mills (Hong et al., 2015).

For the optimization of small-dimension tubes, Leps et al. (2018) used NSGA-II (Non dominated Sorting GA) on a FEM simulation process model. Daddona and Antonelli (2018) and Kriechenbauer et al. (2021) also utilized FEM with GA algorithms for the optimization of forging and deep drawing processes, respectively. To the best of the author's knowledge, no studies on online optimization were identified for the deforming process.

Machining process

Machining process involves controlled material removal to achieve specific shapes, sizes, and surface finishes, categorized under subtractive manufacturing. Extensive research explores optimization techniques for machining processes such as milling, cutting, drilling, electric discharge machining (EDM), and turning. GA and ANN have been widely employed to optimize cutting conditions, considering factors such as production rate, operational cost, and surface roughness.

Cus and Balic (2003) discussed that GA provides accurate results for optimizing machining parameters but requires more time for training and testing. The program integrated with GA is slow but highly reliable. Majumder et al. (2024) employed three desirability-based PSO algorithms – PSO-original, PSO-inertia weight, and PSO-constriction factor – to optimize electrical discharge machining (EDM) process parameters. Their objective was to maximize the material removal rate while minimizing the electrode wear ratio. Among the approaches, the PSO-constriction factor demonstrated the fastest convergence and the best performance for this EDM optimization task. Mukkoti et al. (2020) examined the milling process, focusing on the effects of deep cryogenic treatment on tungsten carbide end mill cutters used for machining P20 steel. They employed NSGA-II for multi-objective optimization to identify the optimal process parameters, balancing trade-offs among material removal rate (MRR), tool wear rate (TWR), and surface roughness (Ra). Other algorithms, including PSO, simulated annealing (SA), and ant colony optimization (ACO), have been applied to different machining processes: multi-pass milling (Rao & Pawar, 2010), turning (Zheng & Ponnambalam, 2010), and abrasive water jet machining (Zain, Haron, & Sharif, 2012), respectively. Huang et al. (2015) introduced a hybrid Cuckoo search and TLBO algorithm for abrasive water jet machining. Modern approaches include the Imperialist competitive algorithm and Krill Herd algorithm for enhanced parameter optimization (Yang et al., 2013; Balaji et al., 2021). Machine learning methods, such as 1D Convolutional Neural Networks, NSGA-III, and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), have been employed to optimize performance metrics, including cutting force, energy efficiency, and surface finish (Wu et al., 2022).

In the direction of online optimization, Huang, Su, and Chang (2022) and Quang et al. (2022) have demonstrated the usage of RL for camshaft and milling process. The details are provided in subsection *Online optimization*.

Joining process

The joining process involves techniques for combining two or more separate materials or components into a single, unified product. The literature on process parameter optimization encompasses a wide range of joining methods, including laser metal inert gas (MIG) welding, submerged arc welding, resistance spot welding, arc welding, laser magnetic welding, laser brazing, and ultrasonic welding. Valera et al. (2017) optimized the resistance spot welding process for dissimilar micro-alloyed TRIP (Transformation Induced Plasticity) sheets using Taguchi DoE. The study identified key process variables through signal-to-noise ratios and assessed their significance via ANOVA against Shear Tensile Strength test results. A direct relationship between nugget diameter and joint strength was established. Electrical current and welding time were found to be the primary factors influencing the results, with current having a slightly greater impact on tensile strength. Rong et al. (2016) optimized laser brazing process by building a prediction model for top and bottom width of weld bead. They exploited machine learning methods over normal feed forward neural network as the prediction model. Using GA, optimal parameter setting was found out. The results are validated on one-third of the experimental data as well as confirmed by verification experiment. DoE appears to be the common trend in the optimization process for joining process. Quang et al. (2022) demonstrated an RL-based adaptive closed-loop control system for laser welding processes, serving as an example of online optimization in joining process.

