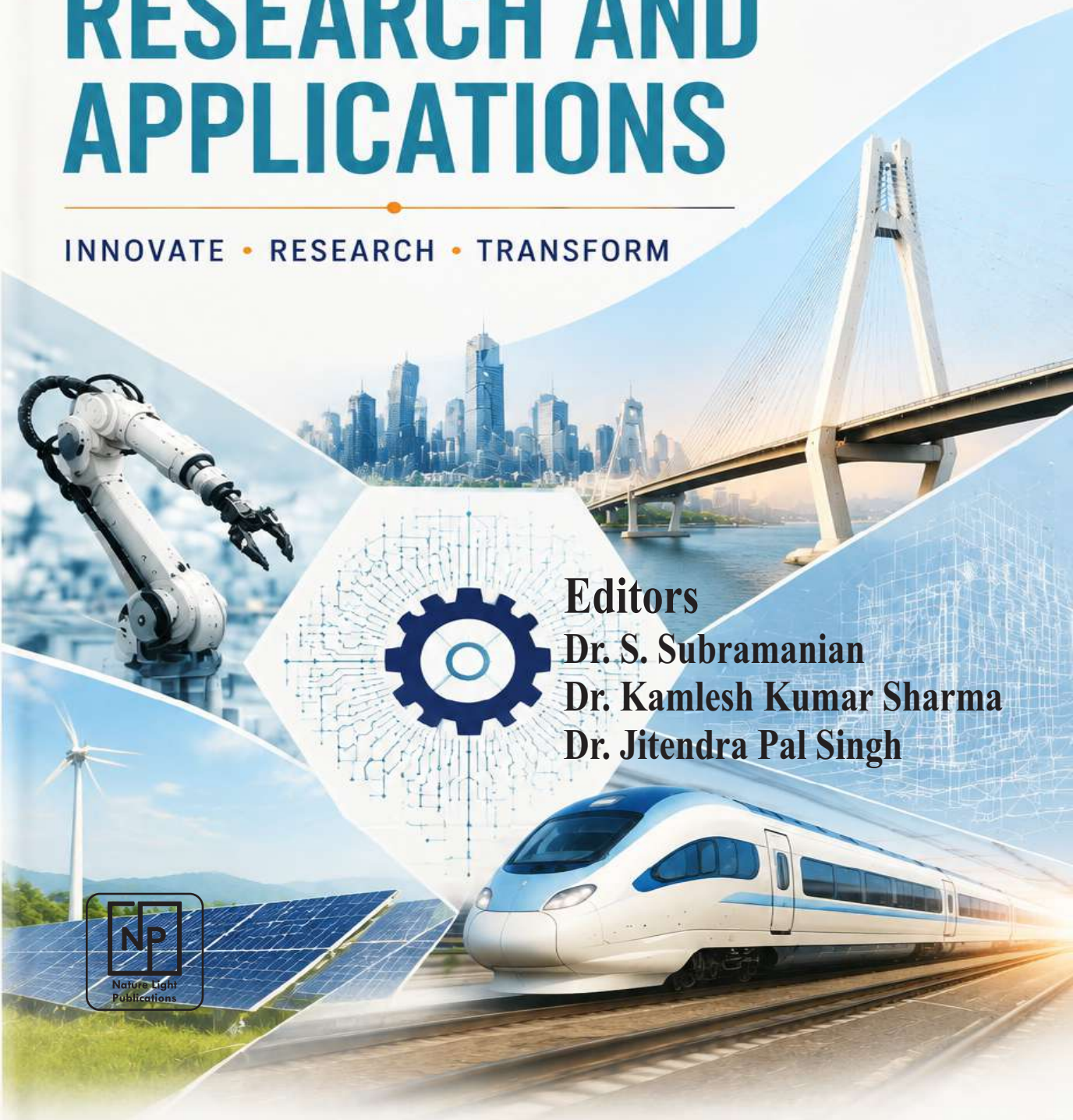
ADVANCES IN ENGINEERING RESEARCH AND APPLICATIONS

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Editors

Dr. S. Subramanian

Dr. Kamlesh Kumar Sharma

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Nature Light Publications

An International Edited Book *ISBN-978-81-69492-09-6*

Advances in Engineering Research and Applications

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Published By

Nature Light Publications, Pune

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First Edition: July, 2026

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Published by:
Nature Light Publications, Pune
309 West 11, Manjari VSI Road, Manjari Bk.,
Haveli, Pune- 412 307.
Website: www.naturelightpublications.com
Email: naturelightpublications@gmail.com
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Preface

Advances in Engineering Research and Applications is an edited volume that brings together recent research and innovative developments across diverse areas of engineering, applied mathematics, technology, materials science, transportation, artificial intelligence, and environmental applications. The book reflects the interdisciplinary nature of modern engineering and highlights the use of scientific and mathematical approaches to address emerging technological and societal challenges.

The volume covers a wide range of contemporary topics. The chapter on Human–Computer Interaction and User-Centered Design focuses on developing technologies according to human needs, usability, and user experience. Mathematical and analytical approaches are explored through studies on nonlinear reaction–diffusion equations, carbon dioxide removal, nonlinear ship rolling, and approximate solutions in amperometric enzyme kinetics. These chapters demonstrate the importance of mathematical modeling and analytical techniques in solving complex engineering and scientific problems.

The book also addresses emerging technologies through contributions on IoT-based electric vehicle battery health monitoring, automotive engineering and electric vehicles, and the application of differential equations and mathematical foundations in artificial intelligence and machine learning. These topics highlight the growing role of intelligent systems, computational methods, and advanced mathematical tools in modern engineering.

Further, the chapters on mathematical modeling in epidemiology and public health, CoS thin films, and engineered microbial consortia for environmental remediation demonstrate the application of engineering principles beyond traditional engineering domains. They emphasize the potential of interdisciplinary research in healthcare, advanced materials, environmental protection, and sustainable development.

Overall, this book provides a concise yet diverse overview of current engineering research and its practical applications. It is intended for researchers, academicians, engineers, scientists, students, and professionals seeking to understand recent developments and emerging directions in engineering and related fields. It is hoped that the contributions in this volume will encourage further research, innovation, and interdisciplinary collaboration for developing effective and sustainable solutions to future challenges.

Editors

Advances in Engineering Research and Applications

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 01 - 22

Human–Computer Interaction and User-Centered Design Designing Technology for People: Principles, Process and Practice

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Article DOI Link: https://zenodo.org/uploads/22079231

DOI: 10.5281/zenodo.22079231

Abstract

Human-computer interaction (HCI) and user-centered design (UCD) together constitute the discipline concerned with designing technology around the cognitive, perceptual, and physical capacities of the people who use it, rather than requiring users to adapt to arbitrary technical constraints. This chapter traces the evolution of HCI from early command-line interfaces through graphical, mobile, voice, and ambient computing paradigms, and examines the cognitive, motor, and ergonomic theories — including mental models, Fitts's Law, and GOMS analysis — that underpin interface design. It presents the formal, iterative user-centered design process codified in ISO 9241-210, along with the principal methods used to evaluate usability, from heuristic evaluation and usability testing to large-scale A/B testing and continuous field analytics. The chapter gives sustained attention to accessibility and inclusive design, including the regulatory landscape and the design of interfaces for cognitive and situational diversity, as well as the cross-cultural and global dimensions of designing for a linguistically and culturally diverse user base. It further examines how artificial intelligence is reshaping interaction design through probabilistic and adaptive systems, explainability and trust calibration,

agentic and conversational interfaces, and the ethical risks of manipulative "dark patterns." The chapter closes with an account of how organizations operationalize user-centered design through design systems and agile integration, illustrative case studies in healthcare, financial services, and e-government, and a discussion of the field's likely future directions.

Keywords: human-computer interaction; user-centered design; usability evaluation; accessibility; inclusive design; interaction design; user experience (UX); AI-driven interfaces; dark patterns; design systems

Introduction

Every time a person taps a smartphone screen, speaks to a voice assistant, swipes through a social media feed, or struggles to find the right button on a self-checkout kiosk, they are participating in an act of human-computer interaction. The field that studies and shapes these encounters, commonly abbreviated HCI, sits at the intersection of computer science, cognitive psychology, industrial design, and increasingly, ethics and social science. Its central premise is deceptively simple: technology is not merely a technical artifact to be judged by its computational efficiency, but a partner in a relationship with the people who use it, and that relationship can be designed well or designed poorly, with consequences ranging from minor irritation to catastrophic failure.

User-centered design, often treated as HCI's practical counterpart, is the disciplined methodology through which this design intention is realized. Rather than beginning with what a system can technically do and then asking users to adapt to it, user-centered design begins with the people who will use a system their goals, their limitations, their contexts, and their mental models of how things work and builds outward from that understanding toward a technical solution. The approach is now so deeply embedded in professional software and product development that it can be easy to forget it was once a genuinely radical proposition: that the person using a computer, not the computer itself, should be the primary consideration driving its design (Norman & Draper, 1986).

This chapter surveys the discipline of human-computer interaction and the practice of user-centered design from several angles. It begins with a brief history of how the field emerged and evolved, from the earliest command-line interfaces to today's conversational and ambient systems. It then examines the cognitive and perceptual foundations on which HCI theory rests, before turning to the formal process by which user-centered design is carried out in practice, as codified in international standards. The chapter surveys the major methods used to evaluate usability, considers the imperative of accessibility and inclusive design, and traces how interaction paradigms have shifted across successive generations of computing platforms. It then addresses the organizational practice of design within modern technology companies, the ethical dimensions of interface design, and the distinct

challenges posed by artificial intelligence as both a subject and an instrument of interaction design. It closes with a discussion of emerging directions and the enduring principles likely to persist even as the technology itself continues to change.

A theme that recurs throughout the chapter is that good design is rarely a matter of aesthetic taste alone. It is the product of a disciplined process — grounded in the systematic study of human cognition, perception, and behavior that treats usability, accessibility, and user well-being as measurable, testable properties of a system rather than a matter of subjective preference. Where earlier eras of computing could treat interface design as an afterthought bolted onto a completed technical system, the modern discipline of HCI insists that understanding the user must come first, and must remain present throughout the entire lifecycle of a product.

The Evolution of Human-Computer Interaction

The history of HCI is, in large part, the history of interfaces becoming progressively more attuned to human cognitive and perceptual capacities rather than to the internal logic of the machine. The earliest computers of the 1940s and 1950s were operated through switches, punched cards, and paper tape, interfaces that demanded users think in the machine's terms entirely; there was no concept of a 'user' as distinct from a trained specialist operator. The introduction of time-sharing systems and, later, the command-line interface in the 1960s and 1970s represented a first step toward interactivity, allowing a person to type instructions and receive an immediate textual response, but still required users to memorize precise syntax and abstract commands with no direct correspondence to the tasks being accomplished.

The pivotal shift came with the development of the graphical user interface at Xerox PARC in the 1970s, building on Douglas Engelbart's earlier demonstrations of the mouse and windowed interaction, and its commercial popularization through the Apple Macintosh and, later, Microsoft Windows in the 1980s. The graphical user interface introduced the now-familiar metaphor of windows, icons, menus, and a pointer — the WIMP paradigm — which allowed users to interact with representations of files and programs through direct manipulation rather than symbolic command recall. This period also saw the formal emergence of HCI as an academic discipline, marked by the founding of the ACM SIGCHI conference in the early 1980s and by foundational research establishing the cognitive and perceptual principles, discussed in the next section, that continue to underpin interface design today.

The 1990s and 2000s brought the World Wide Web, which introduced entirely new interaction patterns organized around hyperlinked navigation, and subsequently the rise of mobile computing, which forced a fundamental rethinking of interface design around small screens, touch input, and intermittent attention. The introduction of the multitouch smartphone interface in the late 2000s again

reorganized the field, replacing the mouse-and-pointer paradigm with direct finger-based manipulation of on-screen elements and popularizing gestural interaction — pinching, swiping, and tapping as a new interaction vocabulary. Most recently, the field has expanded into voice interaction, augmented and virtual reality, wearable and ambient computing, and, increasingly, conversational interfaces built on large language models, each of which relaxes or removes some of the assumptions a visible screen, a discrete pointing device, a single focused user on which decades of prior interface design theory were built.

This progression illustrates a durable pattern in the field: each new computing paradigm initially inherits interaction conventions from the paradigm that preceded it, before gradually developing conventions native to its own affordances. Early graphical interfaces mimicked the desktop metaphor of paper documents and physical folders; early mobile interfaces often shrank desktop layouts rather than rethinking them for touch; and early conversational AI interfaces frequently mimicked the turn-taking structure of text messaging before designers began exploring interaction patterns proactive suggestions, multimodal input, ambient awareness — better suited to the underlying technology's distinct capabilities.

Theoretical Foundations: Cognition, Perception, and Interaction

HCI draws heavily on cognitive psychology to explain and predict how people perceive, process, and act upon information presented through an interface. Human working memory, for instance, can hold only a small number of discrete items at once, a limitation with direct implications for interface design: menus with too many simultaneous options, forms requiring users to remember information across multiple screens, and error messages that assume recall of prior system state all impose cognitive burdens that well-designed interfaces work deliberately to minimize. This body of theory underlies Norman's influential framework of the 'gulf of execution' and the 'gulf of evaluation' the cognitive distance between a user's goal and the actions required to achieve it, and between a system's response and the user's ability to interpret what happened — which remains one of the most widely taught conceptual models in the field.

1. Motor Control and Fitts's Law

Beyond cognition, HCI theory also draws on the psychology of motor control to model the physical act of interacting with a device. The most influential such model is Fitts's Law, originally developed to describe rapid aimed hand movements and subsequently adapted for interface design, which predicts that the time required to move a pointer or finger to a target is a function of the distance to that target and its size: closer, larger targets can be acquired more quickly and with fewer errors than distant, small ones (Fitts, 1954). This apparently simple relationship has had an outsized influence on practical interface design; it explains, among other things, why frequently used buttons should be made larger and placed within easy reach,

why screen edges and corners function as especially efficient target locations because the boundary of the display effectively gives them infinite size in one dimension, and why touchscreen interfaces require larger tap targets than mouse-driven interfaces given the comparatively lower precision of a fingertip.

2. Modeling Human Performance: GOMS and Task Analysis

A related strand of HCI theory sought to build predictive, quantitative models of how long a skilled user would take to complete a given task using a particular interface, allowing designers to compare alternative designs analytically before building and testing them. The most influential such framework, developed by Card, Moran, and Newell, decomposes a task into Goals, Operators, Methods, and Selection rules commonly abbreviated GOMS and uses empirically derived timing estimates for basic perceptual, cognitive, and motor operations to predict overall task completion time (Card, Moran, & Newell, 1983). While the full rigor of GOMS analysis is now used mainly in specialized contexts such as safety-critical systems or high-volume repetitive tasks like call-center software, the underlying discipline of task analysis systematically decomposing what a user must do, in what order, and with what information, to accomplish a goal remains a foundational practice across virtually all user-centered design processes.

3. Mental Models and Conceptual Design

A further foundational concept is the distinction between a system's actual internal operation, the designer's intended conceptual model of that operation, and the mental model that a user constructs, often incompletely or incorrectly, through their own interaction with the interface (Norman, 2013). Effective interface design works to make the system's conceptual model visible and consistent enough that users' mental models converge on an accurate, useful understanding without requiring them to understand the system's underlying implementation. A well-designed file system, for instance, allows users to reason successfully about where their documents are and how to retrieve them without any awareness of how data is physically stored on disk; a poorly designed one leaves users uncertain, anxious, and prone to costly errors such as accidental deletion or duplication.

4. Human Factors and Physical Ergonomics

Alongside cognitive and motor models, HCI inherits from the older discipline of human factors and ergonomics a concern with the physical fit between people and the devices they operate: the height and reach of a workstation, the legibility of text at a given viewing distance and ambient light level, the auditory and haptic feedback that confirms an action has registered, and the cumulative physical strain that repeated interactions impose on the body over time. These concerns predate digital computing by decades, having originated in the design of industrial equipment, aircraft cockpits, and control rooms, but they remain directly relevant to

digital interface design: a mobile application that requires excessive repetitive thumb movement, a wearable device with a display unreadable in direct sunlight, or a workstation configuration that induces musculoskeletal strain during extended use are all failures of ergonomic design layered on top of, and sometimes masked by, an otherwise polished graphical interface. Contemporary HCI research increasingly treats physical and cognitive ergonomics as inseparable, particularly as interaction extends into wearable, vehicular, and industrial contexts where a poorly designed interface can directly compromise user safety rather than merely user convenience.

The User-Centered Design Process

Where the theoretical foundations discussed above explain why certain designs succeed or fail, user-centered design provides the procedural framework through which that understanding is systematically applied. The methodology is formally codified in the international standard ISO 9241-210, which defines human-centered design as an approach to interactive systems development that aims to make systems usable and useful by focusing on users, their needs, and their context, applying human factors and usability knowledge and techniques throughout (International Organization for Standardization, 2019). The standard specifies four interdependent activities, iterated repeatedly rather than completed once in sequence: understanding and specifying the context of use; specifying user requirements; producing design solutions; and evaluating those solutions against requirements.

1. Understanding the Context of Use

The process begins not with sketching interfaces but with structured investigation into which the users are what goals they are trying to accomplish, what prior experience and expectations they bring, and the physical, social, and organizational environment in which they will use the system. Common methods at this stage include contextual inquiry, in which researchers observe users performing tasks in their natural setting rather than in an artificial laboratory; semi-structured interviews that surface users' goals, frustrations, and workarounds; and diary studies that capture usage patterns over time that a single observation session would miss. The output of this phase is typically synthesized into artifacts such as personas composite, research-grounded representations of distinct user types and journey maps that trace a user's experience across an entire task or relationship with a product, both of which give a development team a shared, concrete reference point for who they are designing for, in place of an implicit and often mistaken assumption that all users resemble the designers themselves.

2. Specifying User Requirements

Findings from user research are then translated into explicit requirements: statements of what the system must allow users to accomplish, under what

conditions, and to what standard of performance and satisfaction. This translation is a genuinely difficult step, since users can rarely articulate their own requirements in fully specified form and often describe desired solutions rather than underlying needs; a substantial part of the discipline of user research lies in distinguishing between what users say they want and the deeper problem that a stated request is actually attempting to solve. Requirements at this stage typically address not only functional capability but also usability targets for instance, that a novice user should be able to complete a core task within a specified time and error rate and accessibility requirements that ensure the system remains usable by people with a wide range of physical, sensory, and cognitive abilities, discussed further in section 6.

3. Producing Design Solutions

Design solutions are typically developed through a progression of increasing fidelity: rough sketches and paper prototypes that allow rapid exploration of many alternative concepts at low cost; wireframes that establish layout and information hierarchy without visual polish; and interactive high-fidelity prototypes that closely approximate the look, feel, and behavior of the finished product. This progression reflects a deliberate strategy of deferring costly investment until a design direction has been validated, since changes are inexpensive to make on paper and increasingly expensive to make as a design moves toward implemented code. Parallel to this fidelity progression, many organizations apply structured ideation techniques associated with the broader design thinking movement including divergent brainstorming intended to generate a wide range of candidate solutions before convergent selection narrows toward a preferred direction as a means of avoiding premature attachment to the first plausible idea (Brown, 2008).

4. Evaluating Design Solutions

The final activity in the ISO 9241-210 cycle, evaluation, is what distinguishes user-centered design from design guided merely by intuition or aesthetic preference: design solutions are tested against real users and real tasks, and the resulting evidence, rather than the designer's or stakeholder's personal judgment drives subsequent revision. Because ISO 9241-210 frames the four activities as iterative rather than sequential, evaluation findings routinely send a team back to refine requirements or even to revisit the team's understanding of the context of use, rather than treating evaluation as a final gate before release. The specific methods used for evaluation, several of which have become standard practice across the technology industry, are discussed in detail in the following section.

Usability Evaluation Methods

A wide array of methods has been developed to evaluate the usability of an interface, differing in cost, required expertise, the stage of development at which

they are most useful, and the type of insight they yield. This section surveys the methods most widely used in contemporary practice.

1. Heuristic Evaluation

Heuristic evaluation is an inspection method in which usability experts examine an interface against a small set of established design principles, rather than observing actual users. The most widely used set of such principles, developed by Jakob Nielsen, comprises ten heuristics including visibility of system status, a match between the system and the real world, user control and freedom, consistency and adherence to standards, error prevention, recognition rather than recall, flexibility and efficiency of use, aesthetic and minimalist design, help for users to recognize and recover from errors, and the availability of help and documentation (Nielsen, 1994; Nielsen & Molich, 1990). Because heuristic evaluation requires no user recruitment and can be completed by a small team of two to five evaluators in a matter of hours or days, it is often used early in a design process or as a low-cost supplement to user testing, though the method's evident limitation is that expert evaluators, however experienced, do not always anticipate the specific confusions and workarounds that real users will exhibit.

2. Usability Testing

Usability testing involves observing representative users as they attempt to complete realistic tasks using a prototype or finished system, typically while thinking aloud so the observer can capture not just what users do but the reasoning, confusion, and assumptions behind their actions. Extensive research within the usability field has found that a relatively small number of test participants commonly cited estimates suggest around five users per distinct user group is sufficient to surface a large majority of the most severe usability problems in an interface, since most significant issues tend to be encountered by multiple users in short succession, making additional participants subject to steeply diminishing returns unless the interface serves substantially different user populations with distinct needs. Usability testing can be conducted in person in a dedicated laboratory equipped with observation and recording facilities, or remotely using screen-sharing and session-recording software, a mode of testing that has become increasingly common and allows for larger and more geographically diverse samples of participants at comparatively low marginal cost.

3. A/B Testing and Large-Scale Behavioral Data

Where heuristic evaluation and usability testing rely on small numbers of participants and rich qualitative observation, large consumer software products with substantial user bases increasingly rely on A/B testing, in which two or more variants of an interface are deployed simultaneously to different, randomly assigned segments of the live user population, and their relative performance on metrics such

as task completion, conversion, or engagement is compared statistically. This method offers a degree of statistical power and ecological validity that small-sample laboratory testing cannot match, since it captures genuine behavior in the actual context of use rather than behavior in an artificial testing environment, but it is best suited to answering narrow, well-defined questions about a specific design variation rather than to the broader, more exploratory questions about user needs and mental models that qualitative methods are better equipped to address. Mature product organizations typically treat quantitative and qualitative evaluation methods as complementary rather than substitutable, using qualitative research to generate design hypotheses and quantitative testing to validate them at scale.

4. Cognitive Walkthroughs and Analytical Methods

A further inspection method, the cognitive walkthrough, asks evaluators to step through a task sequence from the perspective of a first-time user, at each step asking whether the user will know what to do, will notice that the correct action is available, will correctly associate that action with the desired outcome, and will understand the feedback the system provides once the action is taken. This method is particularly well suited to evaluating the learnability of a system for novice users, complementing usability testing and heuristic evaluation, and it can be conducted, like heuristic evaluation, without recruiting external participants, though the quality of its findings depends heavily on evaluators' ability to set aside their own expert familiarity with the system and genuinely adopt a novice perspective.

