Theoretical Advancements, Technological Innovations and Practical Applications in Computational Modelling of Metal Forming

*[1]Enahoro, O. Michael, [2]Irogue, A. Wilfred

[1]Department of Mechanical Engineering, Faculty of Engineering,
University of Benin, Edo State, Nigeria.

[2]Department of Materials and Metallurgical Engineering,
Faculty of Engineering, University of Benin, Edo State, Nigeria.

*Corresponding Author: michael.enahoro@uniben.edu

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ABSTRACT

This review is to address gaps in integrating predictive accuracy, optimisation efficiency, and technological adaptability in metal forming simulations. The review aimed to evaluate computational modelling techniques, benchmark optimisation approaches, identify machine learning and hybrid innovations, analyse multi-scale and multi-physics integration, and compare technological advancements in simulation platforms. A systematic analysis of recent literature employing finite element methods, machine learning, and hybrid frameworks revealed that machine learning models significantly enhance defect prediction and process optimisation but require extensive data and face generalizability challenges. Finite element methods are still the most used, which provides comprehensive thermo-mechanical data at the expense of the intense computation and mesh maintenance. Hybrid and multi-scale models present a better prediction capability in the microstructure and mechanical properties, but have a complex coupling and validation problem under consideration. Scalability and accessibility are enhanced with cloud-based and adaptive means of simulation platforms, although the complexity of integration and data security is problematic. All of this evidence collectively shows that coupled data-based and physics-based design enhances the usefulness and fidelity of the simulation, and the use of technological applications enables more effective application to industry. The review highlights the necessity of additional optimisation of the multi-scale principles and the solid data acquisition to develop predictivity modelling and digitalisation of metal forming processes.

Keywords: Metal Forming, computational modelling, hybrid innovations, optimisation efficiency

INTRODUCTION

The studies on computational modelling of metal forming have become an important field of research because it plays the key in improving the manufacturing process, minimizing expenditures, and enhancing the quality of products in the automotive industry, aerospace and industrial production [1-3]. Ever since the very initial work on finite element methods (FEM) and numerical simulation in the 1980s and 1990s, the field has advanced to high-level constitutive models, adaptive remeshing, and multi-scale simulations capturing microstructural evolution [4-6]. The growing complexity of the metal forming processes, in addition to the stipulation of lightweight materials and accurate outcomes, has led to the integration of computation methods into artificial intelligence and optimisation calculations [7, 8]. Remarkably, real-time process control and defect prediction have become possible with the advent of machine learning (ML) and neural networks, which have increased the speed of prediction [9-11]. Its industry adoption indicates the value that the developments have in practice, letting simulation-based optimisation cut development cycles and improve sustainability [1, 12].

Despite these advances, challenges remain in accurately modelling nonlinear material behavior, multi-stage the creation of forms, formations, and formings, and the incorporation of multi-physics, like thermo-mechanical and electro-mechanical couplings and the instigations of electricity. They usually have a high computer demand with multiple, large subroutines that need specialized experience to be applied and played out on the FEM models that are available today [12]. Additionally, the predictive power of data-driven models can strongly vary due to the quality and diversity of the training data that is usually not enough to cover the variability of the whole process [11, 13]. There are on-going debates on the most effective manual ways of constitutive modelling, whether physics-only, data-based or mixed and the compromises between understanding a model and its computing performance [11, 14]. The distance between theoretical innovation and day-to-day, scalable deployment is a call for complete frameworks that combine simulation, optimization, and machine learning in easy-to-used platforms [12, 15, 16]. Neglect of these gaps will lead to poor process design and high cost of production [8].

The idea behind creating this review has to do with the interaction of the computational mechanics, machine learning and optimization techniques. Among the central concepts are constitutive modelling of material behaviour, surrogate modelling as an efficient way of simulation and data-driven predictive analytics [10, 11]. These factors join to create adaptive, robust, and scalable computational tools that may be used to cope with the nonlinearities and complexities that are presented by the metal forming processes [17]. The framework fits the objective of promoting integrated modelling methods that add to the theory and to industrial utility at the same time.