Surface finishing process

Surface finishing is a set of processes applied to the outermost layer of the material or product to enhance its appearance, durability, corrosion resistance, wear resistance, and other desirable characteristics. Xiankun and Haolin (2008) proposed Pareto-PSO, a hybrid optimization technique, for multi-objective optimization of surface grinding. Four process parameters, namely wheel speed, workpiece speed, depth of dressing, and lead of dressing, were optimized against three quality criteria: production cost, production rate, and surface smoothness. They reported better performance with Pareto-PSO over GA and Ant Colony Optimization algorithms for a multi-objective approach. For glass polishing, Wang (2016) used Taguchi DoE, ANOVA, and Grey relational analysis with Genetic-Immune algorithms to optimize glass thickness uniformity.

The algae ball grinding process was optimized using an ANN and an exhaustive search within the constrained solution space for optimizing protein absorbance (Fernando, Maglaya, & Ubando 2017). Roller grinding processes utilized a Response Surface Model (RSM) in combination with a Hybrid Particle Swarm Optimization (PSO) algorithm to optimize surface finish (Chen et al., 2018). Finishing processes for machining deformation have been demonstrated using a Finite Element-based model in ABAQUS, coupled with a meta-reinforcement learning approach utilizing a deep Q-network (DQN) for deformation control (Liu et al., 2022). Büscher et al. (2023) postulated the application of RL for the optimization of cleaning process parameters, thus targeting the removal of contaminants and particulate matter from metallic components via imitation learning. However, they have not presented empirical evidence to support this proposition.

Chemical process

Chemical process refers to a sequence of transformations and reactions that involve a chemical substance to produce a desired product or a specific outcome. Yee et al. utilized NSGA for multi-objective optimization of styrene reactor. Multiple optimized objectives include production, yield, and selectivity of styrene. Gong, Zhao and Bai, (2009) designed orthogonal experiments to train a predictive model using neural networks coupled with GA for optimizing parameters of photosensitive resin solidification process. A similar approach for optimization is reported by Norhalim, Ahmad, and Don (2013) for optimization of enzymatic hydrolysis of xylose production. Salas et al. (2021) demonstrated a simulation-based multi-objective optimization to determine the optimal operating conditions for a natural gas liquids (NGL) recovery unit.

The use of reinforcement learning is not alien to chemical process optimization. Petsagkourakis et al. (2019) utilized RL to optimize bioprocess under unsteady state operation modes and stochastic behaviours. Other online chemical processes using RL include hydrocracking process, solvent switch process, emulsion polymerication. These are detailed in subsection *Online optimization*.

It can be concluded that there is no exact relationship between the process and the optimization algorithm used. Once the process model is available, performing optimization is agnostic of the model.

Online Optimization

Most of the above-mentioned research in various process type refer to offline optimization. This section focuses explicitly on online optimization research encountered in the survey. A total of 11 papers discuss online optimization with dynamic changing situation. RL emerges as the predominant optimization model for online optimization, with nearly 90% adoption, as highlighted in the survey. Since the process state can be considered as a Markov Decision Process (MDP), RL emerges as a promising choice (Sutton & Barto, 2018). A recent publications on online optimization are summarized Table 1.

RL offers a paradigm shift in online optimization for manufacturing processes, enabling adaptive control policies that respond to dynamic disturbances and process drift in real time. Unlike static offline optimization or rule-based feedback systems, RL methods continuously refine decision policies based on accumulated rewards and environmental feedback. This flexibility allows RL to maintain or improve key quality metrics, such as process capability (Cpk), yield, and energy efficiency, despite fluctuating input conditions. As industrial systems increasingly adopt real-time sensing and computing, RL-based controllers are poised to become central components in smart factory deployments. However, translating RL from simulation to practice requires addressing issues like safe exploration, real-time constraint handling, and interoperability with existing infrastructures. As reviewed in the next sections, these challenges present both a research frontier and a deployment opportunity for future adaptive manufacturing process parameter optimization systems.

Table 1
Step by step approach for a comprehensive review for manufacturing process parameter optimization.