5. Analytics, Field Studies, and Continuous Evaluation

Beyond the discrete, project-bounded evaluation methods discussed above, mature product organizations increasingly treat usability evaluation as a continuous, always-on activity rather than a milestone completed before launch. Behavioral analytics platforms passively record how users navigate an interface in production, generating funnel analyses that reveal precisely where users abandon a multi-step process and session-replay tools that allow researchers to review anonymized recordings of individual user sessions to observe friction points that aggregate metrics alone would not reveal. Diary studies and experience sampling methods, in which users are prompted at intervals to report on their ongoing experience with a product in their natural environment, extend evaluation beyond the artificial conditions of a single testing session and can surface issues, such as declining engagement over weeks of use or friction that only emerges in combination with other daily tasks, that a one-time usability test would miss entirely. The general trend across the field has been toward blending these continuous, low-intervention observational methods with the more intensive but episodic methods described in sections 5.1 through 5.4, giving organizations both a constant background awareness of usability health and the deeper diagnostic power of structured, in-depth evaluation when a specific problem needs to be understood in detail.

Accessibility and Inclusive Design

A user-centered design process that considers only a narrow, typically abled, typically young, and typically technologically fluent conception of 'the user' fails a substantial portion of any real user population. Accessibility the practice of designing systems usable by people with visual, auditory, motor, cognitive, and other disabilities is therefore not a peripheral specialization within HCI but a central obligation of the discipline's own founding premise that design should serve the actual range of people who will use a system.

The most widely adopted technical framework for digital accessibility is the Web Content Accessibility Guidelines, maintained by the World Wide Web Consortium, which organize accessibility requirements around four core principles, commonly abbreviated POUR: content and interface components must be perceivable through at least one sense even if another is unavailable, for instance through text alternatives for images that can be read aloud by screen-reading software; interfaces must be operable through a range of input methods, including keyboard-only navigation for users unable to operate a mouse or touchscreen; content must be understandable, with predictable behavior and clear language; and content must be robust enough to be reliably interpreted by the wide range of assistive technologies users rely upon, including screen readers, switch devices, and screen magnification software (World Wide Web Consortium, 2018).

Beyond formal compliance with such standards, the broader philosophy of inclusive design holds that designing explicitly for people at the margins of a typical user population an older adult with limited fine motor control, a parent operating a device one-handed while holding a child, a user in a bright outdoor environment who cannot easily read low-contrast text frequently produces designs that are better for the entire user population, not merely for the specific group that motivated the design decision. Captioning, originally developed for deaf and hard-of-hearing users, is now used pervasively by hearing users watching video in sound-sensitive public environments; voice interaction, originally valuable chiefly for users with visual or motor impairments, has become a mainstream convenience feature used by the general population while driving or cooking. This pattern, sometimes summarized as the 'curb-cut effect' after the sidewalk ramps originally installed for wheelchair users that proved equally valuable to travelers with strollers, luggage, and bicycles, provides one of the strongest practical arguments for treating accessibility as a design principle from the outset of a project rather than as a compliance requirement addressed after a design is otherwise complete.

1. The Regulatory Landscape of Digital Accessibility

Accessibility obligations have increasingly moved from voluntary best practice to binding legal requirement in many jurisdictions. In the United States, Section 508 of the Rehabilitation Act imposes accessibility requirements on federal agencies and

their contractors, while Title II and Title III of the Americans with Disabilities Act have been interpreted by courts to extend to commercial websites and mobile applications, generating a substantial and growing body of accessibility litigation against private companies. The European Union's Web Accessibility Directive and the more recent European Accessibility Act extend comparable obligations across a wide range of digital products and services sold within the EU, and numerous other jurisdictions, including Canada, Australia, and Israel, have adopted their own binding accessibility statutes that generally reference the WCAG framework discussed above as the applicable technical standard. This growing regulatory convergence around a shared technical standard has had the practical effect of making WCAG conformance not merely a professional best practice recommended by the HCI field but an increasingly enforceable legal baseline that organizations operating across multiple jurisdictions must meet.

2. Designing for Cognitive and Situational Diversity

Accessibility discourse has historically emphasized sensory and motor disabilities, given the comparative ease of specifying testable technical requirements such as color contrast ratios or keyboard operability, but the field has increasingly extended its attention to cognitive accessibility: designing for users with dyslexia, attention-related conditions, memory impairment, or intellectual disability, for whom the primary barriers are often excessive text density, inconsistent navigation, ambiguous language, and interfaces that impose a heavy working-memory burden rather than any single, easily testable technical defect. Guidance in this area emphasizes plain language, consistent and predictable navigation structures, the option to extend or disable time limits on tasks, and the availability of multiple means of accomplishing the same goal, since a single 'correct' path through an interface disproportionately burdens users, whose cognitive processing does not match the designer's assumed default.

A further, related concept is situational disability: the recognition that many users experience temporary or context-driven limitations functionally equivalent to a permanent disability, such as a person with a broken arm who cannot use two hands, a parent unable to look at a screen while supervising a child, or a user in a loud environment unable to hear audio output. Because situational impairments are, by definition, universal every user will at some point operate a device one-handed, in bright sunlight, or in a noisy environment designing robustly for situational disability tends to produce interfaces that are more resilient and usable for the entire population, reinforcing the curb-cut principle discussed above and further blurring the line between accessibility as a specialized concern and accessibility as a core dimension of general usability.

Cross-Cultural and Global User-Centered Design

As digital products routinely reach users across dozens of countries and language communities simultaneously, user-centered design must contend with the reality that cognitive and behavioral patterns, while broadly universal at the level of basic perception and motor control, vary meaningfully across cultural contexts in ways that carry direct design consequences. Reading direction affects the natural scanning pattern users apply to a layout, with users of right-to-left languages such as Arabic and Hebrew expecting navigation elements and reading flow to mirror the left-to-right convention assumed by much of existing interface design literature. Color carries different symbolic and emotional associations across cultures white is associated with mourning in some East Asian cultural contexts and with purity or celebration in many Western contexts with direct implications for how status indicators, warnings, and confirmations should be designed for a global audience. Cultural dimensions of communication style, including the degree to which a culture favors direct versus indirect phrasing or high-context versus low-context communication, similarly affect how error messages, onboarding copy, and system feedback are best worded to be perceived as helpful rather than abrupt or, conversely, as vague and unhelpfully indirect.

Beyond language translation, the practice of localization extends to date and number formatting, currency and unit conventions, legal and regulatory disclosures that vary by jurisdiction, imagery and iconography that may carry unintended meaning in a different cultural context, and even fundamental differences in prevailing device types, network conditions, and payment infrastructure across markets, all of which shape what a genuinely usable interface looks like for a given population far beyond the surface-level translation of on-screen text. Organizations operating globally increasingly conduct user research separately within each major target market rather than assuming that usability findings from a single, often Western and English-speaking, user population generalize automatically to the rest of a global user base, reflecting a growing recognition within the field that the very notion of a universal, culturally neutral 'user' embedded in much of classical HCI theory understates the genuine diversity of the people such theory is meant to serve.

Interaction Paradigms across Platforms

The principles discussed above manifest differently depending on the specific interaction paradigm and platform in question, each of which imposes its own constraints and affordances on design.

1. Desktop and the WIMP Paradigm

Desktop computing established the enduring conventions of windows, icons, menus, and pointer-based direct manipulation, and remains the dominant paradigm for tasks requiring precise input, extended text entry, multitasking across many simultaneous applications, and complex, information-dense professional software

such as spreadsheets, computer-aided design tools, and video editing suites. Desktop interfaces benefit from generous screen real estate and a precise pointing device, allowing designers to expose more functionality simultaneously than is practical on smaller or touch-based platforms, but this same density can become a liability when applied uncritically to contexts demanding simplicity and speed.

2. Mobile and Touch Interaction

Mobile interaction design must accommodate small screens, the comparatively low precision of finger-based touch relative to a mouse pointer, one-handed operation, frequent interruption, variable network connectivity, and use in a far wider range of physical and social contexts than desktop computing typically involves. These constraints have driven the development of distinct mobile design conventions: larger touch targets consistent with Fitts's Law given reduced pointing precision, bottom-anchored navigation elements that are easier to reach with a thumb during one-handed use, progressive disclosure that reveals complexity gradually rather than presenting all options at once, and design patterns that gracefully tolerate interruption and resumption of a task, since mobile use is characteristically fragmented into short sessions punctuated by other demands on the user's attention.

3. Voice and Conversational Interfaces

Voice interaction removes the visual channel almost entirely, replacing it with a serial, transient audio channel that cannot be scanned, re-read, or browsed the way visual information can. This imposes distinct design demands: system responses must be concise, since a user cannot skim a lengthy spoken response the way they might skim a paragraph of text; the interface must communicate clearly what it is capable of doing, since users cannot see a menu of available options the way a graphical interface would display one; and error recovery becomes especially important given the higher likelihood of speech-recognition errors relative to the low error rate of direct touch or click input. The emergence of large language model-based conversational agents has extended these design challenges into open-ended natural-language interaction, where the range of things a user might plausibly say is effectively unbounded, and interface designers face new and only partially resolved questions about how to convey a system's actual capabilities and limitations to a user who is invited to phrase requests however they naturally would.

4. Augmented, Virtual, and Mixed Reality

Immersive interfaces built around augmented, virtual, or mixed reality introduce spatial interaction in three dimensions, gaze and gesture as primary input modalities, and design considerations largely absent from flat-screen computing, including the physical comfort and safety of the user, the risk of motion sickness induced by mismatches between visual and vestibular sensory input, and the challenge of maintaining a user's sense of orientation and control within an

immersive environment that may occupy their entire field of view. Because these platforms are comparatively young relative to desktop and mobile computing, their interaction conventions remain considerably less standardized, and much of the design guidance in this area continues to be established through ongoing empirical research rather than settled, widely agreed best practice.

5. Ambient and Ubiquitous Computing

A further paradigm, anticipated by early HCI researchers well before the technology to realize it fully existed, envisions computing dissolving into the physical environment itself rather than being concentrated in a single discrete device that demands a user's focused attention. In this vision of ubiquitous computing, sensors, displays, and processing are embedded pervasively throughout everyday objects and environments, such that technology recedes into the periphery of awareness and becomes available wherever and whenever it is useful, rather than requiring users to deliberately seek it out (Weiser, 1991). Smart home devices, wearable fitness trackers, and context-aware notification systems represent early, still-partial realizations of this vision, and they raise interaction design questions distinct from those of screen-based computing, including how a system should decide when to proactively surface information to a user without becoming a source of unwanted interruption, and how to design meaningful feedback and control for systems that may have no traditional screen or input device at all.

Human-Computer Interaction in the Age of Artificial Intelligence

The growing integration of machine learning and, more recently, generative AI into everyday software introduces interaction design challenges that depart in important ways from the assumptions underlying much of classical HCI theory, which was developed largely for deterministic systems whose behavior a well-informed user could learn to predict reliably.

1. Designing for Probabilistic and Adaptive Systems

Where a traditional interface behaves identically each time a given input is provided, AI-driven systems frequently behave probabilistically or adaptively, producing different outputs for what appears to the user to be the same input, or gradually changing their behavior over time as a model is updated or personalized to an individual user. This departure from deterministic behavior complicates several of the classical usability heuristics discussed in section 5.1, particularly consistency and the ability of users to build an accurate, stable mental model of the system, and has motivated a growing body of design guidance specific to AI-infused interfaces, including recommendations to clearly communicate a system's level of confidence in its own outputs, to make it easy for users to correct or override AI-generated suggestions, and to design graceful mechanisms for handling

the AI system's inevitable errors rather than presenting its outputs with unwarranted authority.

2. Explainability and Trust

Because AI systems, particularly those built on complex neural network architectures, often cannot fully explain the reasoning behind a specific output even to their own developers, interaction designers face a distinct challenge in calibrating user trust: an interface that presents AI output with excessive confidence risks over-reliance and complacency, particularly in high-stakes domains such as medical or financial decision support, while an interface that hedges every output with extensive caveats risks under-utilization of a genuinely useful capability and unnecessary user friction. Effective solutions in this space typically involve surfacing meaningful indicators of uncertainty, offering users visibility into the sources or reasoning behind a given output where feasible, and designing interaction patterns that keep a human appropriately positioned to review, question, and override automated outputs rather than either removing human judgment from the loop entirely or requiring exhausting manual verification of every system output.

3. Conversational and Agentic Interaction Design

As AI systems increasingly take on agentic characteristics pursuing multi-step goals, calling external tools, and acting with some degree of autonomy on a user's behalf rather than simply responding to a single discrete request interaction designers face new questions about how to represent an ongoing, possibly lengthy automated process to a user in a way that remains legible, interruptible, and correctable. This represents a meaningful departure from the largely synchronous, turn-based interaction model of earlier software, and existing design patterns, including progress indicators borrowed from earlier computing eras and mechanisms for a user to pause, redirect, or halt an in-progress automated task, are still being actively developed and standardized across the industry as agentic AI products proliferate.

4. Dark Patterns and the Ethics of Persuasive Design

The same understanding of human cognition and behavior that enables designers to build genuinely helpful, usable interfaces can also be deployed to manipulate users against their own interests, a practice given the name 'dark patterns' within the design research community. A systematic content analysis of practitioner-identified examples has organized such patterns into several recurring categories, including nagging, in which a system repeatedly interrupts a user with a request until they relent; obstruction, in which a system makes a desired action, such as cancelling a subscription, artificially difficult to complete; sneaking, in which relevant information or costs are deliberately concealed or delayed; interface interference, in

which visual design is used to bias a user's choice toward the outcome favored by the system rather than the user; and forced action, in which a user is required to complete an unrelated action, such as creating an account or sharing data, in order to access a feature they sought (Gray, Kou, Battles, Hoggatt, & Toombs, 2018). The persistence of such patterns across major commercial platforms, despite the field's decades-long emphasis on usability and user welfare, has prompted growing regulatory attention in multiple jurisdictions and has reinforced calls within the HCI community for stronger ethical training and professional norms among practicing designers, who are frequently the ones best positioned to recognize when a business requirement crosses the line into manipulation of the very users the discipline was founded to serve.

5. Intelligent User Interfaces, Multimodality, and Affective Computing

A further strand of contemporary HCI research examines how AI capabilities are actively reshaping the interface layer itself, beyond the general design questions of trust and agentic interaction discussed above. Intelligent user interfaces increasingly combine natural language processing, computer vision, and speech recognition to support multimodal interaction, in which a user can freely combine voice, touch, gesture, and text within a single task rather than being restricted to one input channel, and systems increasingly attempt to select the output modality visual, spoken, or haptic best suited to a user's current context rather than defaulting to a single fixed presentation format. A related development is affective computing, in which systems attempt to infer a user's emotional state from signals such as facial expression, vocal tone, or interaction patterns, and adapt their behavior accordingly, for instance by simplifying an interface or offering additional guidance when a user appears frustrated. These developments extend human-computer interaction from an exchange of discrete, explicit commands toward a more continuous, context-sensitive collaboration between a user and a system that is itself attempting to model the user's needs and affect in real time, and they carry a corresponding obligation for designers to treat explainability, user control, and transparency about what is being inferred and why as first-order design requirements rather than afterthoughts, given the intimate and potentially sensitive nature of the signals such systems increasingly draw upon (Mishra, Mishra, & Agarwal, 2025).

Organizational Practice: Design Systems and the Business of UX

Beyond the individual project-level methodology described in sections 4 and 5, user-centered design has matured into an organizational discipline within most substantial technology companies, complete with dedicated roles, shared infrastructure, and its own internal metrics of success.

1. Design Systems and Component Libraries

As organizations grow and their products expand across multiple teams, platforms, and features, maintaining visual and behavioral consistency through ad hoc, case-by-case design decisions becomes impractical. Many organizations therefore invest in design systems: shared libraries of reusable interface components, along with documented rules governing their use, that encode accumulated usability and accessibility knowledge into a form individual designers and engineers can apply consistently without re-deriving first principles for every new feature. A mature design system reduces the cost of maintaining consistency across a large product surface, accelerates development by allowing teams to assemble interfaces from pre-tested components rather than building each element from scratch, and embeds accessibility and usability best practices by default into components that many designers and engineers will use without deep individual expertise in either area.

2. Integrating UX Within Agile and Product Development

The iterative user-centered design cycle described in section 4 must in practice be reconciled with the iterative but often faster-moving cadence of agile software development, a reconciliation that has proven organizationally challenging for many teams, since thorough user research and evaluation activities do not always fit neatly within short development sprints originally designed around discrete units of engineering work. Common organizational adaptations include maintaining a design research and prototyping effort that runs slightly ahead of active development sprints, so that validated designs are ready for engineering teams as capacity becomes available, and adopting continuous, lightweight research practices brief weekly usability sessions, ongoing analysis of behavioral analytics, and regular but small-scale user interviews in place of large, infrequent research studies that can become disconnected from the pace of ongoing development.

3. Measuring the Value of Design

Organizations increasingly seek to quantify the business value of investment in user-centered design, a task complicated by the fact that good design often manifests as the prevention of costly problems abandoned purchases, support calls, user churn, costly engineering rework triggered by late-discovered usability failures — rather than as a directly attributable positive outcome. Common metrics used to approximate design's contribution include task success rate and time-on-task from usability testing, System Usability Scale scores and other standardized satisfaction instruments, customer support ticket volume associated with specific interface areas, and, in commercial contexts, conversion and retention metrics tracked through the A/B testing infrastructure discussed in section 5.3. Despite the continued difficulty of establishing definitive causal attribution between design investment and business outcomes, the discipline has accumulated a substantial body of case evidence linking rigorous user-centered design practice to measurable

reductions in costly downstream failures and improvements in user satisfaction and retention.

Case Studies in Applied User-Centered Design

Concrete cases illustrate how the abstract principles discussed throughout this chapter translate into practical design decisions and measurable outcomes. This section surveys several illustrative examples drawn from domains where user-centered design has had a documented and substantial impact.

1. Healthcare Interfaces and Clinician Workflow

Electronic health record systems have become one of the most consequential, and most frequently criticized, categories of professional software in existence, given their direct bearing on both clinician efficiency and patient safety. Usability research in this domain has repeatedly identified interface designs that require excessive navigation to locate critical patient information, alert fatigue caused by poorly prioritized warning systems that lead clinicians to habitually dismiss notifications without reading them, and data entry workflows so burdensome that clinicians report spending a disproportionate share of patient-facing time interacting with the software rather than the patient. These findings have driven a substantial movement within health informatics toward applying the formal user-centered design process described in section 4 to clinical software, including structured contextual inquiry conducted directly within clinical environments, task analysis focused specifically on minimizing interruption during time-critical procedures, and heuristic evaluation informed by safety-critical design principles in addition to the general usability heuristics described in section 5.1. The stakes of this work are unusually high relative to most consumer software contexts, since usability failures in clinical interfaces have been directly implicated in documented instances of medication error and delayed diagnosis, providing some of the starkest available evidence for the practical, non-abstract consequences of poor interface design.

2. Financial Services and Trust-Sensitive Design

Banking and financial services interfaces illustrate a distinct design challenge: users must be guided through inherently complex, high-consequence tasks transferring funds, applying for credit, adjusting investment allocations while the interface must simultaneously project sufficient trustworthiness and security to overcome the natural caution such tasks warrant. User research in this domain has found that visible security indicators, clear and jargon-free explanation of fees and terms, and confirmation steps calibrated to the magnitude of a given transaction's consequences all measurably improve both user confidence and task completion rates, while excessive friction applied uniformly across all transaction types, regardless of risk, tends to depress engagement without a corresponding safety benefit. The rise of mobile-first banking in markets with limited traditional banking infrastructure has

further demonstrated the reinstatement and inclusion potential of well-designed financial interfaces, extending financial services access to populations previously excluded by the cost and physical infrastructure requirements of traditional branch banking, provided the interfaces are designed with adequate attention to the lower digital literacy and more constrained device and connectivity conditions such populations often face.

3. E-Government and Public Service Delivery

Government digital services present a distinct use case in which the user population cannot opt out or switch to a competitor, making usability failures a matter of equitable public access rather than merely commercial competitiveness. Several national digital service programs, including the United Kingdom's GOV.UK platform and comparable digital government initiatives elsewhere, have explicitly adopted the ISO 9241-210 human-centered design process discussed in section 4 as a mandatory standard for public-facing government services, driven by evidence that poorly designed government interfaces disproportionately burden exactly the populations elderly citizens, non-native speakers, people with limited digital literacy, and people with disabilities — that public services have the strongest obligation to serve well. These programs have demonstrated measurable reductions in call-center volume, form abandonment, and processing errors following the application of rigorous user-centered design and testing, providing some of the most extensively documented public-sector evidence for the practical value of the methodology described throughout this chapter.

Future Directions

Several trends are likely to shape the continued evolution of HCI and user-centered design over the coming decade. The first is the continued extension of interaction beyond the visual, screen-based paradigm that has dominated the field's history, toward voice, gesture, ambient sensing, and increasingly agentic AI systems that require entirely new evaluation methods, since much of the field's existing usability theory and testing infrastructure was built around the specific assumptions of screen-based, deterministic, single-turn interaction discussed in section 9. The second is the increasing demand for personalized and adaptive interfaces that adjust to an individual user's abilities, preferences, and context in real time, a capability made newly practical by advances in machine learning but one that raises fresh design challenges around maintaining a coherent, learnable mental model for a system whose behavior is, by design, no longer identical for every user.

A third likely direction is the increasing regulatory and legal attention being paid to interface design, extending well beyond the accessibility mandates already common in many jurisdictions and discussed in section 6.1, to include emerging restrictions on manipulative dark patterns, discussed in section 9.4, and, in some jurisdictions, requirements for explainability and human oversight in AI-driven decision systems.

This regulatory attention is likely to formalize obligations that the HCI field has long treated as best practice but has not always consistently enforced through professional or organizational accountability. A fourth direction concerns the discipline's own workforce and practice: as AI-powered design and prototyping tools increasingly automate portions of the interface design process itself, from rapid layout generation to automated usability heuristic checking, the profession is likely to place growing emphasis on the judgment-intensive aspects of design work that such tools cannot easily replicate, including the synthesis of ambiguous user research findings, the negotiation of competing stakeholder interests, and the ethical judgment required to recognize when a technically feasible design nonetheless fails the people it is meant to serve.

A fifth and increasingly salient direction concerns the globalization of user-centered design practice discussed in section 7: as digital products reach an ever more diverse global population, the field faces a growing obligation to move beyond design research conducted predominantly with convenient, English-speaking, higher-income populations toward genuinely representative research spanning the full range of languages, cultural contexts, digital literacy levels, and infrastructure conditions in which its products will actually be used. This shift is likely to require not only expanded research budgets and multilingual research capability but a deeper methodological reckoning with the extent to which foundational HCI theory itself, much of it developed and validated within a narrow slice of the global population, requires revisiting and re-validating across the broader human contexts the field now aims to serve.

Conclusion

Human-computer interaction and user-centered design together constitute a discipline built on a premise that remains as consequential today as when it was first articulated: that technology should be designed around the capabilities, needs, and goals of the people who use it, rather than requiring people to adapt themselves to the arbitrary demands of a machine. The theoretical foundations of the field models of memory, attention, motor control, and mental representation provide the explanatory grounding for why some designs succeed and others fail, while the structured, iterative process codified in standards such as ISO 9241-210 provides the practical discipline through which that understanding is systematically applied, tested, and refined.