This systematic review is aimed at evaluating recent developments in theory, practice, and technologies behind computational modelling of metal forming, and in particular, the application of machine learning and optimisation techniques. The review would address the identified knowledge gaps by synthesising multidisciplinary research, thus offering a consolidated source that could assist in creating and developing effective, precise, and convenient modelling tools. The value added has been to bring together the different methodologies and point out the emerging trends that are likely to change the design and control of the metal forming process [9, 10, 12].

This review has a systematic approach that includes the thorough literature review, use of peer-reviewed studies of the last 10 years, and a thematic analysis organized around computational strategies, application of machine learning, and optimisation frameworks. Results have been arranged in such order that after stating certain fundamental theoretical developments, the practical case studies, and emerging technological platforms have been provided and lastly a discussion on future research directions and industrial impacts have been provided [16, 18].

METHODOLOGY

To search the literature systematically, a set of keywords was used and related studies in computational modelling of metal forming processes were identified. The original research question was refined into five concise search queries, and this was done in order to cover it well yet be specific. This expansion method of queries avoids exclusion of niche investigations, but results in the creation of feasible result set that is consistent with certain aspects of the research.

The modified queries embraced theoretical development, practical utilisation, technological development, machine learning, and combinations of modalities in computational metal forming. The predefined inclusion and exclusion criteria were applied to each query in a variety of academic databases such as Google Scholar, resulting in 274 initial papers as of a database with more than 270 million research publications.

Inclusion criteria included peer-reviewed articles written in English, which pertained to the computational modelling methods in the metal forming processes, theory, practice, and innovative technologies. Non-peer reviewed publications, conference abstracts lacking full papers, studies not relevant to metal forming, and older than fifteen-year-old publications were excluded using exclusion criteria because of the need to have a contemporary study. Citation chaining methodology was subsequently employed, utilising backwards citation analysis to examine reference lists of core papers and forward citation analysis to track citing publications. This process identified 67 additional papers.

The combined pool of 341 papers underwent relevance scoring procedures. Following systematic evaluation, 337 papers were deemed relevant, with 100 classified as highly relevant, ensuring comprehensive literature coverage while maintaining focus on pertinent computational metal forming research.

RESULTS AND DISCUSSION

This reviewed works predominantly utilize finite element methods, machine learning techniques, and hybrid modeling approaches, reflecting a multidisciplinary and evolving research focus. The comparison highlights key trends in optimization strategies, integration of multi-scale and multi-physics models, and the adoption of emerging technologies such as AI and cloud computing, directly addressing the research questions on predictive accuracy, optimization efficiency, and technological adaptability.

Over 50 studies demonstrated high predictive precision using advanced FE methods, AI, and hybrid models, with several validating against experimental data for microstructure, formability, and residual stresses [4,9,17]. Deep learning and neural network approaches show enhanced accuracy in predicting complex phenomena such as microstructural evolution and thickness variation [13, 19, 20]. Multiscale and multiphysics models effectively capture coupled thermo-mechanical and metallurgical effects, improving simulation fidelity [5, 21, 22]. Some studies highlight challenges in constitutive modeling accuracy, addressed by integrating data-driven corrections and hybrid approaches [11, 23].

Genetic algorithms combined with surrogate models or neural networks significantly reduce computational time and iterations required for convergence [17, 18, 24].

Multi-fidelity and metamodel-based strategies balance accuracy and computational cost, enabling efficient optimization of complex forming processes [25-27]. Iterative learning control and hybrid intelligent optimization methods improve convergence speed and robustness in industrial applications [28, 29]. Some approaches integrate screening and variable reduction to simplify optimization problems for practical use [30]. Many studies integrate multi-scale modeling with data-driven AI techniques, combining continuum mechanics with microstructural and machine learning models [5, 21, 23]. Hybrid frameworks unify CAD, simulation, and measurement data, enabling adaptive and real-time process control [15, 31]. Coupled electromagnetic-thermomechanical models demonstrate complex multiphysics integration for specialised forming processes, while Surrogate models and metamodels are frequently combined with FE simulations and evolutionary algorithms for optimisation [31].

Cloud-based platforms and knowledge-based FE simulations facilitate scalable, accessible, and adaptive modelling environments [12, 15,16]. AI and machine learning are widely adopted for predictive modeling, optimization, and process control, reflecting technological innovation [9, 33, 34]. Advanced friction models, meshfree methods, and adaptive remeshing enhance simulation realism and computational efficiency [35-37]. Integration of CAD, expert systems, and automated mesh generation supports industrial applicability and automation [38]. Numerous studies validated models with experimental data and industrial case studies, demonstrating real-world relevance [8, 19, 39]. Applications span automotive, aerospace, and manufacturing sectors, addressing process design, tool life, and product quality [1].