Reference	Process	Summary
Guo et al. 2019	Injection Molding	Enhance the process capability index (Cpk) of lens thickness in continuous production from 0.315 to 1.720. An RL actor-critic framework is employed as the optimization model.
Petsagkourakis et al. 2020	Chemical process	RL is used to optimize control policies for batch bioprocesses, focusing on maximizing specific performance metrics like product concentration or economic objectives in uncertain and stochastic environments.
Zimmerling, Poppe, and Kaerger 2020	Textile draping	The optimization of variable geometry in a textile variable is tackled with CNN-based RL actor-critic framework on 20 sample points.
Oh et al. 2021	Chemical process	Addresses the nature of changing requirement in hydro cracker production with RL actor-citic framework to find optimal operating condition.
He et al. 2022	Textile manufacturing	Optimize quality, productivity, and cost in textile manufacturing with deep Q-network (type of RL algorithm). A comparative study shows superior results as compared to NSGA-II and multi-objective PSO.
Liu et al. 2022	Finishing process	Deep Q-network approach is utilized to minimize machining deformation during the finishing process to ensure improved product quality and process efficiency?.
Huang, Su, and Chang 2022	Machining process	Uses unique approach for process model with Graph Neural network to model machine as nodes and material flow as edges for camshaft manufacturing. It uses state-of-the-art value deposition multi-agent RL for optimizing grinding process. Validation on real process data was not conducted.
Quang et al. 2022	Welding process	Uses Q-network to adapt the laser power in real-time based on feedback signals from optical sensors to maintain target weld quality. Since optimization is done on live process, surrogate model is not required.
Li et al. 2023	Machining process	Integrated method to optimize energy consumption and production time in milling operation is reported by optimizing cutting speed, feed rate, and depth based on the degree of tool wear. RL-based proximal policy optimization (PPO) algorithm is used to report reduction of 7.6% energy consumption and 8.6% production time.
Elmaz et al. 2023	Chemical process	An RL-based approach for optimizing a solvent-switch process was developed using the PPO algorithm to manipulate jacket temperature and solvent flowrate. This method reduced process completion time by 25.2% and overall cost by 24.9%, introducing a novel overlapping-phase strategy for solvent evaporation and distillation?
Ballard et al. 2024	Chemical process	Optimization of emulsion polymerization processes for target particle morphology is achieved by controlling monomer feed rates and reactor temperature using the twin-delayed deep deterministic (TD3) RL algorithm. The approach demonstrates nearly identical morphology to reference processes while reducing overall reaction time and improving control over copolymer composition.

Conceptual synthesis framework

As observed from the reviewed articles, a conceptual framework can be derived for manufacturing process parameter optimization. It can be viewed as an end-to-end workflow linking process modeling, optimization type (either online / offline), and optional industrial deployment. In a typical framework, a Process Model captures how inputs affect quality. This can correspond to simulation-based model, data-driven model or even real process with a feedback loop. This model feeds into the optimization stage that identifies optimized parameter settings for static conditions (offline). These settings serve as baselines for an online optimization controller that continuously adjusts parameters in response to disturbances or drift. Finally, the deployment phase integrates the controllers into shop-floor systems (with sensors, PLCs, MES, etc. constituting the data-pipeline), closing the loop by funneling real-time process data into models and optimizers. Such a unified loop ties together data integration, modeling, optimization and deployment in one framework as shown in Figure 5. In terms of algorithms, evolutionary algorithms are mainly used for offline optimization whereas RL-controller are proven to adapt parameters in dynamic setting for online optimization.

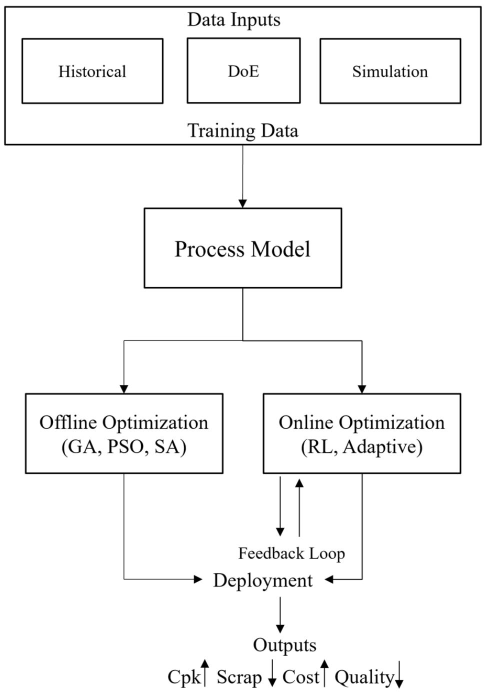

Fig. 5. Conceptual synthesis framework for manufacturing process parameter optimization