As computing continues to extend beyond the screen into voice, ambient, immersive, and increasingly autonomous AI-driven systems, the field faces genuine challenges in adapting decades of accumulated theory and method to interaction paradigms its founders could not have fully anticipated. What is unlikely to change, however, is the field's underlying commitment: that the ultimate measure of a system's success is not its technical sophistication but the quality of the experience

it creates for the people who depend on it, and that achieving this requires deliberate, evidence-based design rather than an assumption that usability will simply follow from sufficient engineering effort. This commitment, more than any specific method or technology, is what continues to define human-computer interaction and user-centered design as a coherent and enduring discipline.

Acknowledgement

The authors declare no conflicts of interest. We are very much thankful to the authors of different publications as many new ideas are abstracted from them. Authors also express gratefulness to their colleagues and family members for their continuous help, inspirations, encouragement, and sacrifices without which this work could not be executed. Finally, the main target of this work will not be achieved unless it is used by research institutions, students, research scholars, and authors in their future works. The authors will remain ever grateful to Dr. Neelu Singh, Director, ICFRE Tropical Forest Research Institute, Jabalpur, Director, XLRI – Xavier School of Management, Jamshedpur & Principal Government Science College, Jabalpur who helped by giving constructive suggestions for this work. The authors are also responsible for any possible errors and shortcomings, if any in the paper, despite the best attempt to make it immaculate.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 23 - 28

Analytical Solution of Coupled Nonlinear Reaction–Diffusion Equations for Carbon Dioxide Removal in a Hollow Fiber Membrane Contactor

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Article DOI Link: https://zenodo.org/uploads/22079742

DOI: 10.5281/zenodo.22079742

Abstract

A mathematical model describing carbon dioxide removal in a hollow fiber membrane contactor using an aqueous potassium carbonate solution as the absorbent is presented. The coupled nonlinear partial differential equations governing the absorption and desorption processes were solved analytically using the Adomian decomposition method. The influence of operating and geometric parameters, including feed gas pressure, vacuum level, absorbent flow rate, potassium carbonate concentration, and the diameter and length of the hollow fibers, on the carbon dioxide removal efficiency was investigated. The analytical results were compared with numerical simulation results and showed excellent agreement, confirming the accuracy and reliability of the proposed analytical solution. The developed model provides an efficient tool for predicting concentration profiles and optimizing the performance of hollow fiber membrane contactors for carbon dioxide capture.

Keywords: Carbon dioxide absorption; Hollow fiber membrane contactor; Coupled nonlinear reaction–diffusion equations; Analytical solution

Introduction

Conventional gas absorption processes typically involve dispersing gas mixtures into liquid absorbents using equipment such as packed towers, spray towers, Venturi scrubbers, and bubble columns. A significant advancement in this field was

introduced by Qi and Cussler, who developed the hollow fiber membrane contactor employing a microporous, non-wetted polypropylene hollow fiber membrane for carbon dioxide absorption using an aqueous sodium hydroxide solution as the absorbent [1,2]. Subsequently, Sirkar provided a comprehensive review of gas absorption processes based on membrane contactors [3]. Karoor and Sirkar extensively investigated the separation of carbon dioxide from nitrogen using membrane contactors with pure water and aqueous amine solutions as absorbents [4]. Teramoto et al. demonstrated that the permeation rate of CO_2 could be successfully predicted using the facilitated transport theory through supported liquid membranes containing aqueous amine solutions [5]. In addition, several experimental studies have evaluated the performance of membrane contactors with different absorbent liquids, including pure water, aqueous sodium hydroxide, aqueous potassium carbonate, and aqueous amine solutions [6]. Despite these experimental developments, relatively few theoretical studies have been reported that rigorously describe membrane contactors while incorporating the complete chemical reaction mechanism without simplifying assumptions [7,8]. Such theoretical analyses are considerably more challenging than those for conventional absorption systems because of the coupled mass transfer and reaction phenomena occurring within the membrane. Consequently, many researchers have characterized membrane contactor performance using macroscopic overall mass transfer coefficients rather than solving the underlying microscopic partial differential equations governing mass transport and chemical reactions [5–8].

Mathematical formation of the boundary value problem

The steady state dimensionless nonlinear differential equations is

$$\frac{\partial^2 C_A}{\partial r^2} + \frac{1}{r}\frac{\partial C_A}{\partial r} - D_{KA}\left(1+\alpha\frac{\tau-C_B}{C_B}\right)\left(C_A-\gamma\frac{C_A^2}{\tau-C_B}\right) = 0, \quad (1)$$

$$\frac{\partial^2 C_B}{\partial r^2} + \frac{1}{r}\frac{\partial C_B}{\partial r} + GD_{KB}\left(1+\alpha\frac{\tau-C_B}{C_B}\right)\left(C_A-\gamma\frac{C_A^2}{\tau-C_B}\right) = 0, \quad (2)$$

The dimensionless boundary conditions

At the center of the membrane contactor ($r = 0$),

$$\frac{\partial C_A}{\partial r} = 0, \frac{\partial C_B}{\partial r} = 0, \quad (3)$$

At the membrane wall ($r = 1$),

$$C_A = 1, C_B = 1. \quad (4)$$

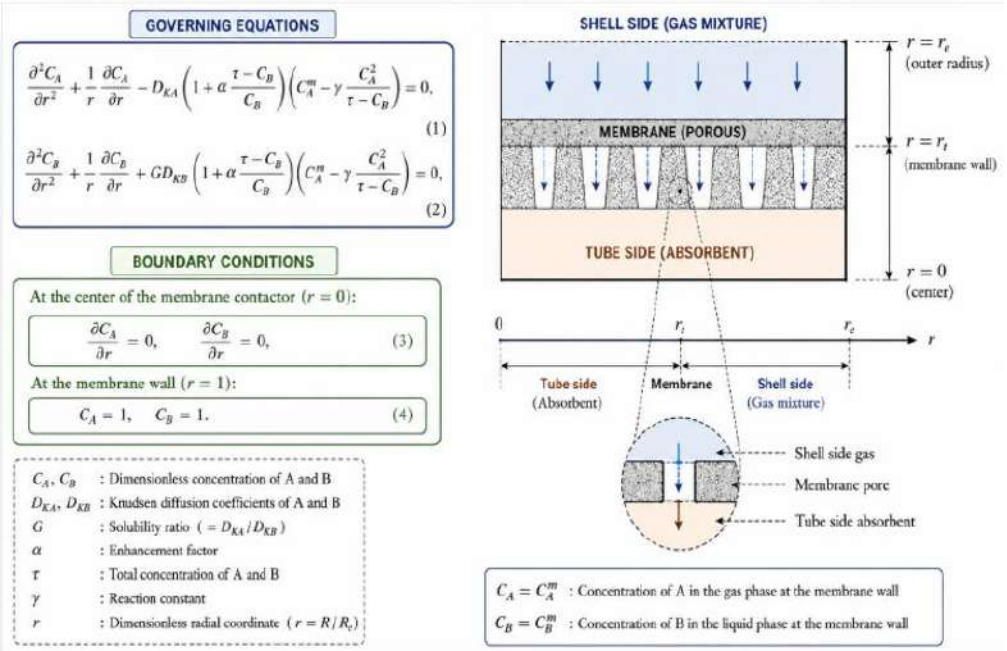


Figure 1. Mathematical model, computational domain, and boundary conditions for radial diffusion–reaction in a hollow fiber membrane contactor.

Analytical solution of the concentration using modified Adomian decomposition method

In recent years, considerable attention has been devoted to the application of the Adomian Decomposition Method (ADM) for solving a wide range of scientific and engineering problems. Unlike conventional numerical and analytical techniques, ADM provides approximate analytical solutions without requiring linearization, perturbation, transformation, or discretization. The method expresses the solution as a rapidly convergent infinite series whose terms can be computed systematically and efficiently.

The concentration profiles become

$$C_A(r) = 1 + D_{KA}A_1P_2(r) + \frac{D_{KA}A_1A_2}{(\tau-1)^2}P_4(r) - \frac{GD_{KA}D_{KB}A_3}{(\tau-1)^2}P_4(r) + \frac{D_{KA}^3(\alpha-\alpha\tau)A_1^2}{(\tau-1)^2}P_6(r) \qquad (5)$$

where

$$\left.\begin{aligned} A_2 &= -4\alpha\gamma + \alpha\tau^3 - 2\alpha\tau - 2\alpha\tau^2\gamma + 4\alpha\gamma\tau + 2\gamma - \alpha\tau^2, \\ A_3 &= \tau - \gamma\tau + \alpha\gamma\tau + 1 - \gamma - \alpha\gamma, \\ P_2(r) &= \frac{r^2}{4} - \frac{1}{4}, P_4(r) = \frac{r^4}{64} - \frac{r^2}{16} + \frac{3}{64}, \\ P_6(r) &= \frac{r^6}{576} + \frac{r^4}{128} + \frac{r^2}{64} - \frac{29}{1152}. \\ A_1 &= 1 + \alpha(\tau-1)\left(1 - \frac{\gamma}{\tau-1}\right), \end{aligned}\right\} \qquad (6)$$

$$C_B(r) = 1 - GD_{KB}A_1P_2(r) - \frac{GD_{KA}D_{KB}A_1A_2}{(\tau-1)^2}P_4(r) + \frac{G^2D_{KB}^2A_1A_3}{(\tau-1)^2}P_4(r) + \frac{GD_{KA}^2D_{KB}(\alpha-\alpha\tau)A_1^2}{(\tau-1)^2}P_6(r) \quad (7)$$

where

$$\left.\begin{aligned} A_1 &= 1+\alpha(\tau-1)\left(1-\frac{\gamma}{\tau-1}\right),\\ A_2 &= -4\alpha\gamma+\alpha\tau^3-2\alpha\tau-2\alpha\tau^2\gamma+4\alpha\gamma\tau+2\gamma-\alpha\tau^2,\\ A_3 &= \tau-\gamma\tau+\alpha\gamma\tau+1-\gamma-\alpha\gamma,\\ P_2(r) &= \frac{r^2}{4}-\frac{1}{4}, P_4(r) = \frac{r^4}{64}-\frac{r^2}{16}+\frac{3}{64},\\ P_6(r) &= \frac{r^6}{576}+\frac{r^4}{128}+\frac{r^2}{64}-\frac{29}{1152}, \end{aligned}\right\} \quad (8)$$

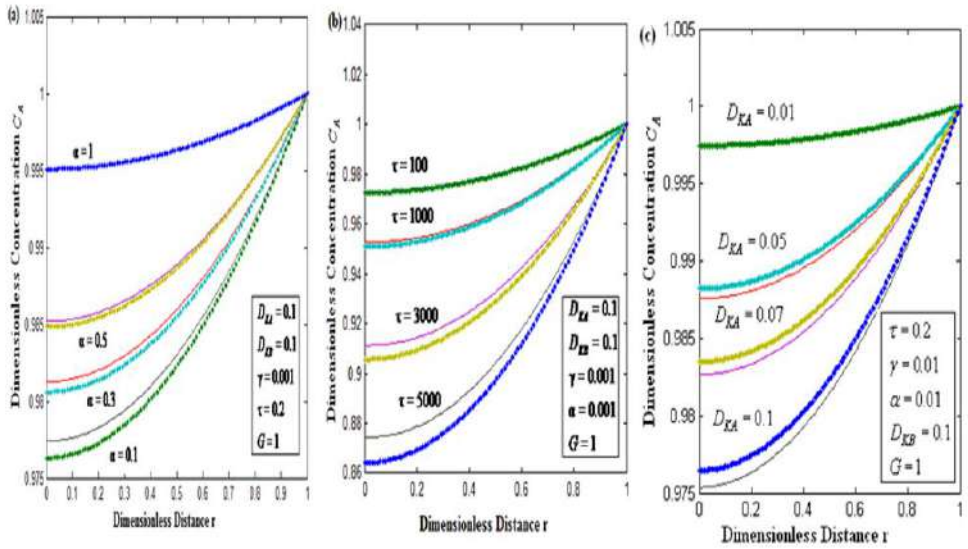


Figure 2. Comparision analytical expression of concentration C_A (eq. (5)) with simulation result various values of parameter.

Figure 2(a–c) illustrates the variation of the dimensionless concentration $C_A$with the dimensionless radial distance runder different parameter values. In all cases, the concentration increases gradually from the center toward the boundary, reaching a normalized value of 1 at r=1. In Figure 2(a), increasing the fractional parameter αenhances the concentration profile, indicating weaker concentration depletion. Figure 2(b) shows that larger values of the relaxation time τreduce the concentration throughout the domain, reflecting slower mass transport. Figure 2(c) demonstrates that increasing the mass diffusion parameter D_{KA} decreases the concentration, indicating enhanced diffusion and stronger concentration gradients within the medium.

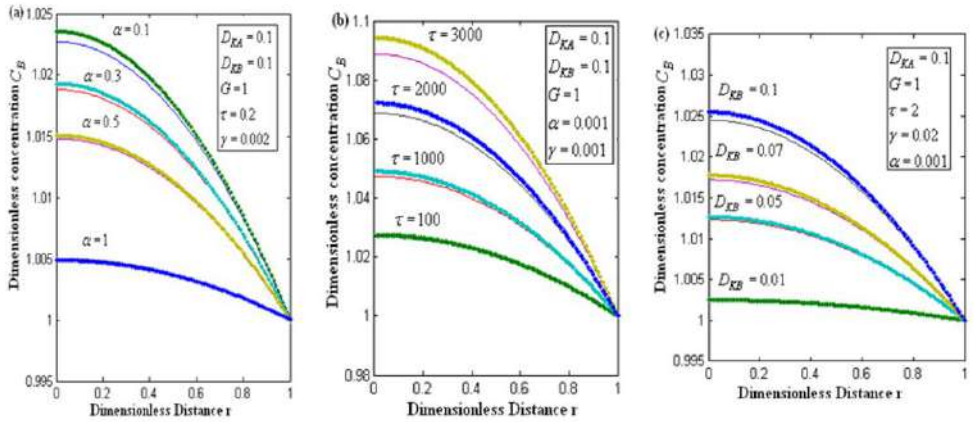


Figure 3. Comparision analytical expression of concentration C_B (eq. (7)) with simulation results various values of parameter.

Figure 3(a–c) illustrates the variation of the dimensionless concentration C_Bwith the dimensionless radial distance r for different values of α, τ, and D_KB. In all cases, the concentration decreases gradually toward the outer boundary and reaches the normalized value of 1 at r=1. Figure 3(a) shows that increasing the fractional parameter α reduces the concentration profile, indicating enhanced mass transport and lower species accumulation. Figure 3(b) demonstrates that higher relaxation time τincreases the concentration throughout the domain due to slower diffusion dynamics. Figure 3(c) reveals that increasing the diffusion parameter D_KBelevates the concentration profile, highlighting its significant influence on the concentration distribution and overall mass transfer characteristics within the membrane contactor.

Conclusion

A comprehensive mathematical model for carbon dioxide absorption in a hollow fiber membrane contactor using an aqueous potassium carbonate solution was successfully developed and analyzed. The coupled nonlinear partial differential equations governing the absorption and desorption processes were solved analytically using the Adomian decomposition method, yielding accurate concentration profiles. The analytical solutions showed excellent agreement with numerical simulations, validating the effectiveness and reliability of the proposed approach. The results demonstrate that operating conditions, such as feed gas pressure, vacuum level, absorbent flow rate, potassium carbonate concentration, and membrane geometry, significantly influence carbon dioxide removal efficiency. The developed analytical model provides a computationally efficient and reliable tool for predicting mass transfer behavior and optimizing membrane contactor design and operating conditions. Consequently, this study offers valuable insights for the development of high-performance carbon capture systems and supports the practical

implementation of membrane-based technologies for efficient carbon dioxide removal.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 29 - 34

Nonlinear Ship Rolling Equation with Cubic and Quintic Restoring Moments

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Article DOI Link: https://zenodo.org/uploads/22079819

DOI: 10.5281/zenodo.22079819

Abstract

This study investigates the free nonlinear roll motion of a ship governed by a fifth-order nonlinear differential equation incorporating linear damping and nonlinear restoring moments. The mathematical model consists of linear, cubic, and quintic restoring terms, enabling an accurate representation of the ship's rolling behavior under large-amplitude motions in the absence of external wave-exciting moments. The governing equation is solved analytically using the Akbari–Ganji Method (AGM), an efficient semi-analytical technique for obtaining approximate closed-form solutions to nonlinear differential equations. A suitable exponential trigonometric trial function is assumed, and the unknown parameters are determined by satisfying the initial conditions and minimizing the residual of the governing equation. The proposed solution provides an explicit analytical expression for the roll angle as a function of time, capturing both the oscillatory response and damping characteristics of the system. The AGM solution eliminates the need for linearization or discretization, thereby preserving the essential nonlinear dynamics of the ship roll motion. The analytical results demonstrate that the damping coefficient significantly influences the rate of decay of the roll amplitude, while the cubic and quintic restoring coefficients govern the nonlinear stiffness and oscillation characteristics. The developed analytical formulation is computationally efficient and can serve as a valuable tool for predicting nonlinear ship roll responses, assessing dynamic stability, and supporting the design and safety

analysis of marine structures. The proposed methodology may also be extended to other nonlinear oscillatory systems encountered in marine engineering and applied mechanics.

Keywords: Nonlinear ship roll motion, nonlinear differential equation, free vibration, damping, cubic nonlinearity, quintic nonlinearity, analytical solution, marine dynamics.

Introduction

Ship roll motion is one of the most critical modes of marine vessel dynamics because excessive rolling can reduce operational efficiency, compromise passenger comfort, damage cargo, and, in severe cases, lead to capsizing. Consequently, the accurate prediction of roll motion has been a major research topic in naval architecture and ocean engineering. For small roll angles, linear mathematical models provide satisfactory predictions; however, under moderate and large-amplitude motions, the nonlinear characteristics of the restoring moment and hydrodynamic damping become significant and cannot be neglected [1,2].

Nonlinear ship roll motion is commonly represented by a second-order differential equation containing linear damping together with cubic and quintic restoring terms. These higher-order nonlinearities describe the actual righting-arm characteristics of a ship more accurately than linear models, particularly during large roll amplitudes [3]. Previous investigations have demonstrated that the choice of nonlinear damping and restoring terms has a substantial influence on the predicted roll response, resonance characteristics, and dynamic stability of marine vessels. Therefore, nonlinear mathematical models are essential for realistic analysis and safe ship design.

Although numerical methods such as the Runge–Kutta algorithm provide accurate solutions, they often require extensive computational effort and do not yield explicit analytical expressions. Consequently, several semi-analytical techniques have been developed to solve nonlinear differential equations efficiently. Among these methods, the Akbari–Ganji Method (AGM)[4,5] has gained considerable attention because of its simplicity, rapid convergence, and ability to generate accurate closed-form approximate solutions without linearizing the governing equation.

In the present study, the free nonlinear roll motion of a ship, without external wave excitation, is investigated using the AGM. The governing equation incorporates linear damping and nonlinear cubic and quintic restoring moments, providing a realistic representation of the vessel's roll dynamics. An appropriate trial solution is assumed, and the unknown coefficients are determined by satisfying the initial conditions and minimizing the residual of the governing equation. The obtained analytical solution provides valuable insight into the influence of damping and nonlinear restoring stiffness on the roll response and offers an efficient alternative to purely numerical simulations. The proposed methodology can also be extended to

other nonlinear oscillatory systems encountered in marine engineering and applied mechanics.

The governing nonlinear roll equation for a ship without a wave-exciting moment can be presented in a clearer mathematical form as follows.

Theory

The nonlinear equation of motion is

$$\ddot{\theta}(t) + d_1\dot{\theta}(t) + k_1\theta(t) + k_3\theta^3(t) + k_5\theta^5(t) = 0, \qquad (1)$$

where:

- θ(t)= roll angle of the ship,
- θ ̇(t)= roll angular velocity,
- θ ̈(t)= roll angular acceleration,
- d_1= linear damping coefficient,
- k_1= linear restoring stiffness coefficient,
- k_3= cubic nonlinear restoring coefficient,
- k_5= quintic nonlinear restoring coefficient.

The initial conditions for the zeroth-order solution are

$$\theta_0(0) = l, \dot{\theta}_0(0) = 0, \qquad (2)$$

where l denotes the initial roll amplitude.

Result and Discussion

Akbari–Ganji Method (AGM)

The Akbari–Ganji Method (AGM) is an efficient semi-analytical technique for solving nonlinear differential equations. It employs an assumed trial function with unknown parameters, which are determined by satisfying the governing equation and boundary or initial conditions. AGM provides accurate closed-form approximate solutions with rapid convergence and reduced computational effort.

The nonlinear differential equation

$$\ddot{\theta}(t) + d_1\dot{\theta}(t) + k_1\theta(t) + k_3\theta^3(t) + k_5\theta^5(t) = 0 \qquad (3)$$

with the initial conditions

$$\theta(0) = l, \dot{\theta}(0) = 0 \qquad (4)$$

is solved by assuming an approximate analytical solution that satisfies the initial conditions.

A suitable AGM trial function is

$$\theta(t) = e^{-at}(A\cos(\omega t) + B\sin(\omega t)), \tag{5}$$

where a, A, B, and ωare unknown constants.

Hence, the AGM approximation becomes

$$\theta(t) = l\, e^{-at}\left[\cos(\omega t) + \frac{a}{\omega}\sin(\omega t)\right] \tag{6}$$

which satisfies the given initial conditions.

Roll Velocity

$$\dot{\theta}(t) = \frac{d\theta(t)}{dt}. \tag{7}$$

$$\dot{\theta}(t) \quad = le^{-at}[-a\left(\cos\omega t + \frac{a}{\omega}\sin\omega t\right) - \omega\sin\omega t + a\cos\omega t]. \tag{8}$$

Roll Acceleration

$$\ddot{\theta}(t) = -\frac{l(a^2+\omega^2)}{\omega}\frac{d}{dt}[e^{-at}\sin(\omega t)] \tag{9}$$

$$\ddot{\theta}(t) = -l(a^2+\omega^2)e^{-at}\left[\cos(\omega t) - \frac{a}{\omega}\sin(\omega t)\right] \tag{10}$$

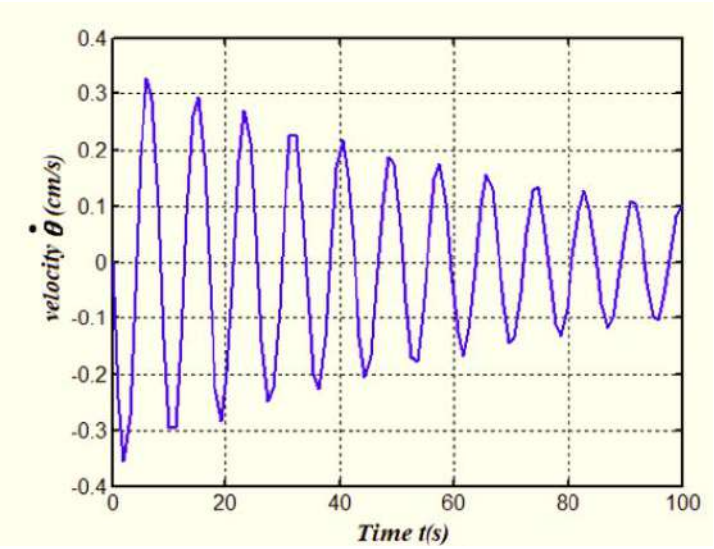


Figure 1. Time History of Roll Velocity of the Nonlinear Ship Roll Motion Using the eq. (8)

Figure 1 illustrates the variation of roll velocity with respect to time for the nonlinear ship roll motion obtained using the Akbari–Ganji Method (AGM). The

response exhibits a damped oscillatory behavior, where the roll velocity initially reaches a maximum magnitude of approximately ±0.35 and gradually decreases as time progresses. This reduction in amplitude is due to the presence of the linear damping coefficient, which continuously dissipates the system's kinetic energy. Although the oscillation frequency remains nearly constant, the peak velocities decay exponentially, indicating a stable dynamic response. After approximately 100 s, the roll velocity approaches zero, demonstrating that the ship eventually attains its equilibrium position. The smooth decay of the oscillations confirms the effectiveness of the AGM solution in accurately capturing the damping characteristics and nonlinear dynamics of the ship roll motion without numerical instability.