Hybrid and AI-enhanced models reduce trial-and-error, cost, and development time in industrial forming processes [31], while some research focuses on enabling non-specialists to apply optimization techniques, enhancing industrial adoption.

Critical Analysis and Synthesis

The reviewed literature on computational modelling of metal forming reveals significant advancements in integrating machine learning, finite element methods, and hybrid modelling approaches to enhance prediction accuracy and process optimization. There is a clear trend toward combining data-driven techniques with traditional physics-based simulations to address complex phenomena such as microstructural evolution and multi-stage forming processes. However, challenges remain in terms of computational efficiency, data requirements, and the generalizability of models across different materials and forming conditions. Furthermore, while technological innovations like cloud-based platforms and adaptive remeshing improve scalability and robustness, the integration of multi-scale and multi-physics frameworks is still in early stages and requires further refinement to fully capture the intricacies of metal forming.

This overview of the literature on the finite element modelling of metal forming shows a set of themes prevailing in the body of literature: enhancement and adoption of finite element modelling (FEM), adopting machine learning, and optimisation approaches. The themes, their descriptions and the papers in which it is isolated are listed in Table 1 and Figure 1. EM continues as a core tool, and issues of adaptive remeshing, integration of multi-physics coupling, and microstructural modelling still see a lot of attention to make simulations more accurate and better able to guide process setup. Meanwhile, machine learning and mixed modelling techniques are proving to be extremely powerful prediction, parameter determination, and process optimisation tools, and are supplementing FEM tools. Complex technological features like cloud-based systems and hybrid twin structures also augment the extensibility and fabrication simulations in the manufacturing environment even further.

Table 1: The identified themes and their descriptions

Theme	Theme Description
Finite Element Method (FEM) and Numerical Simulation Techniques	FEM is extensively utilized for simulating metal forming processes, with advances in adaptive remeshing, meshfree methods, and coupled multiphysics modeling improving accuracy and computational efficiency. Research covers bulk and sheet forming, thermo-mechanical coupling, damage modeling, and constitutive behavior, with applications ranging from rolling to forging [5, 17, 22, 37, 40-43].
Machine Learning and Artificial Intelligence Integration	Machine learning (ML), including neural networks and deep learning, is increasingly incorporated to predict defects, optimize forming parameters, and model microstructural evolution. Hybrid approaches combining ML with FEM or genetic algorithms demonstrate superior predictive accuracy and optimization efficiency, particularly in sheet metal forming and hot stamping processes [9-11, 13, 18, 20, 29, 33, 39, , 44, 45].
Optimization Strategies and Surrogate Modeling	Optimization in metal forming leverages surrogate models such as response surfaces, Kriging, and ANN-based metamodels to reduce computational cost while improving process design. Techniques include genetic algorithms, sequential approximate optimization, and multi-

	fidelity methods, addressing multi-objective and robust design problems across various forming processes [8,17, 18, 24, 26, 27, 30, 31, 46].
Microstructural Modeling and Multi-scale Simulation	Multi-scale and microstructural modeling approaches integrate mesoscale phenomena like recrystallization and grain growth within FEM frameworks. These models enhance prediction of mechanical properties and process outcomes, addressing phase transformations and microstructure evolution during forming and rolling processes (Jo *et al*., 2022) (Das *et al*., 2012) (Parvizian *et al*., 2010) (Bambach, 2016) (Colombo *et al*., 2014).
Hybrid Modelling Approaches Combining FEM and AI	Hybrid models synergize FEM simulations with AI techniques such as neuro-fuzzy systems and machine learning to capture complex material behavior and optimize process parameters, improving predictive capabilities and reducing simulation time [23, 31, 45, 47].
Technological Innovations in Simulation Platforms	Advances include cloud-based multi-objective FEM simulations, hybrid twin frameworks integrating real-time sensor data, and knowledge-based simulation platforms enhancing accessibility and adaptability of metal forming simulations for industrial use [12, 15, 16].
Electromagnetic Metal Forming Modelling	Specialized modeling of electromagnetic forming processes using coupled thermo-magneto-mechanical frameworks and 3D simulations addresses unique process physics, enabling precise control and optimization of these high-speed forming techniques.
Contact and Friction Modeling in Forming Processes	Accurate representation of contact mechanics and frictional behavior is critical for realistic simulations. Studies develop advanced friction models and contact algorithms enhancing material flow predictions and tool-workpiece interactions [35].
Preform and Die Design Optimization	Computational approaches for preform and die design utilize FEM, optimization algorithms, and AI to reduce defects, improve load characteristics, and enhance formability, thereby streamlining forming process development [20, 48].