Survey retrospective

A general two-step procedure can be sketched across various manufacturing processes encountered in this literature review for the process parameter optimization goal. The first step is the construction of the process model. The process model can be either a live process or a surrogate process model. Only a limited number of process optimizations are performed on live processes, typically in cases where the parameters to be optimized are not high-dimensional. For surrogate-based process models, machine learning algorithms significantly outpace statistical or mathematical models in prevalence. Many researchers have advocated training machine learning-based predictive models (process models) using simulation-generated data, owing to the faster inference times these models provide. Others have relied on data generated from DoE. The survey indicates that the use of historical data for predictive models is comparatively limited.

The second step is the optimization of process parameters for the manufacturing process. Depending on the process and the requirements for process parameters a suitable optimization model is used. The optimization model then finds optimized process parameters for desired quality criteria either on a global level with complete control over the parameter space or on a more constrained parameter space. Figure 6 illustrates the share of various algorithms used for optimization. It can be concluded that meta-heuristics algorithms have the maximum share, mainly evolutionary algorithms. GA and PSO combined contribute to more than 40% usage which is because of their versatility and wide applicability. Additionally, a population-based search policy reduces the likelihood of getting stuck in local optima and this enables robust performance in complex optimization challenges. Grid-search accounts for nearly 4% of usage, a relatively low usage owing to the expensive calculation which scales exponentially with increasing dimensions. The use of RL for optimization is also evident from the survey with a 6% share coming from the last 5 years which indicates the rise of online optimization approaches but still with a relatively low share.

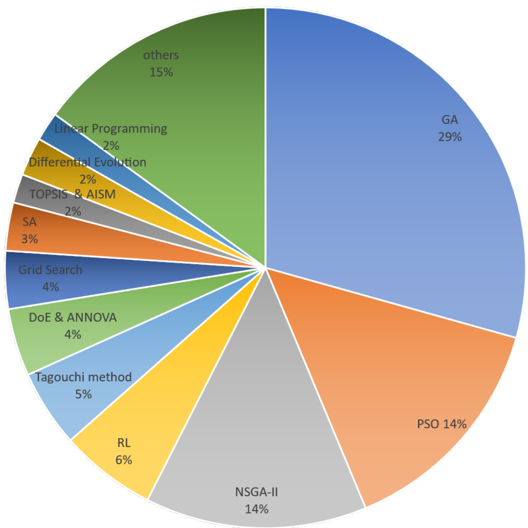

Fig. 6. Pie-chart showing the share of various optimization algorithms encountered in the survey

Scope of Machine Learning

The requirements for optimizing manufacturing process parameters are highly specific to individual use cases. When global optimal parameters are needed and runtime constraints are not a concern, meta-heuristic methods are predominantly employed, falling under the category of offline optimization. Evolutionary algorithms often require substantial runtime due to the absence of pre-trained models, relying instead on systematic or logical searches within the parameter space. As the dimensionality of the problem increases, these algorithms, including grid search methods, experience extended runtimes and reduced efficiency in providing timely results.

From the survey conducted, 12 studies report the application of RL for optimization, 11 of which pertain to online optimization. This approach is particularly suited for environments requiring dynamic adaptability and rapid determination of optimized parameters. Notably, 10 of these studies integrate process models with optimization models, while the remaining one involves direct interaction with live processes. A diverse range of RL algorithms, including Q-learning, policy gradient methods, and actor-critic networks, has been utilized for target optimization. The survey highlights that the primary motivation for adopting RL lies in its potential to create dynamic optimization frameworks capable of real-time adaptation. The findings underscore the growing prevalence of RL in online optimization applications. Addressing research question 2 (RQ2), the following key points are emphasized:

1. The scope of machine learning is wider for the construction surrogate process model but relatively less for the optimization model
2. Reinforcement learning usage is pre-dominant for online optimization.