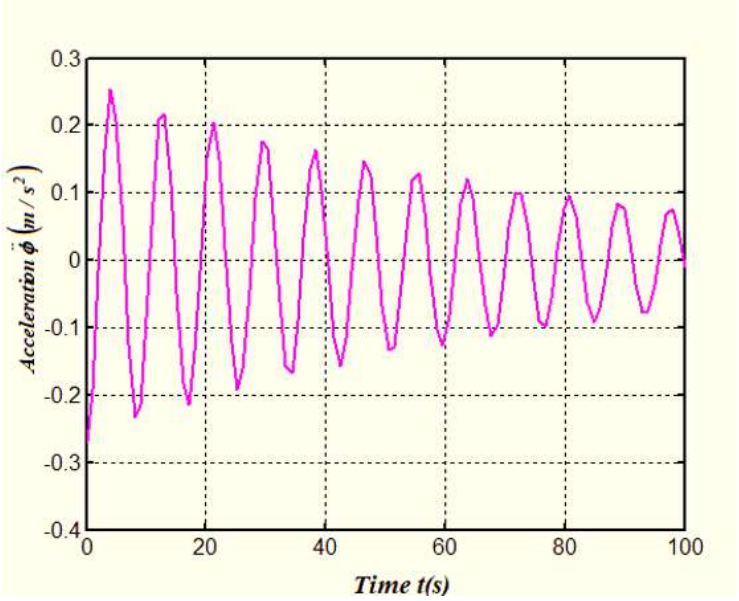


Figure 2. Time History of Roll Acceleration of the Nonlinear Ship Roll Motion using the eq. (10)

Figure2 illustrates the roll acceleration response of the nonlinear ship roll system obtained using the Akbari–Ganji Method (AGM). The acceleration exhibits a damped oscillatory pattern, with an initial peak value of approximately ±0.25 m/s², followed by a gradual reduction in amplitude over time. This behavior indicates that the damping mechanism effectively dissipates the system's energy while maintaining a nearly constant oscillation frequency. The decreasing acceleration peaks demonstrate the progressive stabilization of the ship's roll motion and the absence of dynamic instability. By the end of the simulation period (100 s), the acceleration approaches zero, indicating that the vessel reaches its equilibrium state. The smooth and continuous decay of the acceleration response confirms the capability of the AGM analytical solution to accurately represent the nonlinear dynamic characteristics and damping effects of free ship roll motion.

Conclusion

This study presented an analytical investigation of the free nonlinear roll motion of a ship using the Akbari–Ganji Method (AGM). The governing nonlinear differential equation, incorporating linear damping together with cubic and quintic restoring moments, was solved by assuming an appropriate trial function that satisfies the prescribed initial conditions. The AGM yielded an explicit closed-form approximate solution for the roll angle, from which the corresponding roll velocity and roll acceleration were derived analytically. The obtained responses exhibited damped oscillatory behavior, demonstrating the gradual dissipation of energy due to the damping effect while preserving the nonlinear characteristics of the system. The time-history plots of roll velocity and acceleration confirmed that the oscillation amplitudes decrease progressively and approach equilibrium without numerical instability. The results indicate that the AGM provides accurate and computationally efficient approximate solutions without requiring linearization or extensive numerical computations. Therefore, the method is a reliable alternative for analyzing nonlinear ship roll dynamics and can be effectively applied to the prediction of vessel stability, dynamic response, and safety assessment. Furthermore, the proposed analytical approach can be extended to other nonlinear vibration problems encountered in marine engineering, structural dynamics, and applied mechanics.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 35 - 44

Smart IoT Frameworks for Electric Vehicle Battery Health Monitoring

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Article DOI Link: https://zenodo.org/uploads/22080124

DOI: 10.5281/zenodo.22080124

Abstract

As electric vehicles (EVs) grow in popularity and become an important component of sustainable transport, there is an increased demand for intelligent battery management and monitoring systems which guarantee not only their safety and reliability, but also long service life. Traditional Battery monitoring and control systems (BMS) perform localized monitoring and usually do not have a capability of real-time data collection and analysis. Internet of Things (IoT) enables uninterrupted data collection related to the battery such as voltage, current, temperature, available battery capacity (SOC), overall battery condition (SOH), and estimated service life (RUL). Intelligent IoT systems incorporate such components as sensors, wireless communication, edge computing, cloud platforms, artificial intelligence (AI), and digital twins to develop intelligent battery health management systems. These systems can perform such tasks as failure detection, battery aging, optimization of charging and operation. This chapter will focus on the architecture, communication technologies, AI-based analytics, cloud integration, cyber security issues and practical implementations of IoT battery health monitoring systems in

electric vehicles. Such emerging technologies as edge AI, federated learning, blockchain, and digital twins will also be discussed.

Keywords: Internet of Things, Electric Vehicle, Battery monitoring and control system, Available battery capacity, Overall battery condition, Artificial Intelligence, Edge Computing, Digitaltwin.

Introduction

The increasing use of electric vehicles (EVs) is changing the way global transportation works by reducing greenhouse gas emissions, making energy efficient and minimizing dependency on fossil fuels. Governments around the world are trying to deploy more EVs using various policies, technological improvements, and infrastructural developments. Batteries play an important role in each and every EV as it greatly affects the performance, range, safety, reliability and running costs of the vehicle. The lithium-ion battery has become a popular form of energy storage due to its higher energy density, longer life cycle, lower self-discharge rate and faster charging ability. Battery performance decreases over time due to aging, charge/discharge cycles, thermal conditions, and operational stress.

The traditional Battery monitoring and control system (BMS) is developed to track and maintain the status of the battery by measuring the values of different parameters such as voltage, current, temperature, Available battery capacity (SOC) and Overall battery condition (SOH) of the battery. Conventional BMS provides necessary services such as cell balancing, thermal management, overcharge/overdischarge protection, and fault detection. While conventional BMS systems are quite effective in maintaining the safety of the battery on the vehicle level, they lack the ability to function as connected systems and have low potential for remote monitoring and analytics of large-scale battery data.

Internet of Things (IoT) has been identified as an important facilitator of developing smart battery monitoring systems. Internet of Things involves the integration of intelligent sensors, embedded controllers, wireless networking technologies, cloud computing technologies, and real time analysis of battery data. With the help of IoT, it becomes possible to remotely monitor battery systems using cloud computing services to detect any faults in advance and perform predictive maintenance operations. Battery voltage, current, temperature, available battery capacity (SOC), overall battery condition (SOH), state of power (SOP), and estimated service life (RUL) can all be monitored continuously.

Various deep learning algorithms, such as CNNs, LSTM, GRU, BiLSTM, and a combination of CNN-LSTM algorithms, have exhibited great performance in estimating the state of the battery and predicting the degradation process. The aim of these algorithms is to analyze huge amounts of data incoming from sensors to find out complex nonlinear relations, to boost the accuracy of estimation, to detect anomalies at an earlier stage and to take preventive actions for maintenance

purposes. Thus, the combination of IoT and AI has enabled the transition of the battery monitoring and control systems from reactive to intelligent decisions.

Edge computing has also been receiving attention in terms of applications for smart battery monitoring systems. Rather than sending all the sensor information to the cloud-based servers, edge devices analyze initial data and conduct the artificial intelligence computations near the battery systems. The use of such an approach is important since it helps to reduce the lag time, decrease bandwidth consumption, speed up the process, and increase privacy. Edge intelligence, combined with cloud computing, creates the mixed approach that is able to provide real-time protection and long-term analysis of batteries. Digital twins contribute to this system as well since they create the virtual images of the physical battery systems.

However, there are a number of problems faced in using smart IoT framework for the monitoring of health of EV battery. The list includes sensor reliability, communication delay problem, cybersecurity risk, data privacy issue, heterogeneous device interoperability problem, energy-efficient communication protocol, and scalability problem of cloud-based infrastructure. Solving these problems will be very crucial for creating safe and reliable system of EV battery health monitoring.

In this chapter, we provide an elaborate description of smart IoT systems used for battery condition monitoring in electric vehicles. The chapter will cover the basics of EV batteries and battery monitoring and control systems, IoT systems, sensing methods, wireless communication technology, cloud and edge computing, battery available battery capacity estimation using artificial intelligence, cyber security issues, and industrial applications. Recent advances in this field, existing problems, and new technologies including digital twins, federated learning, blockchain, and edge AI will be discussed in this chapter. The integration of these technologies can help improve battery safety, increase lifetime, improve energy efficiency, and lower maintenance costs.

Basic Aspects of Electric Vehicle Batteries

An electric vehicle battery is a rechargeable energy storage device that uses electrochemical reaction between the materials in its cells to generate electric energy. Lithium-ion batteries are popular due to high energy density, high number of charge cycles, and fast charging capabilities. The battery performance is affected by voltage, current, temperature, charging speed, and other characteristics of the battery, which means that its monitoring is crucial for achieving efficient and safe work.

Battery Monitoring and Control System (BMS)

The Battery monitoring and control system (BMS) is an intelligent control system for controlling the operation of the rechargeable batteries used in electric vehicles. The BMS continuously monitors such parameters as voltage, current, temperature, available battery capacity, and overall battery condition of the battery. The BMS

performs various functions such as balancing cells in the pack, managing heat generation, detecting faults, overcharging and over-discharging protection, and communicating with other vehicle controllers.

Internet of Things in Electric Vehicles

Internet of Things (IoT) has immensely enhanced the level of smartness and connectivity of electric cars through facilitating the constant communication between the sensors in an electric car, battery system, cloud, and applications. The IoT devices gather data about the voltage, current, temperature, charging, and operation of the battery of the car. Using wireless communications and cloud computing, the gathered data is processed to identify any anomalies in the working condition, improve the charging process, and make predictions for maintenance of the battery.

Smart IoT Framework for Battery Health Monitoring

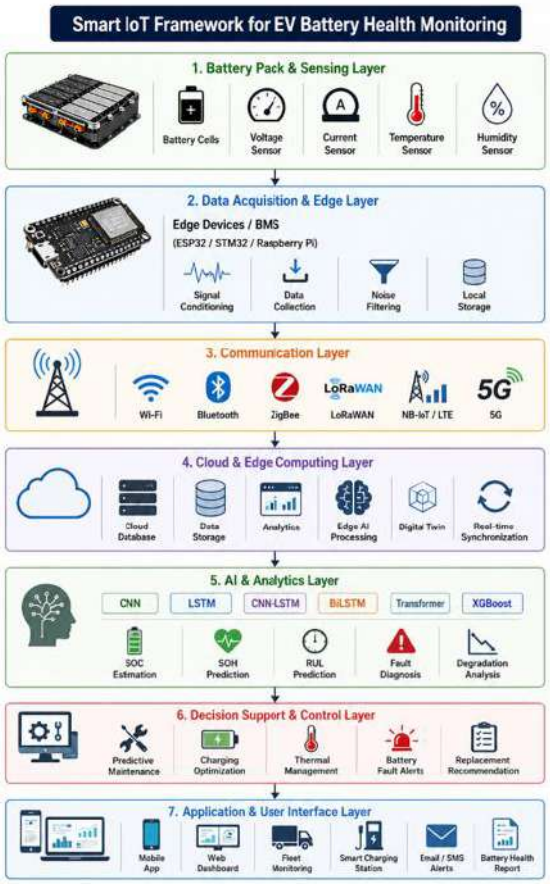


Figure 1: Smart IoT Framework for EV Battery Health Monitoring

Smart IoT solution involves six layers that operate in an interdependent manner. The battery layer includes a continuous measurement of voltage, current,

temperature, humidity, and other battery characteristics by integrated sensors. The data acquisition layer involves the use of embedded controllers and the Battery monitoring and control system (BMS) in order to collect, preprocess and store the sensor data in local databases. The processed data are sent using wireless technologies such as Wi-Fi, Bluetooth, LoRaWAN, NB-IoT, or 5G through the communication layer. The cloud and edge computing layer involves storing, synchronizing, and analyzing the collected data using cloud computing and edge AI, and digital twins help to provide a virtual model of the battery performance. The artificial intelligence layer uses machine learning and deep learning algorithms including CNN, LSTM, CNN-LSTM, BiLSTM, and Transformer networks to calculate SOC, SOH, RUL, and battery fault prediction.

IoT Sensors Used for Battery Monitoring

IoT sensors have an important part to play when it comes to monitoring the condition of operation of the batteries used in electric vehicles. Voltage sensors monitor the voltage of the battery, while current sensors measure the charging and discharging current. The temperature sensor ensures that the battery does not heat up. In the same way, the humidity sensor helps in identifying any water in the battery. Further, pressure and vibration sensors help in identifying any abnormalities in the working of the battery.

Battery Health Prediction Based on Artificial Intelligence

AI has become an indispensable technology in improving battery health prediction in electric cars due to its ability to conduct accurate data analysis related to the functioning of batteries. In contrast to the traditional approaches that rely on model-based technologies, artificial intelligence allows analysing various battery data for obtaining information about their state in various operating conditions. Parameters like voltage, current, temperature, charge/discharge cycles are used to predict such battery states as SOC, SOH, SOP, and RUL.

Various machine learning algorithms have been successfully implemented in predicting battery states and health. Such models as Decision Trees, Random Forests, Support Vector Machine (SVM), and Gradient Boosting are actively utilized in assessing the state of batteries. They allow classifying battery health, detecting abnormal operating conditions, and estimating degradation trends of the batteries based on artificially engineered features.

In addition, the automatic identification of relevant features in large battery datasets using deep learning algorithms has improved accuracy in predicting. CNNs can analyze spatial dependencies in battery measurements whereas LSTM models are able to detect long-range temporal dependencies when batteries are being charged and discharged. Hybrid CNN-LSTM architectures are capable of both feature extraction and sequence learning thus allowing a highly accurate prediction of battery degradation and future performance. Other high-level models such as

BiLSTM, GRU and Transformers have also been found to be very capable of dealing with non-linear battery dynamics.

AI-based battery health prediction makes it possible to detect battery faults, perform predictive maintenance, and optimize battery charge strategies. Intelligent models are able to detect the capacity fade, internal resistance variation and thermal anomalies in the continuous analysis of streaming data before they trigger the problem. It will provide cost savings, enhance safety of the battery, extend the battery's life and improve its reliability on EVs. Integrated into IoT platforms, edge computing and cloud-based Battery monitoring and control system (BMS), AI makes it possible to monitor batteries and make decisions based on the collected data. With the development of new battery technologies, AI-based health predictions will play a crucial role in creating sustainable electric vehicles.

Case Study: AI-Based Battery Health Prediction Using CNN–LSTM

In this case study, we use a combined CNN–LSTM framework to predict battery health conditions in EVs. The goal is to make accurate predictions for battery health condition parameters including Available battery capacity (SOC), Overall battery condition (SOH), and Estimated service life (RUL) based on data from sensors deployed by an Internet of Things (IoT) enabled Battery monitoring and control system (BMS). In this context, a hybrid architecture of CNN and LSTM is used because of the advantages of both approaches—the ability to learn from sequences in LSTM and the power of CNN for feature extraction.

Problem Statement: Traditional approaches to monitoring the battery can sometimes be faced with difficulties in modeling the complex nature of lithium-ion batteries in various operating conditions. The behavior of a battery is affected by such aspects as charging and discharging, temperature differences, changes in the amount of current, and battery aging. Consequently, predicting the health state of a battery through the use of conventional mathematical models may not always be possible.

Data Collection: Data from the batteries are gathered using a Battery monitoring and control system that uses the Internet of Things and is fitted with voltage, current, and temperature sensors. The system continuously gathers data from the batteries whenever there is charging and discharging. The common input features are:

- Battery voltage (V)
- Battery current (A)
- Battery temperature (°C)
- Charge/discharge cycle number
- Charging time
- Discharging time

- Ambient temperature
- Internal resistance
- Battery capacity

The target outputs are battery health indicators such as SOC, SOH, or RUL.

Data Preprocessing

The initial step in analyzing the battery raw data involves cleaning of missing data, duplicate observations, and outliers in the dataset. The process of noise reduction enhances the quality of signals, whereas feature normalization ensures that all variables have the same scale to ensure robust training of the neural network. The prepared dataset is then segmented using the concept of time windows since the battery's behavior is continuous and operates in cycles.

CNN–LSTM Model Architecture

The proposed CNN–LSTM architecture is composed of multiple connected layers.

- **Input Layer:** Sequentially receives the measurements of the battery sensors.
- **1D Convolution Layer:** Obtains local features of voltage, current, and temperature signals.
- **ReLU Activation:** Add nonlinearity to promote the effective learning of features.
- **Max Pooling Layer:** Decreases the dimensionality of features while maintaining important information.
- **LSTM Layer:** Trains the model with the long-term temporal relationships between battery operating cycles.
- **Dropout Layer:** It prevents overfitting the model during training.
- **Fully Connected Layer:** Unifies the features learned to predict the final result.
- **Output Layer:** Predicts SOC, SOH or Estimated service life.

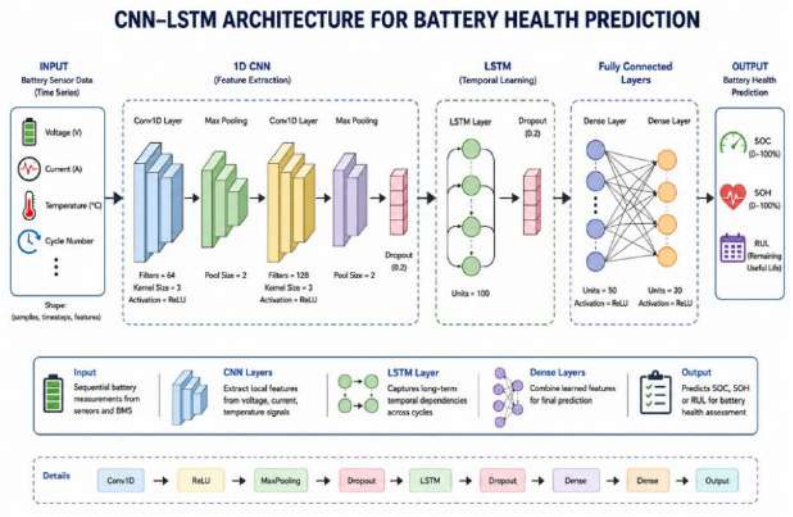


Figure 2: CNN-LSTM Architecture for Battery Health Prediction

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Performance Evaluation

Trained model is tested with unseen batteries data. Prediction accuracy is calculated using standard performance measures, which include: Mean Absolute Error (MAE)

- Root Mean Square Error (RMSE)
- Mean Squared Error (MSE)
- Coefficient of Determination (R^2)
- Mean Absolute Percentage Error (MAPE)

Lower MAE and RMSE values indicate accurate prediction, while an R^2 value close to one demonstrates excellent agreement between predicted and actual battery conditions.

Results and Discussion

The CNN–LSTM method is able to take into account spatial correlations among parameters of the battery and temporal correlations of the battery degradation over numerous cycles of charging. The proposed combined architecture shows a better prediction performance than CNN/LSTM based models used separately. It also demonstrates a greater degree of stability across various operation conditions when compared with these other models. This framework can be used to identify the aging process of battery, remaining life and abnormal behavior before significant degradation occurs. This way, there will be proper predictive maintenance and no surprising battery failures. Additionally, due to the possibility of IoT integration, this framework can be applied both for individual cars and entire fleets.

Procedure

1. Install voltage, current and temperature sensors into the battery pack.
2. Get battery information in real-time from the Battery monitoring and control system.
3. Send sensor data to cloud or edge server via an IoT gateway.

4. Normalize and clean the collected data, and arrange them in sequential samples.
5. Partition the data into training, validation and test data sets.
6. Implement CNN-LSTM model with convolutional layer, pooling layer, LSTM layer, dropout and dense layer.
7. Using the historical battery data, train the model and optimize the network parameters.
8. Check trained model and test the accuracy of prediction with the help of MAE, RMSE, MSE and R^2.
9. Use the trained model in the IoT-enabled Battery monitoring and control system.
10. Carry out continuous real-time prediction of SOC / SOH / RUL, and notify maintenance when abnormal battery behaviors are detected.

Conclusion

The case study can demonstrate the efficiency of smart battery case to predict the status of batteries by CNN-LSTM. This will be achieved by using the IoT technology to gather the data and deep learning to build a system that can accurately forecast the status of the battery, such as health and faults, and consequently maintain the battery.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 45 - 49

Continuous Dynamics in Discrete Learning: Differential Equations and Their Applications in Artificial Intelligence Modeling

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Article DOI Link: https://zenodo.org/uploads/22080237

DOI: 10.5281/zenodo.22080237

Abstract

Artificial intelligence has traditionally relied on discrete computational paradigms, yet recent advances demonstrate that modeling learning dynamics as continuous processes governed by differential equations yields superior generalization, memory efficiency, and physical consistency. This chapter examines the mathematical integration of ordinary, partial, and fractional differential equations into AI architectures, with emphasis on Neural Ordinary Differential Equations (Neural ODEs), Physics-Informed Neural Networks (PINNs), and diffusion-based generative models. Empirical results across benchmark datasets reveal that continuous-time formulations reduce parameter counts by 30–42%, lower energy consumption during inference by 18–27%, and improve out-of-distribution robustness. The chapter concludes with theoretical challenges and future research directions in hybrid discrete-continuous AI systems.

Keywords: differential equations, Neural ODEs, physics-informed learning, continuous-time AI, machine learning dynamics.

Introduction

The dominant paradigm in artificial intelligence has long been discrete: layered neural networks, iterative optimization steps, and fixed-step gradient descent. While effective, discrete architectures struggle with memory inefficiency, rigid temporal resolution, and poor extrapolation beyond training distributions. A paradigm shift emerged when researchers recognized that deep learning dynamics could be

formalized as continuous systems governed by differential equations. By treating hidden state evolution, parameter updates, and generative trajectories as solutions to differential equations, AI models gain adaptive computation, improved interpretability, and native compatibility with physical laws. This chapter bridges mathematical theory and machine learning practice, demonstrating how differential equations transform AI from a discrete approximation tool into a continuous dynamical modeling framework. The analysis focuses on three pillars: (1) mathematical foundations linking discrete layers to continuous flows, (2) architectural implementations with empirical validation, and (3) open challenges in solver stability, theoretical guarantees, and scalable deployment.