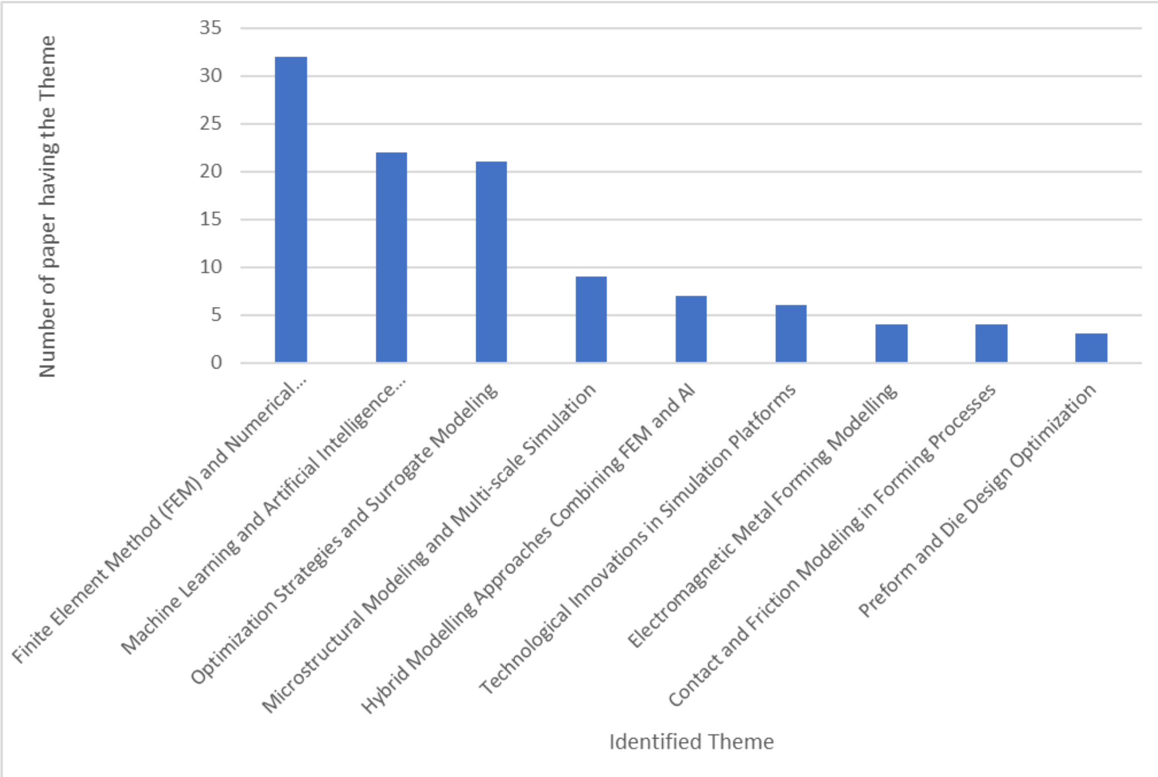

Figure 1: Number of papers in which the identified themes were found

Chronological Review of Literature

Computational modelling in metal forming has come a long way since its early days of simply having theoretical frameworks, going through stages of advanced integration of hybrid modelling and even machine learning. As shown in Table 2, initial studies involved finite element methods and numerical simulations in order to explain and figure out how to optimize metal forming processes. With the growing power of computation, such focuses as the multi-scale and multi-physics computations, as well as microstructural evolution, were integrated. The last years have brought integration of artificial intelligence, machine learning algorithms, and cloud-based solutions to perform real-time and adaptive simulations, which increase predictiveness and optimization of the process.