Implementation challenges

To optimize manufacturing processes (RQ3), effective data collection is crucial. As previously mentioned, optimizing a live process is resource-intensive and prone to waste. When a simulation of the process model is available, the effort required to develop usable surrogate models for optimization is significantly reduced. However, process simulations are often unavailable or infeasible, particularly for interconnected and multi-stage manufacturing systems. To address this limitation, historical quality and production data can be utilized to train a predictive quality model. In the absence of such data, a DoE approach should be employed to collect useful data for the development of the optimization model. Regardless of the approach, training of a predictive quality model demands substantial data science expertise, which poses a greater challenge for manufacturing companies compared to software companies.

One significant challenge in manufacturing process optimization is the dynamic nature of influencing factors over time. Variations in supply chain dynamics, such as changes in material quality, availability, or sourcing, can impact process stability and outcomes. Environmental factors, including temperature, humidity, or other site-specific conditions, may further alter process behavior. Additionally, workforce-related shifts, such as changes in skill levels or operational practices, can introduce variability. These changes may render previously validated process models inaccurate or obsolete, as they fail to account for the evolving conditions. Consequently, continuous monitoring of process parameters and their relation to the quality parameter is essential to detect deviations and recalibrate the models. Without such adaptive measures, optimization strategies may lose their effectiveness, leading to increased scrap rates, inefficiencies, or degraded product quality.

As the dimensionality of the control parameter space increases, the execution time for an optimization model grows significantly. This significantly limits the application of optimization models in online settings, where real-time recommendations for control parameters are essential. According to the survey, online optimization is demonstrated with RL algorithm. However, training RL algorithms requires extensive datasets, comparable to those used for developing predictive quality models. The complexity of the task further escalates with an increase in the number of optimization targets and control parameters.

To validate optimized parameters in offline optimization (static processes), conducting a series of experimental tests with the optimized process parameters is generally sufficient to confirm the efficacy of the optimization approach. This is commonly referred to as industrial validation. However, applying the same validation methodology to online optimization (dynamic processes) is more complex and depends heavily on the level of industrial digitalization. A robust industrial validation for online optimization requires a well-established IT infrastructure, databases for efficient data collection, and streaming pipelines to process real-time data. Additionally, the availability of appropriate sensors and Internet of Things (IoT) devices are essential to enable accurate real-time data acquisition. To develop a comprehensive end-to-end data lifecycle pipeline for the manufacturing industry, apart from IT infrastructure and data science expertise, a willingness to adapt to new digitalization frameworks is required.

A forward-thinking approach is essential, emphasizing long-term optimization strategies aimed at reducing scrap rates, rather than relying solely on short-term results. However, this approach can be challenging due to the business models of certain industry sectors.

With the advancement of digitalization, manufacturing processes are generating an increasing volume of data across various stages. For parameter optimization, relying solely on a small subset of data from DoE may be insufficient, particularly in processes influenced by multiple manufacturing stages, which produce high-dimensional data for each charge number. Effectively utilizing this complex, high-dimensional data remains a significant challenge for both process model and optimization model.

Research directions

This section highlights key research directions derived from the challenges identified and the conducted literature survey. The prevalent use of evolutionary algorithms, such as GA and PSO, for process parameter optimization is well-supported. However, their limitations in real-time applications due to computational runtime constraints are a significant concern. This observation underscores the need for transitioning toward real-time optimization techniques, with Reinforcement Learning (RL) emerging as a promising alternative. The growing availability of real-time data and the demand for adaptable solutions in dynamic manufacturing environments further emphasizes the necessity of exploring RL and other advanced machine learning methodologies in online optimization contexts.

Manufacturing processes are inherently subject to variations over time due to factors such as machinery and tool wear, material variability, environmental conditions, and human influences. Addressing these challenges requires continuous monitoring of process models. As highlighted in the literature, surrogate models are commonly trained using data derived from DoE, simulations, or historical datasets. Nevertheless, it is essential to recognize that approaches to continuous validation and monitoring may differ across manufacturing processes. A dedicated monitoring module is therefore imperative to tailor validation efforts and ensure the robustness and reliability of surrogate models.