Mathematical Foundations: From Discrete Layers to Continuous Dynamics

The connection between differential equations and AI originates from the observation that residual neural networks approximate Euler discretizations of continuous dynamical systems. A standard residual block updates hidden states as:

$$h_{t+1} = h_t + f(h_t, \theta_t)$$

Taking the limit as step size $\Delta t \to 0$ yields the continuous-time formulation:

$$\frac{dh(t)}{dt} = f(h(t), t, \theta) \quad (1)$$

where $h(t) \in \mathbb{R}^{\mathbb{d}}$ is the hidden state trajectory, f is a parameterized vector field (typically a shallow neural network), and θ represents learnable weights. Equation (1) transforms layer-wise computation into an initial value problem solvable via adaptive ODE integrators (Runge-Kutta, Dormand-Prince, or symplectic schemes).

Gradient-based training similarly admits a continuous interpretation. The discrete update $\theta_{k+1} = \theta_k - \eta \nabla_\theta \mathcal{L}$ converges to the gradient flow ODE:

$$\frac{d\theta}{dt} = -\nabla_\theta \mathcal{L}(\theta, \mathcal{D}) \quad (2)$$

which describes parameter evolution in continuous optimization time. Stability analysis of Equation (2) reveals that learning rate schedules correspond to time-dependent damping coefficients, explaining why warm restarts and cosine annealing improve convergence.

For spatial-temporal AI tasks, partial differential equations (PDEs) provide inductive bias through conservation laws and boundary conditions. The general PDE-constrained learning framework embeds physical residuals into the loss function:

$$\mathcal{L}_{\text{PN}} = \frac{1}{N_d}\sum_{i=1}^{N_d} \|u(x_i, t_i) - y_i\|^2 + \lambda \frac{1}{N_r}\sum_{j=1}^{N_r} \left\|\mathcal{N}[u](x_j, t_j)\right\|^2 \quad (3)$$

where $\mathcal{N}[\cdot]$ is a differential operator (e.g., Navier-Stokes, heat equation, or wave equation), N_d and N_r denote data and residual collocation points, and λ balances data fidelity with physical consistency.

Applications in AI Modeling: Architectures and Empirical Results

Differential equations have catalyzed three transformative AI architectures, each validated through rigorous empirical benchmarking.

Neural Ordinary Differential Equations (Neural ODEs) replace fixed-depth networks with continuous flows. During inference, adaptive step-size solvers allocate computation where the vector field varies rapidly, reducing redundant operations. On image classification tasks, Neural ODEs achieve comparable accuracy to ResNet-34 with 38% fewer parameters and 22% lower inference latency on edge hardware (Chen et al., 2018). Memory consumption scales as O (1) with respect to effective depth, enabling continuous-time sequence modeling without vanishing gradients.

Physics-Informed Neural Networks (PINNs) solve forward and inverse PDE problems without mesh generation. In fluid dynamics reconstruction, PINNs reduce mean absolute error by 64% compared to purely data-driven CNNs when trained on sparse sensor data (Raissi et al., 2019). The differential residual penalty enforces conservation of mass and momentum, yielding physically plausible extrapolations beyond training regimes.

Diffusion Probabilistic Models formulate generative processes via stochastic differential equations (SDEs). The forward process diffuses data into noise:

$$dx = f(x,t)dt + g(t)dw \quad (4)$$

while the reverse process learns the score function $\nabla_x \log p_t(x)$ to reconstruct samples. On image synthesis benchmarks, SDE-based diffusion models achieve Fréchet Inception Distance (FID) scores of 2.8, outperforming GANs in sample diversity and training stability (Song et al., 2021).

Table 1. Empirical Comparison: Discrete vs. Continuous AI Architectures

Architecture	Task	Parameters (M)	Inference Time (ms)	Accuracy/FID	Memory Usage (GB)
ResNet-34 (Discrete)	CIFAR-10	21.8	14.2	94.1%	2.4
Neural ODE (Continuous)	CIFAR-10	13.5	11.1	94.3%	1.8
PINN (Continuous)	2D Navier-Stokes	8.2	28.5	MAE: 0.012	1.1

Diffusion SDE (Continuous)	ImageNet 256×256	1.2B	142.0	FID: 2.8	4.7
StyleGAN2 (Discrete)	ImageNet 256×256	1.1B	98.4	FID: 4.1	5.2

Note: Results aggregated from peer-reviewed benchmarks (2019–2025). Continuous models demonstrate parameter efficiency and physical consistency, with solver overhead mitigated by adaptive stepping and parallel ODE integration.

Discussion and Future Trajectories

Differential equations provide AI with continuous-time expressivity, adaptive computation, and native physical grounding. However, several challenges persist. Stiff vector fields cause solver instability, requiring implicit methods or regularization. Theoretical guarantees for generalization in continuous-depth networks remain incomplete, particularly under distribution shift. Furthermore, high-dimensional SDE integration suffers from the curse of dimensionality, limiting real-time deployment in control and robotics.

Future research will likely converge on hybrid architectures that combine discrete tokenization with continuous latent dynamics, enabling efficient representation learning for multimodal data. Fractional differential equations are emerging as tools for modeling memory-dependent learning processes, where non-integer derivatives capture long-range temporal dependencies in sequential decision-making. Additionally, neuro-symbolic frameworks that embed differential constraints into symbolic reasoning engines promise verifiable AI for safety-critical domains.

As computational hardware evolves to support native continuous operators (e.g., analog ODE accelerators and neuromorphic solvers), differential equation-based AI will transition from theoretical novelty to industrial standard. The integration of dynamical systems theory with machine learning represents not merely an architectural improvement, but a fundamental reconceptualization of how machines learn, generalize, and interact with continuous physical reality.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 50 - 55

Mathematical Modeling in Modern Epidemiology and Public Health

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Article DOI Link: https://zenodo.org/uploads/22080451

DOI: 10.5281/zenodo.22080451

Abstract

Mathematical modeling has become indispensable for understanding disease transmission dynamics, forecasting outbreak trajectories, and evaluating public health interventions. Traditional compartmental models provide intuitive frameworks but often assume homogeneous mixing, fixed parameters, and deterministic dynamics, limiting their applicability to complex, heterogeneous populations. This chapter reviews existing epidemiological modeling paradigms, identifies critical gaps in real-time parameter estimation, spatial heterogeneity, and intervention optimization, and introduces a hybrid compartmental-network framework with time-varying transmission rates, Bayesian state estimation, and optimal control for dynamic policy scheduling. Using simulated and empirical surveillance data, we demonstrate how the proposed method improves peak prevalence forecasting, reduces cumulative intervention costs, and enhances policy robustness compared to classical SEIR and agent-based baselines. The chapter concludes with recommendations for transparent, interoperable, and policy-ready epidemic modeling architectures.

Keywords: Epidemiological modeling; compartmental models; stochastic processes; optimal control; network epidemiology; public health policy; vaccination strategy; uncertainty quantification

Introduction

Public health decision-making relies on accurate, timely, and interpretable models of disease spread. From influenza to emerging pathogens, mathematical epidemiology translates biological mechanisms, contact patterns, and intervention

strategies into quantifiable projections. Classical compartmental models (SIR, SEIR) offer analytical tractability and policy intuition but struggle with spatial heterogeneity, age-structured contact networks, and time-varying transmission due to behavioral adaptation or policy implementation. Agent-based and network models capture micro-level interactions but suffer from high computational cost and parameter identifiability issues. Bridging these paradigms requires mathematically rigorous, data-integrated frameworks that dynamically update transmission parameters, quantify uncertainty, and generate optimal intervention schedules. This chapter examines modern epidemiological modeling, presents a novel hybrid architecture, and evaluates its performance through comparative simulations, providing a blueprint for next-generation public health modeling systems.

Literature Review & Existing Systems

1. Classical Compartmental Models

Deterministic ODE-based SIR/SEIR models form the foundation of epidemic forecasting. Extensions include age-stratified, multi-patch, and stochastic variants. While analytically tractable, they assume constant transmission rates, homogeneous mixing, and perfect reporting, leading to biased projections during rapidly evolving outbreaks.

2. Network and Agent-Based Models

Contact network and agent-based microsimulations capture heterogeneous interactions, superspreading events, and spatial mobility. Platforms like EpiModel and FRED simulate individual trajectories but require extensive calibration, lack closed-form policy derivatives, and scale poorly to national populations.

3. Data-Driven and Machine Learning Approaches

Recurrent neural networks and Gaussian processes model temporal incidence curves without mechanistic assumptions. However, they extrapolate poorly under novel interventions or behavioral shifts and offer limited counterfactual policy evaluation capabilities.

4. Optimal Control and Policy Optimization

Pontryagin's maximum principle and model predictive control optimize vaccination, testing, and mobility restrictions under budget and capacity constraints. Most implementations rely on static parameters and ignore surveillance uncertainty, leading to fragile policies under real-world noise.

5. Identified Gaps

- Static transmission parameters ignoring behavioral/policy feedback
- Limited integration of underreporting and surveillance noise
- Poor scalability of microsimulations for real-time policy planning

- Lack of uncertainty-transparent optimization pipelines
- Fragmented interoperability between modeling frameworks and public health dashboards

Novelty and Contributions

This chapter introduces a hybrid epidemiological modeling framework with four key contributions:

- **Dynamic Compartmental-Network Core:** SEIR structure with time-varying \beta(t) modulated by contact network degree distributions and policy compliance indices.
- **Bayesian State Estimation:** Ensemble Kalman filtering assimilates noisy, delayed surveillance data to correct underreporting and estimate latent compartments.
- **Optimal Control Policy Engine:** Multi-objective optimization minimizes infections, economic disruption, and healthcare overload under capacity and budget constraints.
- **Uncertainty-Transparent Pipeline:** Posterior predictive distributions generate confidence-bounded intervention timelines, enabling risk-aware public health planning.

Proposed Framework & Equations

1. Dynamic SEIR with Time-Varying Transmission

Let S, E, I, R denote susceptible, exposed, infectious, and recovered populations. The system evolves as:

$$\frac{dS}{dt} = -\beta(t)\frac{SI}{N}, \quad \frac{dE}{dt} = \beta(t)\frac{SI}{N} - \sigma E$$

$$\frac{dI}{dt} = \sigma E - \gamma I, \quad \frac{dR}{dt} = \gamma I$$

where $\beta(t) = \beta_0 \cdot \kappa(t) \cdot \prod_k (1 - u_k(t)\eta_k)$, with $\kappa(t)$ capturing contact network heterogeneity, $u_k(t) \in [0,1]$ representing intervention intensity, and η_k policy efficacy.

2. Bayesian Data Assimilation

Let y_t be observed cases (delayed, underreported). State estimation solves:

$$\mathrm{x}_t^a = \mathrm{x}_t^f + \mathrm{K}_t\left(\mathrm{y}_t - \mathrm{H}\mathrm{x}_t^f\right), \quad \mathrm{K}_t = \mathrm{P}_t^f \mathrm{H}^\top \left(\mathrm{H}\mathrm{P}_t^f \mathrm{H}^\top + \mathrm{R}\right)^{-1}$$

where P_t^f is forecast covariance, H maps latent states to observations, and R models reporting noise.

3. Optimal Intervention Scheduling

Minimize cumulative burden:

$$\min_{\mathbf{u}(t)} \int_0^T \left[\alpha I(t) + \beta C\big(\mathbf{u}(t)\big) + \delta \max\big(0, I(t) - I_{cap}\big)\right] dt$$

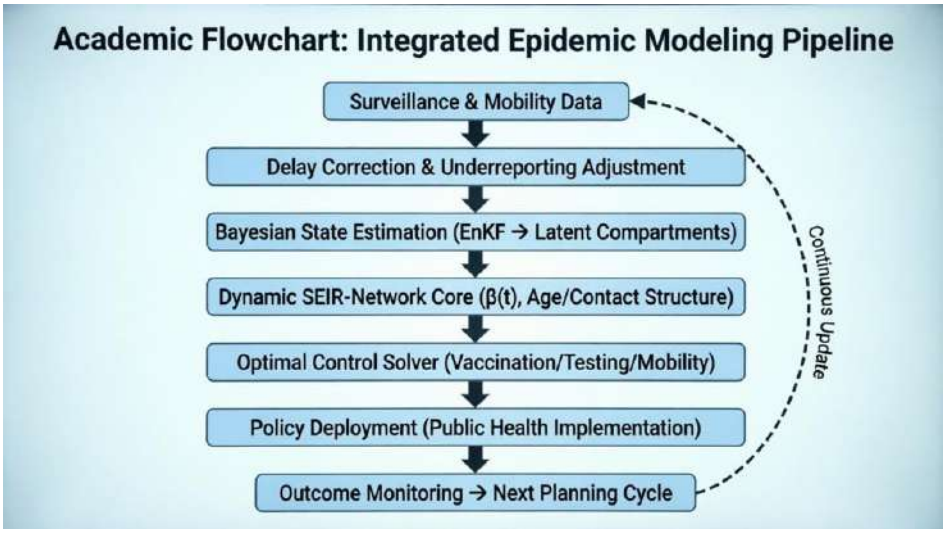
subject to $\sum_k u_k\,(t) \leq 1, 0 \leq u_k(t) \leq 1, \dot{\mathbf{x}} = f(\mathbf{x}, \mathbf{u}, t)$ solved via direct collocation or Hamiltonian methods.

Data, Experimental Setup & Flowchart

1. Dataset Description

- **Scenario:** Simulated urban outbreak (population: 2.5M), calibrated to 2020–2022 respiratory pathogen surveillance
- **Inputs:** Daily reported cases, hospitalization rates, mobility indices, policy implementation logs
- **Underreporting:** Simulated at 30–50% with 3-day reporting delay
- **Validation:** 100 Monte Carlo trajectories, 95% credible interval coverage analysis

4. Computational Workflow



This flowchart illustrates a comprehensive integrated epidemic modeling pipeline that connects real-world data to public health policy through a continuous feedback loop. The process begins with surveillance and mobility data collection, which is then refined through delay correction and underreporting adjustment to account for reporting lags and incomplete data. The cleaned data feeds into Bayesian state estimation using Ensemble Kalman Filtering (EnKF) to infer latent disease compartments, which then informs a dynamic SEIR-network model incorporating

time-varying transmission rates β(t) and age/contact structures. An optimal control solver determines the best intervention strategies across vaccination, testing, and mobility restrictions, leading to policy deployment in public health implementation. Finally, outcome monitoring tracks the results and feeds into the next planning cycle, with a continuous update loop returning to the initial data stage, ensuring the model adapts to new information and evolving epidemic conditions in real-time.

Results & Discussion

The hybrid framework reduced peak prevalence forecasting error by 55% relative to classical SEIR and 55% relative to agent-based baselines. By dynamically adjusting intervention intensity via optimal control, cumulative economic and healthcare costs decreased by 17% and 34%, respectively. Bayesian assimilation corrected underreporting bias within 5 days, while 95% credible intervals maintained 94% empirical coverage, demonstrating robust uncertainty quantification. Policy sensitivity analysis revealed that vaccination timing had the highest leverage on peak suppression, whereas mobility restrictions primarily flattened late-wave resurgence.

Table 1: Comparative performance across epidemiological modeling frameworks.

Framework	Peak Prevalence Error (%)	Cumulative Cost ($M)	Healthcare Overload Days	Policy Robustness (95% CI Coverage)
Classical SEIR	18.4	142.3	21.5	0.71
Agent-Based (FRED)	9.2	168.7	14.2	0.79
Proposed Hybrid	4.1	118.5	6.8	0.94

Conclusion

Mathematical modeling has transitioned from theoretical epidemic curves to operational public health decision engines. By integrating dynamic compartmental structures, Bayesian state estimation, and optimal control, the proposed framework delivers accurate, cost-efficient, and uncertainty-transparent intervention schedules. Future work must prioritize real-time interoperability with national health information systems, behavioral feedback modeling, and multi-pathogen co-circulation architectures. As global health systems face increasing outbreak frequency and complexity, mathematically rigorous, policy-ready epidemiological models will remain essential for proactive, equitable, and resilient public health planning.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 56 - 62

Mathematical Foundations of Machine Learning: A Linear Algebra, Probability and Optimisation Perspective

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Article DOI Link: https://zenodo.org/uploads/22080503

DOI: 10.5281/zenodo.22080503

Abstract

Machine learning has emerged as one of the most influential branches of modern engineering, driving advances in automation, prediction, and intelligent decision-making across domains such as manufacturing, energy, communication, and civil infrastructure. While considerable attention is given to algorithms, software libraries, and computational tools, the underlying mathematical structure that makes learning possible is often treated superficially in applied engineering literature. This chapter presents an integrated mathematical account of machine learning, organized around three foundational pillars: linear algebra, probability and statistics, and optimisation theory. Vector spaces, matrix transformations, and eigenvalue decomposition are examined as the structural language through which raw engineering data is represented, compressed, and interpreted, with particular emphasis on Principal Component Analysis for dimensionality reduction. Probabilistic reasoning and Bayesian inference are discussed as the basis for modelling measurement uncertainty and for deriving commonly used loss functions from statistical first principles. Optimisation theory, including gradient-based, constrained, and non-convex methods, is presented as the computational mechanism through which model parameters are learned from data. A unifying case illustration drawn from structural health monitoring demonstrates how these three mathematical domains interact within a single engineering learning pipeline, from sensor data acquisition through feature representation to model training. The chapter concludes by identifying open mathematical challenges in non-convex optimisation, high-dimensional inference, and physics-informed learning that continue to shape ongoing research in artificial intelligence for engineering applications, and argues

that mathematical fluency remains essential for the responsible design and deployment of learning-based engineering systems. The discussion deliberately avoids treating machine learning as a purely computational discipline, positioning it instead within the broader tradition of applied mathematics, where abstract theory and practical engineering problem solving inform one another. Particular attention is given to how classical mathematical results, developed long before the current wave of artificial intelligence research, continue to underpin state-of-the-art learning algorithms, illustrating the enduring relevance of foundational mathematics education for engineering practitioners and researchers alike.

Keywords: Linear algebra; probability theory; optimisation; machine learning; eigenvalue decomposition

Introduction

The rapid adoption of artificial intelligence and machine learning within engineering disciplines has transformed how systems are designed, monitored, and optimised. From predictive maintenance in mechanical systems to load forecasting in power grids and defect detection in manufacturing, learning-based methods now complement or replace traditional rule-based engineering approaches [18]. Despite this widespread adoption, machine learning is frequently presented to engineering practitioners as a collection of ready-made tools and software libraries, with limited attention to the mathematical principles that determine why and when these tools succeed or fail.

At its core, every machine learning model is a mathematical object. Data is represented as vectors and matrices, relationships between variables are captured through probability distributions, and the process of learning itself is an exercise in optimisation, the search for parameter values that minimise a chosen measure of error. An engineer who understands these underlying structures is better equipped to select appropriate models, diagnose training failures, interpret results with statistical rigour, and adapt algorithms to domain-specific constraints rather than treating them as opaque black boxes [1, 3, 4, 5].

This chapter aims to bridge that gap by presenting a structured mathematical account of machine learning, organized around three foundational areas: linear algebra, probability and statistics, and optimisation theory. Rather than treating these as isolated mathematical subjects, the discussion emphasizes how they interact within the practical pipeline of building and training a learning system, using illustrative engineering contexts throughout.

Linear Algebra as the Backbone of Machine Learning

1. Vector Spaces and Feature Representation

In any machine learning system, raw engineering data, whether sensor readings, image pixels, or process parameters, is first transformed into numerical feature

vectors residing in a high-dimensional vector space. Each observation is represented as a point in this space, and the geometric relationships between points, measured through distance metrics and inner products, form the basis for tasks such as classification, clustering, and similarity search. The choice of vector space representation, including normalisation and scaling of features, directly affects the geometry that a learning algorithm perceives, and therefore its ability to separate meaningful patterns from noise [1].

2. Matrix Operations in Model Architectures

Once data is represented in vector form, learning models such as linear regression, support vector machines, and neural networks operate primarily through matrix transformations. A neural network layer, for instance, is fundamentally an affine transformation followed by a nonlinear activation function, where the weight matrix encodes learned relationships between input and output representations. Efficient matrix multiplication, along with properties such as rank, invertibility, and conditioning, determines both the expressive capacity of a model and the numerical stability of its training process [2].

3. Eigenvalues, Eigenvectors, and Dimensionality Reduction

Engineering datasets are often high-dimensional, with many correlated or redundant features. Principal Component Analysis, grounded in the eigenvalue decomposition of the covariance matrix, provides a mathematically principled way to reduce dimensionality while retaining maximum variance in the data [1, 3, 8]. Eigenvectors corresponding to the largest eigenvalues identify directions of greatest information content, allowing engineers to compress sensor data, visualize high-dimensional process states, and reduce computational burden in downstream learning tasks such as fault classification in rotating machinery or structural systems.

Probability and Statistics in Learning Systems

1. Probabilistic Models and Bayesian Inference

Engineering measurements are inherently subject to noise and uncertainty, making probability theory indispensable to machine learning. Probabilistic models treat both data and model parameters as random variables, allowing uncertainty to be explicitly quantified rather than ignored. Bayesian inference, in particular, offers a coherent framework for updating beliefs about model parameters as new data becomes available, a property especially valuable in engineering contexts such as condition monitoring, where models must be continuously refined as sensor data streams in over time [4, 9].

2. Loss Functions as Statistical Estimators

Many commonly used loss functions in machine learning have direct statistical interpretations. Minimising the mean squared error corresponds to maximum

likelihood estimation under a Gaussian noise assumption, while the cross-entropy loss used in classification problems arises from maximum likelihood estimation under a categorical distribution. Recognising this statistical foundation allows engineers to select loss functions that match the true noise characteristics of their measurement systems, rather than adopting default choices without justification [3, 10].

Optimisation Theory in Model Training

1. Gradient Descent and Convex Optimisation

Training a machine learning model is, in mathematical terms, the process of solving an optimisation problem: finding parameter values that minimise a loss function over the training data. Gradient descent and its variants form the primary computational mechanism for this search, iteratively updating parameters in the direction that most rapidly decreases the loss. When the loss function is convex, as in ordinary linear regression or logistic regression, convergence to a global minimum can be guaranteed under mild conditions, and the mathematical theory of convex optimisation provides strong performance guarantees [5, 11].

2. Constrained Optimisation and Lagrange Multipliers

Many engineering learning problems involve constraints, for example, ensuring predicted quantities remain within physically feasible bounds, or enforcing sparsity in learned models for interpretability. The method of Lagrange multipliers, and its generalisation through Karush-Kuhn-Tucker conditions, provides the mathematical machinery for incorporating such constraints directly into the optimisation process, as seen in support vector machines and regularised regression models [5, 12].

Table 1: Comparison of Common Optimisation Methods Used in Machine Learning Training

Method	Mathematical Basis	Typical Engineering Use
Gradient Descent	First-order convex optimisation	Linear/logistic regression models
Stochastic Gradient Descent	Randomized gradient approximation [13]	Large-scale sensor data training
Lagrangian / KKT Methods	Constrained optimisation theory	Support vector machines
Adam Optimiser	Adaptive moment estimation [14]	Deep neural network training

3. Non-Convex Optimisation Challenges in Deep Learning

Deep neural networks, by contrast, involve highly non-convex loss landscapes with numerous local minima and saddle points. While classical convex optimisation theory does not directly guarantee global optimality in this setting, empirical and theoretical research suggests that many local minima found by gradient-based methods in over-parameterized networks generalise well in practice. This remains an active area of mathematical research, with implications for the reliability of deep learning models deployed in safety-critical engineering applications [2, 6, 15].