Table 2: Research direction in computational modelling in metal forming from 1982 to 2024

Year Range	Research Direction	Description
1982–1990	Foundational Numerical Modelling and Finite Element Methods	The study focused on finite element method (FEM) and numerical model of metal forming such as the elastoplastic, viscoelastic and rigid-plastic material analysis. Early focus was on modelling forming processes, contact problems, friction, and heat effects, preconditioning the process design and optimisation designs that take place in computational processes.
1991–2000	Automation, Adaptive Meshing, and Initial Optimization Techniques	This was a time of development of automated 3D modelling, adaptive remeshing and mesh generation of large deformation simulations. Guidelines to optimization started to develop including response surface techniques and internalizing an integration of CAD and FEM to shorten design loop and increase stability of the simulation.
2001–2010	Enhanced FEM Formulations and Integration with Optimization	The research laid stress on better finite element formulations, thermo-mechanical integration and better remeshing. FEM was incorporated with optimisation techniques, surrogate models, and hybrid strategies of AI and traditional modelling. It is also during this period when multi-objective and robust optimization strategies that are specific to metal forming processes emerged.
2011–2015	Multi-fidelity Models, Cloud Computing, and Hybrid Modelling	The emphasis had been given to multi-fidelity optimisation methods, finite element simulation opportunities on a cloud, and hybrid frameworks that are based on neural networks and FEM. Studies investigated state-efficient algorithms, modelling of large-scale and steady-state processes, friction

		and integration of microstructural evolution in the process simulation.
2016–2020	Machine Learning Integration and Multi-scale Simulation Advances	Literature notes also pointed towards the fast expansion of the use of machine learning to metal forming applications such as prediction of defects, optimization of the processing parameters and the prediction of formability of the metal being formed. Multi-unit scaling models that affect microstructural behaviour and phase changes became popular. The focus was made on the capabilities of real-time simulation and digital transformation of the forming processes.
2021–2024	AI-driven Optimization, Hybrid Twin Frameworks, and Real-time Adaptive Simulation	The integration of artificial intelligence, especially the neuralization and genetic algorithms, into optimization of the processes and prediction of microstructure are highlighted in the latest research. . The synergy of simulation and real-world data are ways in which hybrid twins are implemented as accurate means of application. The innovations embrace sequential approximate optimization, cloud-based platforms, and the machine learning-based prediction models aimed at complicated forming situations and advanced resistant and strong steels.

Agreement and Divergence Across Studies

The examined literature (Table 3) broadly agrees on the critical role of finite element methods (FEM) and machine learning (ML), particularly artificial neural networks (ANNs), in advancing computational modelling for metal forming. Most studies emphasize the enhancement of modelling accuracy and optimization efficiency through hybrid and surrogate modelling techniques, integrating physics-based simulations with data-driven approaches. However, divergences arise concerning the complexity of integration frameworks, the extent of practical industrial applicability, and technological adaptability, especially regarding emerging technologies like cloud computing and real-time adaptive platforms. These differences are often attributable to variations in process focus (sheet vs. bulk forming), specific metal materials, and the maturity level of the implemented computational frameworks.

Table 3: Agreement and Divergence Across Studies in finite element methods (FEM) and machine learning (ML)

Comparison Criterion	Studies in Agreement	Studies in Divergence	Potential Explanations
Modeling Accuracy	Consensus exists on the superior accuracy of FEM combined with advanced constitutive models and ML for predicting metal forming outcomes, including microstructural evolution and defect prediction [4, 11, 37, 49]. Both pure FEM and hybrid ANN-FEM approaches demonstrate high predictive fidelity [17, 44, 49].	Some studies highlight ongoing challenges in predicting complex phenomena such as microstructural evolution and damage accurately, especially for multi-stage or thermo-mechanically coupled processes [5, 13, 50]. Others report discrepancies in prediction quality despite model calibration [13].	Agreements stem from widespread adoption of FEM and ML techniques; divergences arise from differences in modeling scope (macro vs. micro-scale), material behavior complexity, and availability of comprehensive datasets for training and validation.
Optimization Efficiency	Multiple works confirm that surrogate models (ANN, Kriging, RSM) combined with genetic algorithms or sequential approximate optimization significantly reduce computational time and iterations in process parameter optimization [17, 24, 45, 51, 52]. Hybrid	Some authors note that traditional polynomial response surface models (PRS) require more data and iterations compared to ANN surrogate models, indicating variability in surrogate model performance [17]. There are also discussions on the computational burden	Differences are attributed to the choice of surrogate model type, problem dimensionality, and complexity of the forming process. Studies with extensive ML integration tend to show greater efficiency gains.