Paranjape et al. (2023) proposed a holistic framework leveraging RL for optimizing manufacturing process parameters. The efficacy of this approach, particularly concerning computational runtime, was demonstrated through comparative analyses using industrial datasets. However, the study lacks an industrial validation of the proposed framework, which is a critical requirement for translating such methodologies into practical applications. Additionally, the deployment and operationalization of advanced machine learning techniques face significant challenges, including the need for robust IT infrastructure, seamless real-time data integration, and scalability across heterogeneous manufacturing setups. The development of an integrated framework that addresses these aspects – encompassing data integration, surrogate modeling, optimization, and deployment into production – remains a vital area for future research.

In summary, the outlined research directions are timely and align with emerging trends in industrial digitization and intelligent manufacturing. They advocate for innovative approaches leveraging historical data, exploring alternative machine learning methodologies, and addressing operational challenges such as deployment and model monitoring. These considerations establish a strong foundation for advancing both research and practical applications in manufacturing optimization. Future research should also quantify the financial benefits of adaptive optimization methods, linking improvements such as defect reduction or faster changeovers to measurable economic indicators such as ROI and cost savings.

Economic and Management Perspectives

While the preceding sections focus on the technical foundations of process parameter optimization, it is equally important to acknowledge the economic and managerial implications of these methods in industrial environments. Industrial optimization ultimately aims to improve cost efficiency, productivity, and sustainability; therefore, economic objectives should accompany technical ones to ensure managerial relevance.

Several studies have incorporated cost-related or financial criteria into their optimization formulations. While most research focuses on technical measures such as defect rate, process capability (Cpk), or throughput, cost-oriented targets are equally important. Some RL-based scheduling and adaptive control studies have optimized for return on investment (ROI) or total production cost, linking algorithmic performance to financial outcomes. For example, Asadi et al., (2023) demonstrated that optimizing the reduction schedule in a tandem cold rolling mill can significantly reduce power consumption and improve process efficiency, and Lu et al. (2020) achieved a 10% decrease in electricity cost during battery assembly optimization. These examples demonstrate how advanced control can provide direct financial benefits.

Within the proposed conceptual framework (cf. Fig. 5), the economic dimension intersects with digital maturity. Highly digitalized manufacturing systems, equipped with real-time sensing and predictive maintenance, can incorporate dynamic cost variables such as energy pricing and production demand into optimization models. This alignment supports managerial key performance indicators such as cost, ROI, and operational efficiency.

Multi-objective metaheuristic methods identified in the literature, including Pareto-based approaches, often consider production cost or energy consumption as additional objectives. Similarly, performance measures such as overall equipment effectiveness (OEE) and first-pass yield (FPY) provide economically relevant indicators of efficiency. Integrating these economic factors with technical performance enables a more comprehensive evaluation of process improvements.

Conclusion

This paper aims to provide a concise overview of manufacturing process parameter optimization techniques. The three research questions introduced in section *Introduction*, which address optimization methods, the scope of machine learning applications, and the challenges in manufacturing process parameter optimization, are systematically explored and collectively addressed throughout the paper. A summary of these discussions is provided in the section *Survey Retrospective*. The key findings of this research are as follows:

- Process parameter optimization is a well-founded problem, with significant research already conducted for offline optimization scenarios.
- The survey reveals that data-driven approaches are prevalent, relying on data collected through DoE, orthogonal experiments, and historical datasets. However, the contribution of historical data was found to be comparatively low.
- Most process parameter optimization methods employ a joint framework, integrating a process model followed by an optimization model.
- Evolutionary algorithms, such as GA and PSO, are commonly utilized for offline optimization, particularly for identifying global optima.
- RL has been applied to online process parameter optimization, primarily in domains such as textiles, injection molding, machining, and chemical processes. This indicates significant potential for extending RL applications to other manufacturing processes.

With most of its seminal research for online optimization conducted in recent years, it presents substantial avenues for continued investigation. Constructing a comprehensive, end-to-end data-driven framework for manufacturing process optimization poses intricate challenges due to multifaceted considerations, thus inviting further academic and industrial research endeavors.

Data Availability

Data sharing is not applicable to this article as no new data was generated or analyzed during the study. However, the data supporting the findings of this study are available here https://github.com/akshay-paranjape/LitSurMPPO

Disclosure statement

No potential conflict of interest was reported by the author(s).

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