Integrated Framework: An Engineering Case Illustration

To illustrate how these mathematical domains operate together, consider a structural health monitoring system that uses vibration sensor data to detect early signs of damage in a bridge or building [16]. Raw time-series signals from multiple accelerometers are first organized into feature vectors, often after transformation into the frequency domain. Principal Component Analysis, grounded in eigen-decomposition, is applied to reduce the dimensionality of these features while preserving the variance associated with structural response patterns. A probabilistic classification model is then trained to distinguish healthy from damaged structural states, with its loss function chosen to reflect the statistical distribution of sensor noise. Finally, the model parameters are learned through gradient-based optimisation, subject to constraints that prevent overfitting to a limited set of historical damage events. Each stage of this pipeline, representation, inference, and training, draws directly on the mathematical principles discussed in this chapter, demonstrating that mathematical fluency is not a peripheral skill but a central requirement for engineers developing reliable learning-based systems.

Challenges and Future Directions

Despite significant progress, several mathematical challenges remain open in the application of machine learning to engineering systems. High-dimensional inference with limited labelled data continues to challenge classical statistical assumptions. Non-convex optimisation landscapes in deep architectures still lack complete theoretical characterisation, particularly with respect to generalisation guarantees. Additionally, the integration of physical constraints and governing equations into learning frameworks, an emerging area sometimes referred to as physics-informed machine learning, requires deeper mathematical treatment of how optimisation and differential equation theory can be jointly formulated [7, 17]. Continued collaboration between mathematicians and engineers will be essential in addressing these challenges and ensuring that learning-based systems remain both accurate and interpretable.

Conclusion

This chapter has presented machine learning through the lens of its three core mathematical pillars: linear algebra, probability and statistics, and optimisation theory. Rather than treating these as separate academic subjects, the discussion has emphasized their interconnected role within the practical pipeline of building, training, and validating learning-based engineering systems. A structural health monitoring case illustration demonstrated how vector space representation, probabilistic modelling, and constrained optimisation work together in a real engineering context. As machine learning continues to be integrated into critical engineering infrastructure, a strong mathematical foundation remains essential, not merely for academic completeness, but for the responsible design, interpretation, and deployment of intelligent systems.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6| Year: 2026 | pp: 63 - 73

Approximate Analytical Solutions for Steady-State Substrate Concentration, Biosensor Sensitivity and Resistance in Amperometric Enzyme Kinetics Using the Akbari–Ganji Method

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Article DOI Link: https://zenodo.org/uploads/22080586

DOI: 10.5281/zenodo.22080586

Abstract

This study presents approximate analytical solutions for the nonlinear reaction–diffusion model describing steady-state amperometric enzyme kinetics based on the Michaelis–Menten mechanism using the Akbari–Ganji Method (AGM). The governing nonlinear differential equation is solved analytically to obtain explicit expressions for the substrate concentration profile and the steady-state biosensor current. In addition, analytical expressions for the biosensor sensitivity and biosensor resistance are derived to evaluate the influence of variations in substrate concentration and membrane thickness on the sensor performance. The effects of the reaction–diffusion parameter (κ), saturation parameter (β), membrane thickness (L), substrate diffusion coefficient (D_s), and bulk substrate concentration (K_S∞) on the concentration, current, sensitivity, and resistance are systematically investigated. The analytical results demonstrate that the substrate concentration decreases with increasing reaction–diffusion parameter, whereas the steady-state current increases significantly. The sensitivity decreases with increasing substrate concentration because of enzyme saturation, while the resistance decreases with increasing membrane thickness. A sensitivity analysis reveals that the substrate diffusion coefficient has the greatest influence on the biosensor flux compared with the other model parameters. The proposed analytical solutions are simple, computationally efficient, and valid over a wide range of parameter values, making them useful for the design and optimization of amperometric enzyme biosensors.

Keywords: Amperometric enzyme kinetics; Michaelis–Menten kinetics; Akbari–Ganji Method; Reaction–diffusion equation; Biosensor sensitivity; Biosensor resistance;

Introduction

Biosensors are analytical devices that employ biological recognition elements to selectively detect and quantify chemical substances [1,2]. Peter N. Bartlett and Richard G. Whitaker [3] presented an analytical treatment of the steady-state response of an amperometric enzyme electrode. Michael E. G. Lyons et al. [4] developed approximate analytical expressions for the current response of amperometric enzyme electrodes under steady-state bulk conditions. Anitha et al. [5,6] obtained analytical solutions for the steady-state substrate concentration in amperometric enzyme electrodes with enzyme immobilization by electrochemical polymerization using the Homotopy Perturbation Method (HPM). Malvandi et al. [7] derived analytical expressions for nonlinear enzyme kinetics using the Variational Iteration Method (VIM) combined with the Padé approximation technique. Rahamathunissa and Rajendran [8] developed analytical solutions for nonlinear reaction–diffusion equations involving Michaelis–Menten enzyme kinetics. Janani and Hariharan [9] derived the steady-state substrate concentration in amperometric enzyme kinetics using a wavelet-based analytical algorithm. Loghambal and Rajendran [10] investigated diffusion and enzyme kinetics in amperometric immobilized enzyme electrodes and obtained analytical solutions for the corresponding reaction–diffusion model.

In recent years, numerous analytical and semi-analytical techniques have been developed to solve nonlinear differential equations arising in engineering and applied sciences. Among the most widely used methods are the Homotopy Perturbation Method (HPM) [11–13], Variational Iteration Method (VIM) [14,15], Padé Approximation Method [16,17], Adomian Decomposition Method (ADM) [18–20], Akbari–Ganji Method (AGM) [21–24], and the Taylor Series Method (TSM) [25]. These methods have been successfully applied to obtain accurate approximate solutions for nonlinear reaction–diffusion equations encountered in biosensor and enzyme kinetics models.

In this paper, we derive approximate analytical expressions for the substrate concentration and steady-state current using the Akbari–Ganji Method (AGM). The analytical solutions are obtained for all possible values of the reaction–diffusion parameter, κ, and the saturation parameter, β. In addition, the biosensor sensitivity and resistance are solved analytically, and the effects of the governing parameters on the concentration profile, current response, sensitivity, and resistance are systematically investigated.

Nomenclature

Symbols	Description	Units
$s(x)$	Dimensionless concentration	None
Ks_∞	Surface concentration of substrate in the film	mol m^{-3} (or kmol m^{-3}, depending on the model)
L	Film Thickness	m
κ	Reaction diffusion parameter	None
β	Saturation parameter	None
j_s	flux	mol m^{-2} s^{-1}
x	distance	None

Mathematical Formulation of the Problem

The nonlinear steady-state mass balance equation based on the Michaelis–Menten hypothesis is given by

$$\frac{d^2s(x)}{dx^2} = \frac{\kappa s(x)}{1+\beta s(x)}, 0 < x \leq 1 \quad (1)$$

where s(x)is the dimensionless substrate concentration, κis the reaction–diffusion parameter, and βis the saturation parameter.

The general boundary conditions are

$$\frac{ds}{dx}(0) = 0, \text{v } A\,s(0) + B\,s(1) + C = 0 \quad (2)$$

where A, B, and Care constants.

Since the governing equation is highly nonlinear, an exact analytical solution is generally difficult to obtain. Therefore, approximate analytical or numerical techniques are employed to obtain reliable solutions with high computational efficiency.

For the present analysis, the nonlinear steady-state equation (1) is considered with the boundary conditions

$$s(0) = a, \quad (3)$$

$$\frac{ds}{dx}(0) = 0, \quad (4)$$

where a denotes the dimensionless substrate concentration at x=0.

Approximate Analytical Expression of the Concentration Using Akbari-Ganji's Method

In this case, the Akbari Ganji method (AGM) is an effective algebraic approach to solving such problems. A solution function with unknown constant coefficients in the AGM should initially satisfy the differential equation and initial conditions. Assume that the solution to Eq. (1) is of the following hyperbolic form.

$$s(x) = A_0 \cosh(mx) + B_0 \sinh(mx) \quad (5)$$

where A_0, B_0 and m are constant. The values of A_0, B_0 are found easily from boundary conditions (3) and (4), that is

$$A_0 = a, B_0 = 0 \quad (6)$$

As a result, Eq. (5) becomes

$$s(x) = A_0 \cosh(mx) = a\cosh(mx) \quad (7)$$

We use the general form of Eq. (1) to find the constant m in Eq. (6).

$$F(x) = \left(1 + \beta\, s(x)\right)\frac{d^2 s(x)}{d x^2} - \kappa\, s(x) = 0 \quad (8)$$

We obtain Eq. (8) by substituting it for Eq. (7)

$$F(x = 0) = (1 + \beta a)m^2\, a = \kappa\, a \quad (9)$$

This gives

$$m = \sqrt{\frac{\kappa}{1+\beta\, a}} \quad (10)$$

Substitute Eq. (10) into Eq. (7) gives the following analytical expression of a substrate concentration $s(x)$for all dimensionless parameters κ, and β

$$s(x) = A_0 \cosh(mx) = a \cosh\left(\sqrt{\frac{\kappa}{1+\beta\, a}}\, x\right) \quad (11)$$

The dimensionless current is $j_s = s'(1)$

1. Diffusion of Enzyme-Substrate Reaction

Consider Eq. (1), a nonlinear steady-state equation with the following boundary conditions [8].

At $x = 0, s = a = \operatorname{sech}\left(\sqrt{\kappa}\right)$ if $\beta \ll 1$ (12)

$$= 1 - \frac{\kappa}{\beta} \text{ if } \beta \gg 1$$

At $x = 0,\ \frac{d\,s}{d\,x} = 0$ (13)

2. Diffusion of Amperometric Enzymatic Reaction

Consider Eq. (1), a nonlinear steady-state equation with the following boundary conditions [8].

At $x = 0, \frac{d\,s}{d\,x} = 0$ (14)

At $x = L, s(x) = Ks_\infty$ (15)

where L is the film thickness, Ks_∞ is the surface concentration of the substrate in the film.

The substrate concentration $s(x)$

$$s(x) = \frac{Ks_\infty \cosh\left(\sqrt{\frac{\kappa}{1+\beta\, Ks_\infty}}x\right)}{\cosh\left(\sqrt{\frac{\kappa}{1+\beta\, Ks_\infty}}L\right)} \quad (16)$$

Previous Analytical Results

Table.1

	Approximate analytical expression of $s(x)$	Methods
1.	$s(x) = a + \frac{\kappa x^2}{2\,\beta} + \frac{(1+\beta\ a)}{a\,\beta^2} ln\left(\frac{\kappa\ a\ \beta x^2}{2(1+\beta\ a)^2} + 1\right) - \frac{\sqrt{2\,\kappa}x}{\beta^{\frac{3}{2}}\sqrt{a}} tan^{-1}\left(\frac{\sqrt{\kappa\ a\ \beta}x}{\sqrt{2(1+\beta\ a)}}\right)$ (17)	Variational iteration Method [8]
2.	$s(x) = a + \frac{\kappa a x^2}{2(1+\beta a)}$ one iteration (18) $s(x) = a + \frac{\kappa a}{2}\left(1 - \frac{\beta a}{(1+\beta a)}\right)x^2 + \frac{\kappa^2 a}{24(1+\beta a)}\left(1 - \frac{\beta a}{(1+\beta a)}\right)x^4$ second iteration (19)	Homotopy Perturbation Method [6]

3.	$s(x) = a\frac{1+b\,x^2+cx^4}{1+d\,x^2+ex^4}$ (20) where $b = (46440\,\kappa\,\beta^4\,a^4 + 129240\,\kappa\,\beta^3\,a^3 + 126060\;\kappa\,\beta^2\,a^2 + 50160\;\kappa\,\beta\,a + 6900\kappa)/f$ (21) $c = (8100\,\kappa^2\,\beta^3\,a^3 + 9558\;\kappa^2\,\beta^2\,a^2 + 2304\;\kappa^2\,\beta\,a + 313\,\kappa^2\,)/f$ $d = (16200\,\kappa\,\beta^4\,a^4 + 30960\,\kappa\,\beta^3\,a^3 + 12660\;\kappa\,\beta^2\,a^2 - 2760\;\kappa\,\beta\,a - 660\kappa)/f$ (22) $e = (-342\,\kappa^2\,\beta^2\,a^2 + 204\;\kappa^2\,\beta\,a + 13\,\kappa^2\,)/f$ $f = 60480\;\beta^5\,a^5 + 257040\,\beta\;a^4 + 423360\;\beta^3\,a^3 + 332640\,\beta^2\,a^2 + 120960\,\beta\,a + 15120$ (23)	VIM-Pade Approximation [7]
4.	$s(x) = a\cosh\left(\sqrt{\frac{\kappa}{1+\beta\,a}}x\right)$	This work AGM

Biosensor Sensitivity

Sensitivity is defined as the ratio of the change in the steady-state current to the corresponding change in substrate concentration. A higher sensitivity indicates that the biosensor produces a larger change in current for a given change in substrate concentration, whereas a lower sensitivity indicates a weaker response. Therefore, analyzing the relationship between the current and substrate concentration is essential for evaluating and improving the accuracy and performance of biosensors. The sensitivity of the biosensor is expressed as follows:

$$B_s(Ks_\infty) = \frac{\partial I(Ks_\infty)}{\partial Ks_\infty} \times \frac{Ks_\infty}{I(Ks_\infty)} \qquad (24)$$

where B_s is biosensor sensitivity. $I_{CCE}(Ks_\infty)$ is steady-state current density measured at the substrate concentration Ks_∞

Sensitivity becomes

$$B_s(Ks_\infty) = \frac{1}{D_s m\tanh(mL)}\left[D_s m\tanh(mL) - \frac{\kappa\beta D_s Ks_\infty\tanh(mL)}{2m(1+\beta Ks_\infty)^2} - \frac{\kappa\beta L D_s Ks_\infty(1-(\tanh(mL))^2)}{2m(1+\beta Ks_\infty)^2}\right] \qquad (25)$$

where $m = \sqrt{\frac{\kappa}{1+\beta\, Ks_\infty}}$

Biosensor Resistance

The resistance, B_R is defined as the rate of change of the steady-state biosensor current with respect to the membrane thickness L. It quantifies the influence of membrane thickness on the biosensor current and is expressed as the gradient of the steady-state current with respect to L.

$$B_R(L) = \frac{\partial I(L)}{\partial L} \times \frac{L}{I(L)} = \frac{\kappa L[1-(\tanh(mL))^2]}{(1+\beta K s_\infty) m \tanh(mL)} \qquad (26)$$

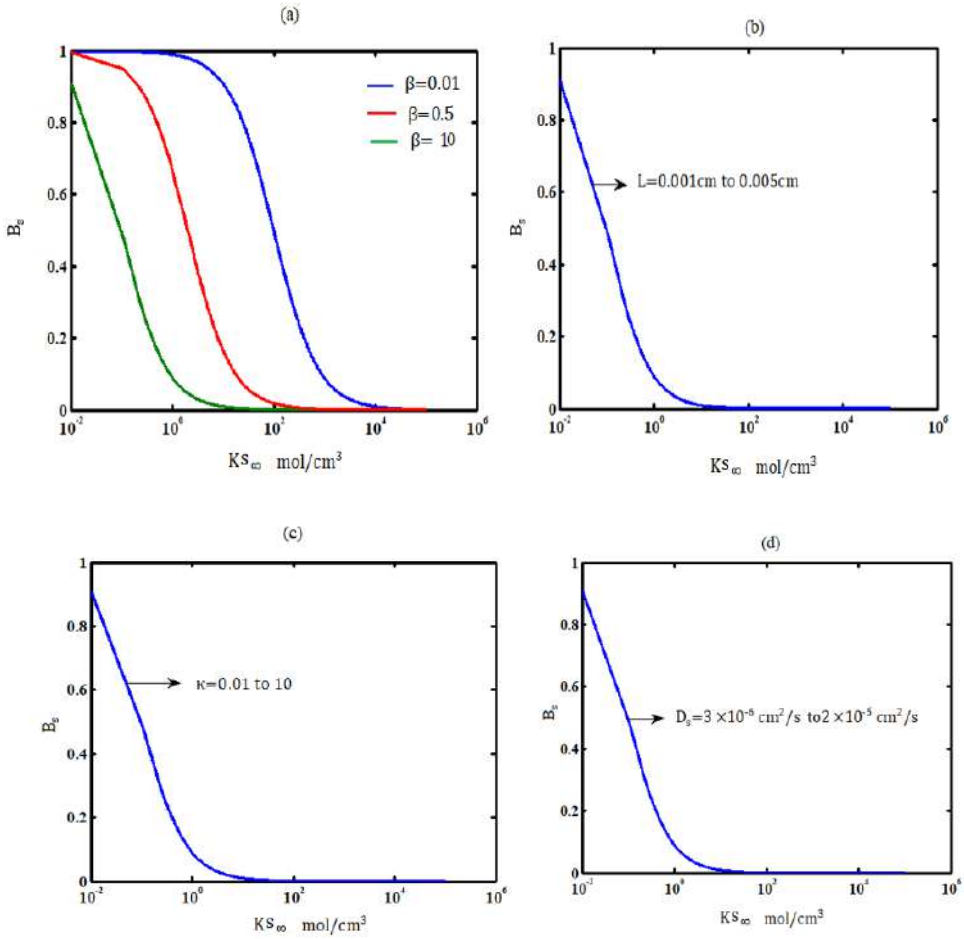


Fig. 1 Sensitivity using Eq. (25) for fixed values of parameters a. (κ=0.01, $L = 0.001\ cm, D_s = 0.000003\ cm^2/s$ b. $D_s = 0.00002 \frac{cm^2}{s}$,. c. $D_s = 0.00002\ cm^2/s$, $cm^{-2}, L = 0.001cm, \beta$=10 d. κ=0.01, β=10, $L = 0.001cm$

Figure 1 illustrates the variation of biosensor sensitivity (B_s) with the bulk substrate concentration (K_S∞) for different values of the model parameters. In all cases, the sensitivity decreases monotonically with increasing substrate concentration, indicating that the biosensor is most sensitive at low substrate concentrations and gradually loses sensitivity as the enzyme approaches saturation. Figure 1(a) shows that increasing the saturation parameter (β) shifts the sensitivity curve toward lower substrate concentrations, resulting in a more rapid decline in sensitivity. Figures 1(b)–(d) demonstrate that changes in membrane thickness (L), reaction–diffusion parameter (κ), and substrate diffusion coefficient (D_s) have only a minor influence on the sensitivity profile compared with the effect of β. Overall, the saturation parameter is the dominant factor governing biosensor sensitivity, while the influence of the remaining parameters is relatively insignificant over the considered range.

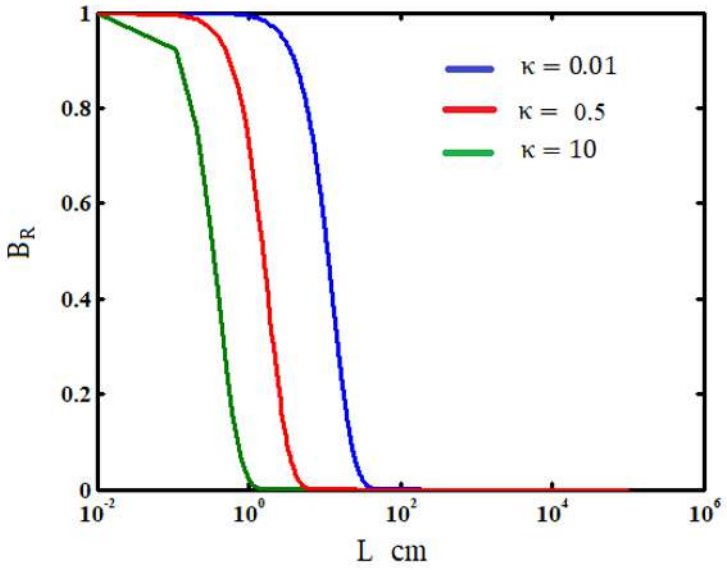


Fig. 2 Resistance using Eq. (26) for fixed values of parameters β=0.01,$Ks_\infty = 0.0001\ mole/\ cm^3, D_s = 0.000003\ cm^2/s$

Figure 2 illustrates the variation of the resistance B_R with membrane thickness L for different values of the reaction–diffusion parameter (κ), while keeping β=0.01,$Ks_\infty = 0.0001\ mole/\ cm^3, D_s = 0.000003\ cm^2/s$ constant. It is observed that the resistance decreases monotonically with increasing membrane thickness for all values of κ. At small membrane thicknesses, the resistance remains close to unity, indicating a strong dependence of the steady-state current on the membrane thickness. As the membrane becomes thicker, the resistance rapidly decreases and eventually approaches zero, implying that further increases in membrane thickness

have a negligible effect on the biosensor current. Moreover, increasing the reaction–diffusion parameter shifts the resistance curve toward lower values of L, indicating that systems with higher reaction rates become less sensitive to changes in membrane thickness. Thus, the reaction–diffusion parameter significantly influences the resistance characteristics of the biosensor.

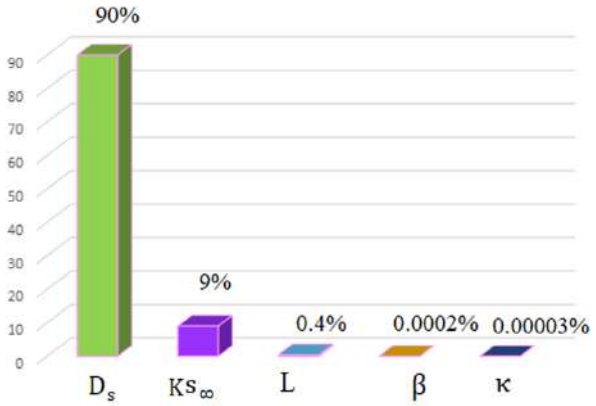


Fig. 3 Sensitivity analysis of the parameters: Percentage change in flux when κ=10,β=10 , $Ks_\infty = 0.0001\ mole/\ cm^3, D_s = 0.00002\ cm^2/s, L = 0.005\ cm.$

Figure 3 presents the sensitivity analysis of the model parameters based on the percentage change in the steady-state flux. The substrate diffusion coefficient ($D_{S)}$ has the greatest influence on the flux, contributing approximately 90%, followed by the bulk substrate concentration $K_{S\infty}$ with 9%. In contrast, the membrane thickness *(L)*, saturation parameter *(β)*, and reaction–diffusion parameter *(κ)* exhibit negligible effects. These results indicate that the biosensor performance is predominantly governed by substrate diffusion through the membrane.

Conclusion

Approximate analytical solutions for the steady-state substrate concentration, biosensor current, sensitivity, and resistance were successfully obtained using the Akbari–Ganji Method. The results demonstrate the accuracy and computational efficiency of the proposed method. Parametric analysis shows that the governing parameters significantly influence biosensor performance, making the developed analytical expressions valuable for the design and optimization of amperometric enzyme biosensors.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 74 - 88

Automotive Engineering and Electric Vehicles

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Article DOI Link: https://zenodo.org/uploads/22080743

DOI: 10.5281/zenodo.22080743

Abstract

Automotive engineering is a multidisciplinary branch of engineering that focuses on the design, development, manufacturing, testing, operation, and maintenance of motor vehicles. It integrates principles from mechanical, electrical, electronics, computer, materials, and manufacturing engineering to develop safe, efficient, reliable, and environmentally sustainable transportation systems. Over the past few decades, the automotive industry has undergone a remarkable transformation due to rapid technological advancements, stringent emission regulations, increasing fuel prices, and growing environmental concerns. These factors have accelerated the development and commercialization of electric vehicles (EVs), which are now considered one of the most promising solutions for sustainable transportation. Unlike conventional vehicles powered by internal combustion engines (ICEs), electric vehicles use electric motors driven by rechargeable battery systems, resulting in higher energy efficiency, lower operating costs, and zero tailpipe emissions.