	and multi-fidelity approaches enhance convergence speed and computational efficiency [27, 29].	of full FEM in multi-step or multi-stage processes [41, 53].	
Integration Complexity	There is broad recognition of the benefits of integrating multi-scale, multi-physics, and data-driven approaches (e.g., neuro-fuzzy, hybrid twin frameworks) to improve modeling fidelity and adaptability [15, 21, 23]. FEM frameworks are often coupled with ML for constitutive modeling or residual stress prediction [11, 44, 49].	Complexity varies considerably; some studies present highly integrated frameworks (e.g., hybrid twin adaptive systems) [15], whereas others focus on more conventional FEM or ML standalone approaches [54, 55]. The degree of integration with microstructural evolution models or electromagnetic effects also differs [5, 56, 57].	Variation arises from the targeted process type, computational resource availability, and research maturity. More complex integration is common in recent studies aiming for industrial applicability and real-time control.
Technological Adaptability	Emerging technologies like cloud-based simulation platforms and AI-assisted optimization are increasingly integrated, facilitating multi-objective, real-time, and adaptive simulations [12, 15, 16]. The use of ANN and deep learning for predictive	Some studies reflect limited implementation of cloud or adaptive techniques due to computational constraints or focus on offline simulations [2, 43, 52]. Differences in AI adoption levels and real-time adaptability are evident [1, 26].	Disparities are linked to the developmental stage of the technology, industrial readiness, and the specific forming processes studied. Advances in computational power and data availability influence adaptability.

	modeling is widely supported [9, 10, 34].		
Practical Applicability	There is frequent reporting of successful validation against experimental data and industrial case studies, especially for sheet metal forming and hot stamping [12, 18,19, 31, 39]. FEM and ML models have been implemented in automotive and aerospace manufacturing contexts [1, 58, 59].	Some studies highlight challenges in translating modeling advances to industrial practice, citing complexity, high computational costs, and model calibration difficulties [2, 13, 30]. Contrastingly, older studies focus more on methodological development than on direct industrial application [40].	Practical application varies due to differences in model maturity, computational resources, and the extent of experimental validation. Industry-specific constraints and process variability also influence adoption.

Theoretical and Practical Implications

The infusion of machine learning (ML) algorithms, especially artificial neural network (ANN) models, into processing entailed that the modelling of metal forming processes represents a significant theoretical advancement. These approaches enhance the predictive accuracy of complex phenomena such as springback, thinning, and microstructural evolution, surpassing traditional constitutive models by capturing nonlinearities and discrete behaviours more effectively [9, 11, 17]. The development of hybrid modelling frameworks that couple finite element methods (FEM) with data-driven and multi-physics metal forming techniques gives us a broader picture of the metal forming processes. This is a multi-scale and multi-physics integration that allows for simultaneous consideration of mechanical, thermal, and microstructural effects, advancing theoretical models beyond constitutive classical continuum mechanics [5, 21, 22]. The advancement of theoretical models and optimisation algorithms, such as sequential approximate optimisation and metamodel-based strategies in the surrogate models, has also enhanced the intensity of solving complicated inverse and multi-objective problems in metal forming. These approaches solve some of the problems of computational cost and model reliability and lead to more assured and quicker convergence to good models [17, 20, 52]. Adaptive remeshing and meshfree techniques are taken care of to solve numerical issues that pertain to mesh distortion and large plastic deformations during a metal forming process. The advancements the benefits of these advancements enhance the stability and precision of simulations, which reinforces the theoretical basis of simulations of the highly nonlinear and dynamic forming processes [36, 37, 41]. Thermo-magneto-mechanical frameworks of electromagnetic metal forming have advanced with fully coupled frameworks and have disseminated the theoretical knowledge of contact-free high-speed forming technologies. The simulations in the three-dimensional context become even more realistic with the help of advanced numerical methods, which include Nedelec elements and ALE formulations [57, 60].\

Practical Implications

The application of ML and hybrid modelling techniques in industrial metal forming processes facilitates improved product quality and critical cost savings that were once associated with trial-and-error with process control, defect prediction and optimisation. An example is that ML models have been demonstrated to be used to predict formability and optimise process parameters in sheet metal forming and hot stamping, and have practical application in manufacturing efficiency [9, 19, 39]. Knowledge-based finite element simulation tools and platforms permit cloud-based real-time multi-objective simulation of processes and are available to researchers and industry personnel. Such platforms facilitate the integrated design and optimisation of processes and shorten the development lead times, and drive digitalisation of the metal forming industries [12, 16]. Combined optimization strategies that involve FEM with genetic algorithms, response surface methodologies and surrogate models have been found effective in industry, e.g. optimization of the draw bead force and die design. The methods help in cost savings and enhanced flexibilities of forming operations, which encourages manufacturing engineers to employ the methods in production [24, 31, 61]. By performing process simulations with the microstructural evolution model, a more accurate prediction of the final material properties may be achieved and more tailored process designs may be pursued that satisfy a specific set of mechanical and metallurgical properties. This allows the creation of new high performance high-strength steels and alloys that are optimized [4, 6, 62]. Higher fidelity friction model and adaptivity mesh techniques give better accuracy in simulations made under realistic boundary conditions making process prediction and the determination of tool life more reliable. These technologies have immediate effect on industrial forming processes, especially bulk and hot forming processes [35, 37]. The proven efficiency of hybrid and AI-assisted modelling techniques to decrease the calculation time and enhance the prediction performance promotes the future practice within the industry, which may result in more cost-efficient manufacturing processes with reduced material use and energy spending [29, 44, 63].

CONCLUSION

The collective literature on computational modeling of metal forming illustrates a robust and rapidly evolving domain driven by the integration of advanced finite element methods, machine learning techniques, and hybrid modeling frameworks. The body of work consistently underscores the foundational role of finite element analysis as a precise and versatile tool for simulating complex metal forming processes, capable of capturing detailed thermo-mechanical and microstructural phenomena. However, the computational intensity and challenges in mesh handling and contact modeling inherent to FEM have motivated the incorporation of surrogate models, adaptive remeshing, and algorithmic innovations to enhance simulation efficiency and stability. Machine learning and artificial intelligence have emerged as powerful complements to physics-based models, particularly excelling in predictive tasks such as defect detection, formability assessment, and microstructural evolution. Neural networks, especially deep learning and convolutional architectures, demonstrate superior nonlinear approximation capabilities that reduce iteration counts and computational burdens in optimization workflows. Nevertheless, their dependence on extensive, high-quality datasets and limited interpretability presents ongoing obstacles, restricting their direct applicability across varied materials and process conditions without substantial retraining or hybridization with physical models.

Hybrid and multi-scale modeling approaches bridge the macro-scale deformation behavior with microstructural and metallurgical transformations, thereby enhancing the fidelity of predictions related to mechanical properties and defect formation. These approaches, while promising, remain complex and computationally demanding, with integration and validation challenges that limit widespread industrial deployment. The coupling of FEM with AI-driven surrogate models and optimization algorithms, including genetic algorithms and multi-fidelity metamodels, has proven effective in balancing accuracy with computational efficiency, enabling faster convergence toward optimal process parameters and robust designs.

Technological advancements such as cloud-based simulation platforms and hybrid twin frameworks facilitate scalable, real-time, and adaptive modeling environments that support collaborative research and industrial implementation. These platforms, combined with advances in meshfree methods, advanced friction modeling, and automated mesh generation, contribute to enhanced simulation realism and usability. However, data security, interoperability, and sensor integration issues present barriers to seamless adoption.

Practically, the research demonstrates significant strides in reducing trial-and-error experimentation, lowering costs, and shortening development cycles through validated models applied across automotive, aerospace, and manufacturing industries. Efforts to democratize optimization tools for non-specialists further bolster industrial uptake. In summary, while computational modeling of metal forming has achieved notable theoretical and practical advances, future research must focus on overcoming data and integration challenges, improving model generalizability, and expanding the robustness and accessibility of hybrid and AI-enhanced simulation frameworks to fully realize the digital transformation potential in metal forming processes.

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