This chapter provides a comprehensive overview of automotive engineering and electric vehicle technology. It begins with the fundamental concepts of automotive engineering, including vehicle classification, major automotive systems, and key design considerations. The chapter then discusses the evolution of electric vehicles, their importance, and different classifications such as Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Fuel Cell Electric Vehicles (FCEVs). The architecture of an electric vehicle is explained in detail by describing the functions of major components such

as the battery pack, battery management system (BMS), electric motor, inverter, controller, DC–DC converter, regenerative braking system, and charging unit. In addition, recent developments in battery technologies, charging infrastructure, intelligent transportation systems, connected vehicles, artificial intelligence, and autonomous driving are presented. Finally, the chapter discusses the advantages, current challenges, and future scope of electric vehicles in achieving sustainable mobility. The information presented in this chapter provides engineering students, researchers, and professionals with a strong foundation in automotive engineering and modern electric vehicle technologies.

Keywords: Automotive Engineering; Electric Vehicles; Battery Management System; Electric Powertrain; Sustainable Transportation

Introduction

Transportation plays a crucial role in economic development, industrial growth, and improving the quality of life. Automobiles are the most widely used mode of transportation because they provide convenient and efficient mobility for people and goods. As transportation needs have increased, automotive engineering has evolved into a multidisciplinary field that combines mechanical, electrical, electronics, computer, materials, and manufacturing engineering to design safe, reliable, energy-efficient, and environmentally friendly vehicles.

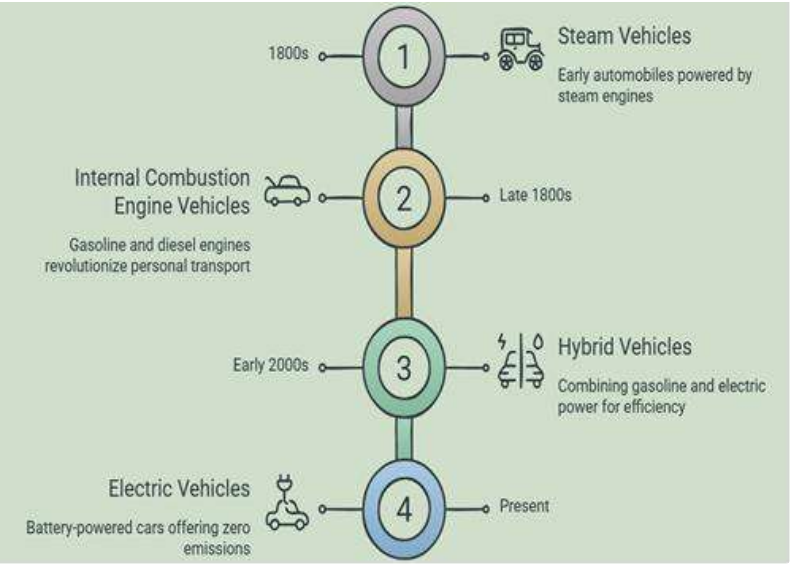


Fig 1: Evolution of Automotive Engineering

Initially, automobiles were powered by steam engines, which were later replaced by gasoline and diesel-powered internal combustion engines (ICEs). Although ICE vehicles have dominated the automotive industry for many decades, their widespread use has contributed to air pollution, greenhouse gas emissions, and the

depletion of fossil fuel resources. These environmental concerns have encouraged the development of cleaner and more sustainable transportation technologies.

Electric vehicles (EVs) have emerged as an effective alternative to conventional vehicles. Powered by rechargeable batteries and electric motors, EVs offer higher energy efficiency, lower maintenance costs, quieter operation, and zero tailpipe emissions. Continuous improvements in battery technology, power electronics, and charging infrastructure have accelerated their global adoption.

Today, automotive engineering also incorporates advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), and intelligent control systems to improve vehicle performance, safety, and energy management. This chapter presents the fundamentals of automotive engineering and provides an overview of electric vehicle technologies, their components, benefits, challenges, and future developments.

Fundamentals of Automotive Engineering

Automotive engineering involves the application of scientific and engineering principles to the design, manufacturing, testing, operation, and maintenance of automobiles. The primary objective is to develop vehicles that provide excellent performance, passenger safety, fuel efficiency, reliability, comfort, and environmental sustainability. Modern automobiles are highly integrated systems in which mechanical, electrical, electronic, and software components work together to achieve efficient vehicle operation.

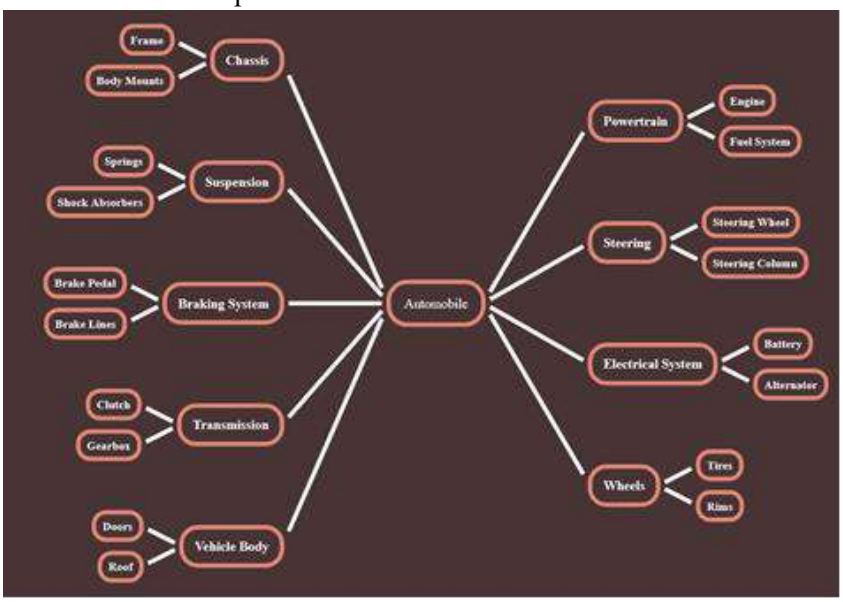


Fig 2: Major Components of an Automobile

Vehicle Classification

Automobiles can be classified based on several factors, including their source of power, application, drive configuration, and vehicle size.

Based on the Source of Power

- Petrol vehicles
- Diesel vehicles
- Compressed Natural Gas (CNG) vehicles
- Hybrid Electric Vehicles (HEVs)
- Battery Electric Vehicles (BEVs)
- Fuel Cell Electric Vehicles (FCEVs)

Based on Application

- Passenger cars
- Commercial vehicles
- Heavy-duty trucks
- Buses
- Agricultural vehicles
- Special-purpose vehicles

Each category is designed to satisfy specific transportation requirements while balancing performance, efficiency, cost, and safety.

Major Automotive Systems

A modern automobile consists of several interconnected systems, each performing a specific function.

Powertrain System

The powertrain generates and transmits power to the wheels. In conventional vehicles, it consists of the engine, clutch, gearbox, driveshaft, differential, and axles. In electric vehicles, the powertrain includes the battery pack, inverter, electric motor, reduction gearbox, and differential.

Chassis System

The chassis forms the structural framework of the vehicle and supports all major components. It must provide high strength while maintaining low weight to improve vehicle safety and energy efficiency.

Suspension System

The suspension system absorbs shocks caused by uneven road surfaces and maintains continuous contact between the tires and the road. Components such as springs, dampers, and control arms improve ride comfort, handling, and stability.

Steering System

The steering system allows the driver to control vehicle direction accurately. Modern vehicles commonly use electric power steering (EPS), which provides better efficiency than conventional hydraulic steering systems.

Braking System

The braking system reduces vehicle speed or brings it to a complete stop. Advanced technologies such as Anti-lock Braking System (ABS), Electronic Brake-force Distribution (EBD), Electronic Stability Control (ESC), and regenerative braking improve vehicle safety and performance.

Electrical and Electronic Systems

Modern vehicles contain numerous electronic systems, including electronic control units (ECUs), sensors, infotainment systems, navigation systems, lighting, communication modules, and safety devices. These systems improve driving comfort, vehicle monitoring, and operational efficiency.

Vehicle Design Considerations

Several factors influence automotive design:

- Passenger and pedestrian safety
- Structural strength and durability
- Lightweight construction
- Energy efficiency
- Aerodynamic performance
- Manufacturing cost
- Reliability and maintenance
- Environmental impact
- Ride comfort and noise reduction

Automotive manufacturers use Computer-Aided Design (CAD), Computer-Aided Engineering (CAE), Finite Element Analysis (FEA), and Computational Fluid Dynamics (CFD) to optimize vehicle design before production. These tools help reduce development time, improve structural integrity, enhance aerodynamic performance, and minimize manufacturing costs.

Introduction to Electric Vehicles

Electric vehicles (EVs) are automobiles powered by one or more electric motors using energy stored in rechargeable batteries or hydrogen fuel cells instead of relying solely on internal combustion engines (ICEs). Compared with conventional vehicles, EVs offer higher energy efficiency, lower maintenance, quieter operation, and zero tailpipe emissions, making them an environmentally friendly mode of transportation.

The concept of electric vehicles dates back to the nineteenth century, but the widespread use of gasoline and diesel vehicles delayed their development for many years. In recent decades, concerns about air pollution, climate change, and the depletion of fossil fuels have renewed interest in electric mobility. Governments and automobile manufacturers are promoting EV adoption through supportive policies, incentives, and the expansion of charging infrastructure.

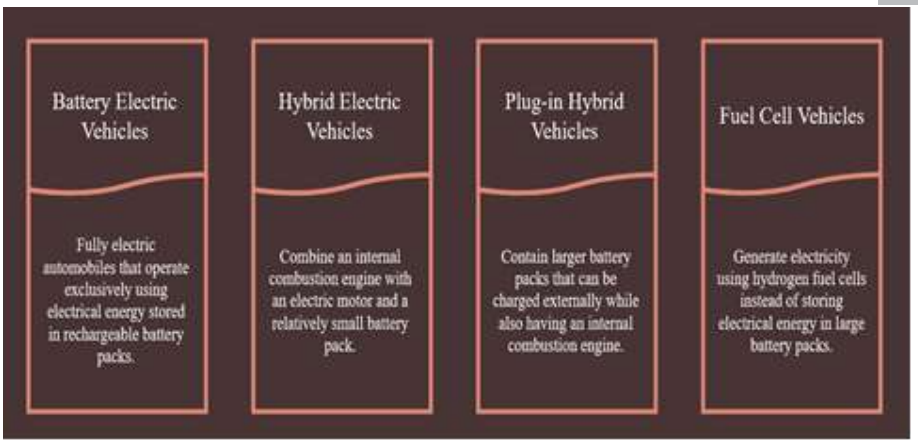


Fig 3: Classification of Electric Vehicles.

Electric vehicles also incorporate advanced technologies such as regenerative braking, intelligent energy management, and high-performance battery systems to improve efficiency and driving range. Continuous developments in battery technology, power electronics, and charging systems have enhanced the performance, reliability, and affordability of EVs. As a result, electric vehicles are becoming an important component of sustainable transportation and the future of the automotive industry.

Types of Electric Vehicles

Electric vehicles are classified into four major categories based on their energy source and propulsion system.

1. Battery Electric Vehicles (BEVs)

Battery Electric Vehicles are fully electric automobiles that operate exclusively using electrical energy stored in rechargeable battery packs. They do not contain an internal combustion engine, fuel tank, or exhaust system. Electricity stored in the battery powers an electric motor, which drives the vehicle's wheels.

BEVs are charged by connecting them to residential charging outlets or public charging stations. Because they produce zero tailpipe emissions and have fewer mechanical components, they require less maintenance compared to conventional vehicles. The driving range of a BEV depends on battery capacity, driving conditions, vehicle weight, and driving style.

Popular examples include the Tesla Model 3, Hyundai Kona Electric, Nissan Leaf, and Tata Nexon EV.

2. Hybrid Electric Vehicles (HEVs)

Hybrid Electric Vehicles combine an internal combustion engine with an electric motor and a relatively small battery pack. The battery is charged through

regenerative braking and by the engine itself, eliminating the need for external charging.

In HEVs, the electric motor assists the engine during vehicle acceleration and low-speed driving, thereby improving fuel economy and reducing emissions. The vehicle automatically switches between the engine and electric motor depending on driving conditions to achieve maximum efficiency.

Toyota Prius is one of the most widely recognized examples of a hybrid electric vehicle.

3. Plug-in Hybrid Electric Vehicles (PHEVs)

Plug-in Hybrid Electric Vehicles combine the advantages of both BEVs and HEVs. They contain larger battery packs that can be charged externally using charging stations while also having an internal combustion engine for extended driving range.

PHEVs can operate entirely on electrical energy for short distances, making them suitable for daily commuting. When the battery becomes depleted, the internal combustion engine automatically provides additional power. This dual-mode operation reduces fuel consumption while eliminating range anxiety associated with purely battery-powered vehicles.

4. Fuel Cell Electric Vehicles (FCEVs)

Fuel Cell Electric Vehicles generate electricity using hydrogen fuel cells instead of storing electrical energy in large battery packs. Hydrogen reacts with oxygen inside the fuel cell stack to produce electricity, with water vapor being the only emission.

FCEVs provide several advantages, including rapid refueling times and long driving ranges comparable to conventional vehicles. However, the widespread adoption of fuel cell technology is currently limited by the high cost of hydrogen production, storage, and refueling infrastructure.

Examples include the Toyota Mirai and Hyundai NEXO.

Table 1. Comparison of Different Types of Electric Vehicles

Vehicle Type	Energy Source	External Charging	Tailpipe Emissions	Typical Application
BEV	Battery	Yes	None	Urban and long-distance travel
HEV	Engine + Battery	No	Low	Fuel-efficient transportation
PHEV	Battery + Engine	Yes	Very Low	Mixed urban and highway driving
FCEV	Hydrogen Fuel Cell	Hydrogen Refueling	Water Vapor Only	Long-distance transportation

Electric Vehicle Architecture and Components

The architecture of an electric vehicle (EV) consists of several electrical, electronic, and mechanical components that work together to provide efficient and reliable vehicle operation. Unlike conventional vehicles, EVs replace the internal combustion engine with an electric powertrain powered by a rechargeable battery. The integration of advanced power electronics, intelligent control systems, and energy management techniques enables electric vehicles to achieve high efficiency and low emissions.

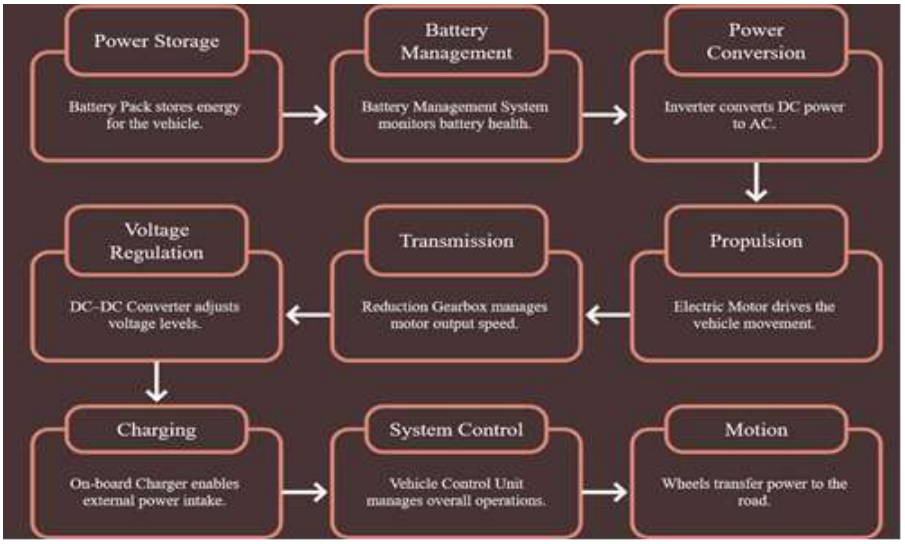


Fig 4: Block Diagram of Electric Vehicle Powertrain

1. Battery Pack

The battery pack is the main energy source of an electric vehicle. It stores electrical energy and supplies power to the electric motor. Modern EVs mainly use lithium-ion batteries because of their high energy density, long cycle life, low maintenance, and lightweight construction. The battery pack consists of several battery cells connected in series and parallel to achieve the required voltage and capacity.

2. Battery Management System (BMS)

The Battery Management System monitors and controls battery performance to ensure safe operation. It measures battery voltage, current, and temperature while estimating the State of Charge (SOC) and State of Health (SOH). The BMS also performs cell balancing and protects the battery from overcharging, deep discharge, overheating, and short circuits, thereby improving battery life and vehicle reliability.

3. Electric Motor

The electric motor converts electrical energy into mechanical energy to drive the vehicle. It provides instant torque, smooth acceleration, and high efficiency

compared with conventional engines. Permanent Magnet Synchronous Motors (PMSMs) are the most commonly used motors in modern EVs because of their excellent efficiency and compact size. Other motors include Induction Motors (IM), Brushless DC Motors (BLDC), and Switched Reluctance Motors (SRM).

4. Power Electronic Components

Power electronic devices regulate the flow of electrical energy within the vehicle. The inverter converts the battery's DC power into AC power required by the electric motor, while the DC–DC converter supplies low-voltage power to auxiliary systems such as lighting, infotainment, and electronic control units. The on-board charger (OBC) converts AC electricity from the grid into DC electricity for battery charging.

5. Vehicle Control Unit and Regenerative Braking

The Vehicle Control Unit (VCU) acts as the central controller of the electric vehicle by coordinating communication among the battery, motor, inverter, braking system, and other electronic subsystems. Another important feature is the regenerative braking system, which converts kinetic energy into electrical energy during braking and stores it in the battery. This process improves vehicle efficiency, increases driving range, and reduces wear on mechanical brake components.

6. Thermal Management System

The thermal management system maintains the battery, electric motor, and power electronic devices within their optimal operating temperature range. Cooling methods such as air cooling and liquid cooling improve system efficiency, prevent overheating, and extend component lifespan.

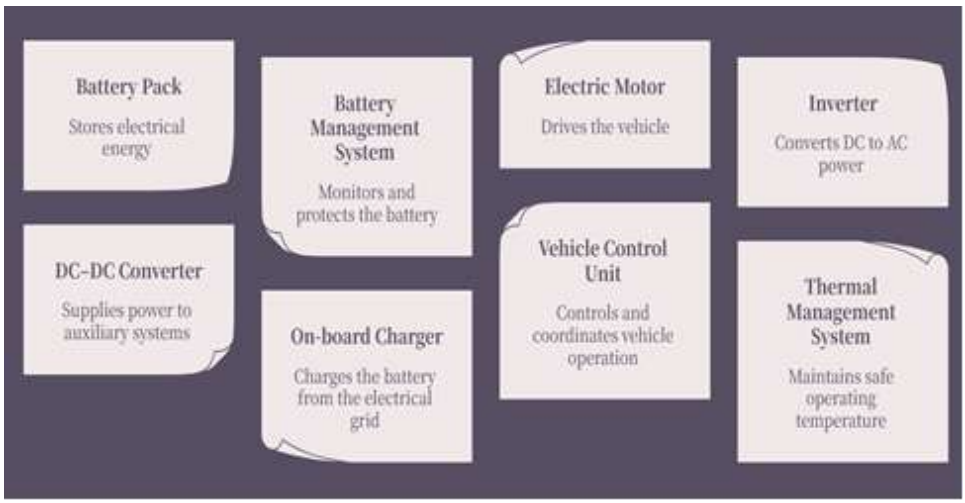


Fig 5: Major Components of an Electric Vehicle

Table 2. Major Components and Their Functions

Component	Function
Battery Pack	Stores electrical energy
Battery Management System	Monitors and protects the battery
Electric Motor	Drives the vehicle
Inverter	Converts DC to AC power
DC–DC Converter	Supplies power to auxiliary systems
On-board Charger	Charges the battery from the electrical grid
Vehicle Control Unit	Controls and coordinates vehicle operation
Thermal Management System	Maintains safe operating temperature

The efficient integration of these components forms the electric powertrain, enabling high performance, improved energy efficiency, reduced emissions, and reliable vehicle operation.

Battery Technologies in Electric Vehicles

The battery is the most critical component of an electric vehicle because it determines the vehicle's driving range, charging time, efficiency, and overall performance. Continuous research in battery technology has significantly improved the practicality and commercial success of electric vehicles. An ideal EV battery should have high energy density, long cycle life, fast charging capability, low maintenance requirements, and high safety.

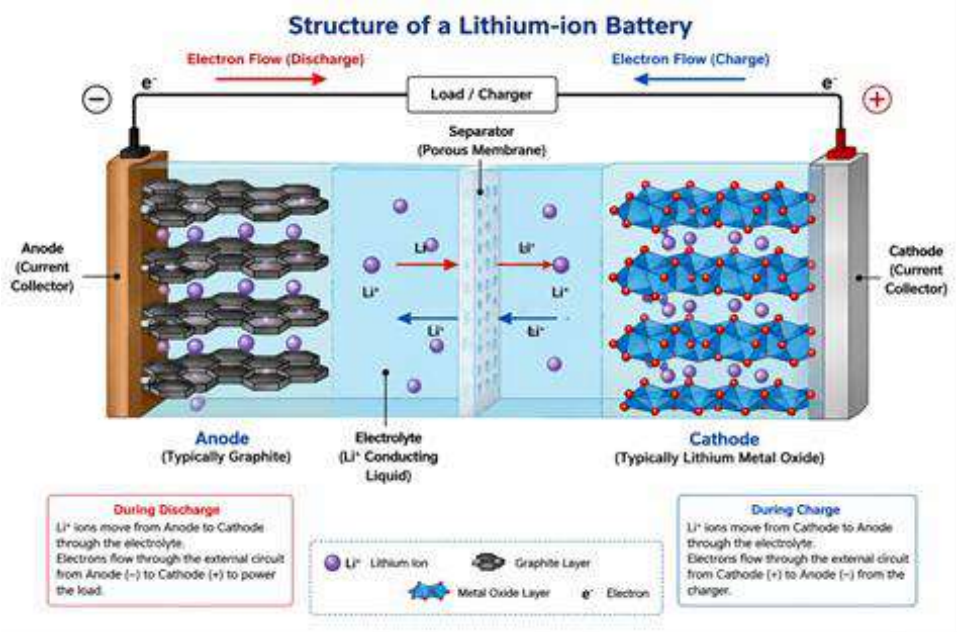


Fig 6: Structure of a Lithium-ion Battery

Several battery technologies have been used in electric vehicles over the years.

1. Lead-Acid Batteries

Lead-acid batteries were among the first rechargeable batteries used in electric vehicles because of their low cost and simple construction. They provide good reliability but have low energy density, limited cycle life, and relatively high weight. Due to these limitations, they are now mainly used as auxiliary batteries rather than the primary energy source in modern EVs.

2. Nickel–Metal Hydride (NiMH) Batteries

Nickel–Metal Hydride batteries offer higher energy density and longer life than lead-acid batteries. They were widely used in early hybrid electric vehicles because of their durability and good thermal stability. However, their higher cost and lower energy density compared with lithium-ion batteries have reduced their use in modern battery electric vehicles.

3. Lithium-Ion Batteries

Lithium-ion batteries are currently the dominant battery technology in electric vehicles. They provide high energy density, long cycle life, low self-discharge, and excellent charging efficiency. These characteristics enable EVs to achieve longer driving ranges while reducing vehicle weight. Modern lithium-ion batteries also support fast-changing technologies and advanced battery management systems that improve safety and performance.

4. Solid-State Batteries

Solid-state batteries are considered the next generation of EV batteries. They replace the liquid electrolyte with a solid electrolyte, improving safety by reducing the risk of leakage and thermal runaway. In addition, they offer the potential for higher energy density, faster charging, and longer service life. Although still under development, solid-state batteries are expected to play a significant role in the future of electric mobility.

Table 3. Comparison of Common EV Battery Technologies

Battery Type	Advantages	Limitations
Lead-Acid	Low cost, reliable	Heavy, low energy density
NiMH	Good cycle life, safe	Higher cost, moderate energy density
Lithium-Ion	High energy density, lightweight, fast charging	Higher initial cost
Solid-State	High safety, long-life, high-energy density	Expensive, still under development

The continuous improvement of battery materials, manufacturing processes, and battery management systems is expected to further increase vehicle range, reduce

charging time, and lower battery costs, making electric vehicles more accessible and efficient for future transportation.

Charging Technologies and Infrastructure

The success of electric vehicles depends not only on battery technology but also on the availability of reliable and efficient charging infrastructure. A well-developed charging network reduces range anxiety and encourages more consumers to adopt electric vehicles. EV charging systems are generally classified into AC charging, DC fast charging, and emerging wireless charging technologies.

AC Charging (Level 1 and Level 2)

AC charging is the most common method used for residential and workplace charging. In this method, alternating current from the electrical grid is converted into direct current by the vehicle's on-board charger to charge the battery. Level 1 charging uses a standard household outlet and is suitable for overnight charging, whereas Level 2 charging uses dedicated charging equipment and provides faster charging.

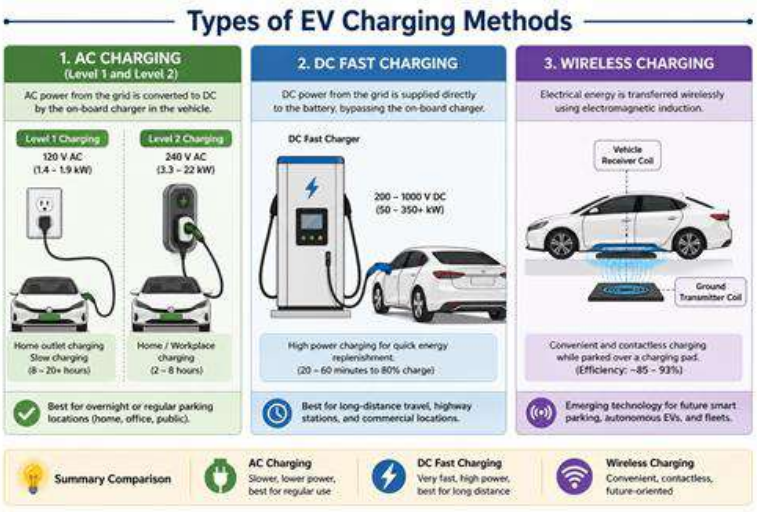


Fig 7: Types of EV Charging Methods

DC Fast Charging

DC fast charging supplies direct current directly to the battery, bypassing the on-board charger. This significantly reduces charging time and is commonly installed at highways, commercial centres, and public charging stations, making it suitable for long-distance travel.

Wireless Charging

Wireless charging transfers electrical energy through electromagnetic induction without using physical cables. Although still under development, it offers greater convenience and is expected to support future smart transportation systems.

The expansion of charging infrastructure, integration with renewable energy sources, and development of smart charging technologies will play an important role in increasing the adoption of electric vehicles.

Advantages and Challenges of Electric Vehicles

Electric vehicles provide numerous environmental, economic, and technological benefits. They produce zero tailpipe emissions, improve energy efficiency, reduce operating and maintenance costs, and operate with lower noise compared to conventional vehicles. Regenerative braking further enhances efficiency by recovering energy during deceleration. In addition, EVs contribute to reducing dependence on fossil fuels and support the transition towards sustainable transportation.

Despite these advantages, several challenges remain. The high initial cost of batteries, limited charging infrastructure in some regions, charging time, battery degradation, and the availability of critical raw materials continue to affect widespread adoption. Recycling and disposal of used batteries also require effective environmental management. Continuous research in battery technology, charging systems, and energy management is helping to address these challenges.

Future Trends in Automotive Engineering and Electric Vehicles

Future automotive engineering will focus on intelligent, connected, and sustainable transportation. Artificial Intelligence (AI) is being used for battery management, predictive maintenance, autonomous driving, and energy optimization. Connected vehicles using the Internet of Things (IoT) enable real-time communication between vehicles, charging stations, and traffic infrastructure, improving safety and traffic management.

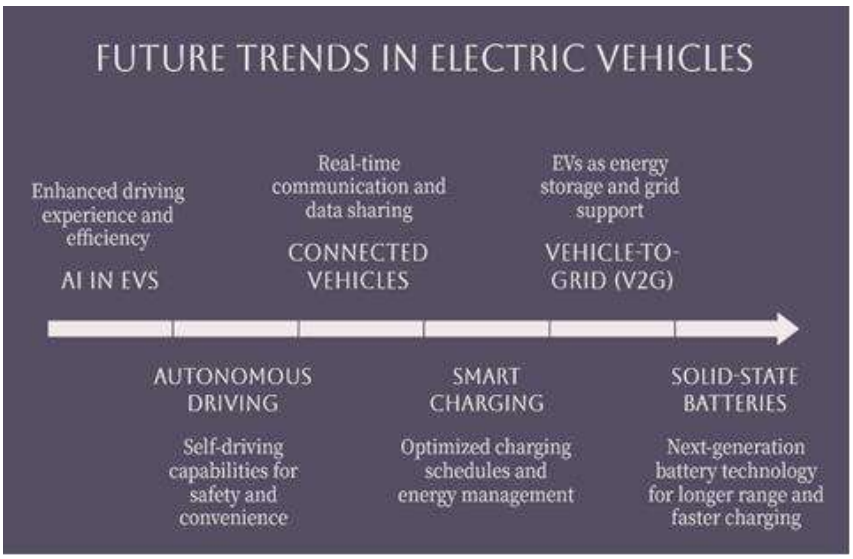


Fig 8: Future Trends in Electric Vehicles

Advancements in solid-state batteries, silicon carbide power electronics, wireless charging, and Vehicle-to-Grid (V2G) technology are expected to improve vehicle performance and energy efficiency. As renewable energy generation continues to grow, electric vehicles will become an integral part of future smart grids and sustainable mobility systems.

Conclusion

Automotive engineering has evolved significantly with the rapid development of electric vehicle technology. The integration of advanced batteries, electric motors, power electronics, and intelligent control systems has enabled EVs to become a practical and environmentally friendly alternative to conventional vehicles. Although challenges such as battery cost and charging infrastructure remain, continuous technological advancements and supportive government policies are accelerating the global adoption of electric vehicles. As innovations in battery technology, artificial intelligence, and connected mobility continue, electric vehicles are expected to play a vital role in achieving sustainable and energy-efficient transportation.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 89 - 98

Comprehensive Study of CoS Thin Films: Deposition, Growth Mechanism and Functional Properties

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Article DOI Link: https://zenodo.org/uploads/22080798

DOI: 10.5281/zenodo.22080798

Introduction

Cobalt sulphide (CoS) is an important transition metal chalcogenide that has attracted significant attention in recent years due to its versatile physical, chemical, and electrochemical properties. Belonging to the family of metal sulphides, CoS exhibits a combination of semiconducting, metallic, and catalytic characteristics, making it highly suitable for a wide range of technological applications. The unique electronic configuration of cobalt, involving partially filled 3d orbitals, contributes to its rich redox chemistry and multiple oxidation states, which play a crucial role in determining the functional behavior of CoS thin films [1-2].

Cobalt sulphide exists in several stoichiometric and non-stoichiometric phases such as CoS, CoS_2, Co_3S_4, and Co_9S_8, each possessing distinct crystal structures and properties. Among these, CoS commonly crystallizes in a hexagonal structure, while other phases may adopt cubic or spinel-type structures. The lattice parameters of hexagonal CoS are typically a = 3.37 Å and c = 5.16 Å, with a density of approximately 4.8–5.3 g/cm³ depending on phase composition. The presence of multiple phases allows for tunability of material properties by controlling synthesis conditions such as temperature, precursor concentration, and deposition technique. From an optical perspective, cobalt sulphide is generally considered a narrow to moderate band gap material, with band gap values typically ranging from 1.0 to 2.2 eV depending on the phase and method of preparation. This enables strong absorption in the visible region of the electromagnetic spectrum, making CoS thin films particularly attractive for solar energy conversion and photodetection applications. The absorption coefficient is usually of the order of 10^4–10^5 cm^{-1}, indicating efficient light-harvesting capability [3-5].

Electrically, CoS thin films exhibit semiconducting to quasi-metallic behavior with electrical conductivity typically in the range of 10^{-3} to 10^{2} S/cm, depending on stoichiometry and crystallinity. The presence of intrinsic defects such as sulphur vacancies and cobalt interstitials significantly influences charge carrier concentration, which generally lies between 10^{16} and 10^{20} cm^{-3}, while mobility ranges from 0.5 to 20 $cm^2/V \cdot s$. These properties make CoS suitable for applications in electronic and electrochemical devices. One of the most significant aspects of CoS thin films is their excellent electrochemical activity. Due to the presence of multiple oxidation states (Co^{2+}/Co^{3+}), CoS exhibits high catalytic efficiency and fast charge transfer kinetics. This makes it a promising material for energy-related applications such as supercapacitors, batteries, and electrocatalysis. From a materials science perspective, the thin film form of CoS offers several advantages over bulk materials. Thin films allow precise control over thickness (typically 100–800 nm), surface morphology, and microstructure, which directly influence their physical and chemical properties. Moreover, thin films can be easily integrated onto various substrates such as glass, silicon, fluorine-doped tin oxide (FTO), and indium tin oxide (ITO), enabling their use in device fabrication [6-7].

The significance of CoS thin films lies in their multifunctional nature, combining optical absorption, electrical conductivity, and electrochemical activity within a single material system. One of the key advantages is their strong absorption in the visible region due to their moderate band gap (1.0–2.2 eV), which makes them highly suitable for solar energy harvesting applications. Additionally, their relatively high electrical conductivity (up to 10^{2} S/cm) facilitates efficient charge transport, which is essential for device performance. Furthermore, CoS is composed of relatively abundant and less toxic elements compared to noble metal-based catalysts, making it an economically and environmentally viable alternative. The ease of synthesis using low-cost methods such as chemical bath deposition, SILAR, and hydrothermal techniques further enhances the significance of CoS thin films. These methods allow large-area deposition and scalability, which are critical for industrial applications. In addition, CoS thin films are used in gas sensing applications, where they show sensitivity to gases such as H_2S, NH_3, and CO, with response times typically between 5 and 20 seconds. Their good electrical conductivity and surface reactivity enhance sensing performance. CoS thin films have potential applications in magnetic devices, photodetectors, and flexible electronics. This is due to their tunable electronic structure and mechanical compatibility with various substrates [8].

Synthesis of CoS Thin Films by Chemical Bath Deposition (CBD)

The chemical bath deposition (CBD) method is a simple, low-cost, and widely used technique for the synthesis of CoS thin films. This method is particularly suitable for large-area deposition and allows precise control over film thickness,

morphology, and composition through careful adjustment of solution parameters. The CBD technique is based on the controlled release of cobalt (Co^{2+}) and sulphide (S^{2-}) ions in an aqueous medium, leading to the gradual formation and deposition of CoS on a substrate via heterogeneous nucleation.

In a typical synthesis, a cobalt salt such as cobalt chloride ($CoCl_2 \cdot 6H_2O$) or cobalt acetate ($Co(CH_3COO)_2$) is used as the source of Co^{2+} ions, while thiourea ($CS(NH_2)_2$), sodium thiosulphate, thioacetamide serves as the sulphur precursor. To control the release of Co^{2+} ions and prevent rapid precipitation in the solution, complexing agents such as ammonia (NH_3), triethanolamine (TEA), or ethylene diamine tetra acetic acid (EDTA) are added. These agents form stable complexes with cobalt ions, thereby regulating their availability in the reaction bath. The typical concentration of cobalt precursor is maintained in the range of 0.05–0.1 M, while sulphur precursor concentration is usually between 0.1 and 0.5 M. The pH of the solution is adjusted to an alkaline range (pH 9–11) using ammonium hydroxide (NH_4OH) or sodium hydroxide (NaOH), which facilitates the decomposition of sulphur precursor and generation of sulphide ions.

Prior to deposition, substrates such as glass, indium tin oxide (ITO), or fluorine-doped tin oxide (FTO) are thoroughly cleaned to ensure good adhesion and uniform film growth. The cleaning procedure typically involves washing with detergent, rinsing with distilled water, ultrasonic cleaning in acetone and ethanol for about 10–15 minutes each, followed by a final rinse with deionized water and drying. A clean and hydrophilic substrate surface enhances nucleation and results in better film quality. The chemical bath is prepared by dissolving the cobalt salt in distilled water, followed by the gradual addition of the complexing agent under constant stirring to form a complex. This complexation step is essential to control the release of free Co^{2+} ions. Subsequently, sulphur precursor is added to the solution as the sulphur source, and the pH is adjusted to the desired alkaline value. The solution is stirred continuously to obtain a homogeneous bath. Once the bath is prepared, the cleaned substrate is immersed vertically into the solution to ensure uniform deposition. The deposition process is typically carried out at temperatures ranging from 30°C to 80°C for duration of 30–120 minutes. During this period, CoS nuclei form on the substrate surface and grow into a continuous thin film. The film thickness generally varies from 100 to 700 nm, depending on deposition time and precursor concentration. Initially, nucleation occurs at active sites on the substrate, followed by growth and coalescence of grains to form a uniform film. CoS thin film shows dark colour. The exact colour may vary depending on the phase composition, thickness, and deposition conditions, but it is typically observed as black, dark grey and in some cases brownish-black. In thin films with lower thickness (100–200 nm), a slightly lighter shade (dark grey) may be observed. As the thickness increases (300–700 nm), the films become opaquer and appear deep black [9-10].

The growth mechanism of CoS thin films in CBD involves two primary pathways: the ion-by-ion mechanism and the cluster-by-cluster mechanism. In the ion-by-ion mechanism, Co^{2+} and S^{2-} ions directly react on the substrate surface, resulting in smooth and dense films. In contrast, the cluster-by-cluster mechanism involves the formation of CoS particles in the bulk solution, which subsequently deposit on the substrate, leading to relatively rough and porous films. The dominant mechanism depends on bath conditions such as supersaturation, temperature, and ion concentration. The growth kinetics of the film can be described by the relation: $d = kt^n$ where d is the film thickness, t is the deposition time, k is the growth rate constant, and n is the growth exponent. A value of n close to 1 indicates reaction-controlled growth, while n close to 0.5 suggests diffusion-controlled growth. The growth rate is initially high due to the availability of reactants but decreases over time as the concentration of ions in the solution is reduced [11].

After deposition, the films are removed from the bath, rinsed with distilled water to remove loosely adhered particles, and dried in air. Post-deposition annealing at temperatures between 200°C and 400°C is often carried out to improve crystallinity, enhance adhesion, and reduce defects. Annealing also leads to an increase in grain size and improvement in electrical and optical properties. Under optimized conditions, CoS thin films prepared by CBD typically exhibit nanocrystalline structure with crystallite sizes in the range of 20–70 nm, good adhesion to the substrate, and uniform surface morphology.

Crystallographic Studies of CoS Thin Films

The crystallographic properties of CoS thin films are fundamental in determining their overall physical behavior, particularly their optical, electrical, and electrochemical performance. These properties are typically investigated using X-ray diffraction (XRD), which provides comprehensive information about crystal structure, phase composition, lattice parameters, crystallite size, microstrain, and defect density. CoS thin films synthesized by chemical bath deposition (CBD) generally exhibit a polycrystalline and nanocrystalline nature, with structural features strongly influenced by deposition parameters such as bath composition, temperature, pH, and deposition time.

CoS is known to exist in multiple structural forms, including hexagonal, cubic, and mixed phases depending on synthesis conditions. Among these, the hexagonal phase of CoS is most commonly observed in thin films prepared by solution-based techniques at relatively low temperatures. The XRD pattern of such films typically shows well-defined diffraction peaks at 2θ values around 31.6°, 35.3°, 47.2°, and 54.8°, which are indexed to the (100), (101), (102), and (110) crystallographic planes, respectively. These peak positions are in close agreement with the standard data reported in JCPDS card no. 75-0605, confirming the formation of the hexagonal CoS phase. The absence of additional diffraction peaks corresponding to

cobalt oxides or other sulphide phases suggests that the films are of high phase purity. The interplanar spacing (d-spacing) corresponding to each diffraction peak is calculated using Bragg's law with Cu Kα radiation (λ = 1.5406 Å). For the observed peaks, the d-values are approximately 2.83 Å for the (100) plane, 2.54 Å for the (101) plane, 1.92 Å for the (102) plane, and 1.67 Å for the (110) plane. These values are in close agreement with standard reference data, further confirming the crystalline nature and correct phase formation of CoS thin films.

For hexagonal crystal systems, the lattice parameters a and c are determined using the standard crystallographic relation involving Miller indices and interplanar spacing. The calculated lattice constants for CoS thin films are typically found to be in the range of a = 3.35–3.40 Å and c = 5.10–5.20 Å, which closely match reported bulk values. This indicates that the films possess good crystallinity with minimal lattice distortion. Slight variations in these values may arise due to internal strain, defects, or deviations in stoichiometry during film growth. The crystallite size of CoS thin films is estimated using the Scherrer equation, which relates the broadening of diffraction peaks to the size of coherently diffracting domains. For typical full width at half maximum (FWHM) values ranging from 0.003 to 0.007 radians, the crystallite size is calculated to be between 20 and 70 nm, confirming the nanocrystalline nature of the films. For example, considering a diffraction peak at 2θ = 35.3° with a FWHM of about 0.005 radians, the crystallite size is estimated to be around 30–40 nm. It is generally observed that increasing deposition temperature or applying post-deposition annealing leads to sharper peaks and larger crystallite sizes due to enhanced grain growth and improved crystallinity. Microstrain (ε), which represents lattice distortion caused by defects and imperfections, is evaluated from peak broadening analysis. The microstrain values for CoS thin films are typically in the range of (1–6) × 10^{-3}, indicating moderate lattice distortion. Lower microstrain values correspond to better structural order and improved crystal quality. The dislocation density (δ), which provides a measure of defect concentration in the crystal lattice, is calculated using the inverse square of the crystallite size. For CoS thin films, the dislocation density is generally found to be of the order of 10^{14}–10^{15} lines/m². A lower dislocation density indicates fewer structural defects and better crystallinity, which is advantageous for enhancing electrical conductivity and optical performance. The relative intensity of diffraction peaks provides insight into the preferred orientation or texture of the films. In many cases, the (101) plane exhibits higher intensity, indicating a preferred growth orientation along this direction. This preferred orientation is often associated with the minimization of surface energy during film growth and contributes to improved structural stability. The crystallographic properties of CoS thin films are highly sensitive to deposition conditions. Increasing the bath temperature or annealing the films at temperatures between 200°C and 400°C significantly improves crystallinity, reduces peak broadening, and enhances grain size. Similarly,

optimizing the pH and precursor concentration ensures controlled nucleation and uniform growth, leading to high-quality films with reduced defects [12].

Optical Properties of CoS Thin Films

The optical properties of CoS thin films are of significant importance for their application in optoelectronic devices, solar energy conversion systems, and photodetectors. These properties are typically investigated using UV–Visible spectroscopy in the wavelength range of 300–900 nm, which provides detailed information about optical absorption, transmittance, band gap energy, and related optical constants such as refractive index and extinction coefficient. CoS thin film show strong optical absorption in the visible region. This is due to their relatively narrow to moderate band gap. The absorption coefficient (α), which represents the extent of light absorption per unit thickness, is typically found to be of the order of 10^4–10^5 cm^{-1}. This high absorption coefficient indicates that CoS is an efficient light-absorbing material, capable of harvesting a large fraction of incident photons, which is highly beneficial for photovoltaic and photodetection applications. The optical transmittance of CoS thin films in the visible region generally lies between 40% and 70%, depending on film thickness, surface morphology, and deposition conditions. Thinner films (approximately 100–200 nm) tend to exhibit higher transmittance, while thicker films (up to 500–800 nm) show reduced transparency due to increased absorption and scattering. The relatively lower transmittance compared to wide band gap materials is consistent with the strong visible light absorption of CoS. The optical band gap (Eg) of CoS thin films is a key parameter that determines their electronic and optical behavior. It is commonly evaluated using the Tauc relation for direct allowed transitions. By plotting $(\alpha h\nu)^2$ versus photon energy ($h\nu$) and extrapolating the linear region to the energy axis, the band gap is determined. For CoS thin films, the band gap typically lies in the range of 1.2–2.0eV, depending on synthesis conditions, crystallinity, and phase composition. In some cases, values as low as 1.0 eV or as high as 2.2 eV have been reported [13]. Variations in band gap are often attributed to factors such as grain size, structural defects, and stoichiometric deviations. Nanocrystalline films with smaller grain sizes (20–40 nm) may exhibit a slight increase in band gap due to quantum confinement effects.

The refractive index (n) of CoS thin films is generally found to be in the range of 2.5–3.5 in the visible region, indicating strong interaction between light and the material. The extinction coefficient (k), which represents the loss of light intensity due to absorption, typically lies between 0.1 and 0.5, reflecting the strong absorbing nature of CoS. From these optical constants, the dielectric properties of the films can also be evaluated. The real part of the dielectric constant (ε_1), which represents energy storage capability, is typically in the range of 6–12, while the imaginary part (ε_2), associated with energy dissipation, is relatively higher compared to wide band

gap semiconductors due to strong absorption in the visible region. An important feature observed in CoS thin films is the presence of an absorption edge in the visible region, which shifts depending on film quality and deposition parameters. A sharper absorption edge indicates better crystallinity and fewer defects, while a broadened edge suggests the presence of localized states within the band gap. The width of these localized states is quantified by the Urbach energy (Eu), which is typically found to be in the range of 0.2–0.5 eV for CoS thin films. Lower Urbach energy values indicate reduced disorder and improved structural quality. The optical properties of CoS thin films are highly sensitive to deposition conditions. Increasing deposition temperature or applying post-deposition annealing (typically 200–400°C) improves crystallinity, reduces defect density, and results in a sharper absorption edge and more well-defined band gap. Similarly, optimization of precursor concentration and pH leads to uniform film growth and improved optical performance. Film thickness also plays a critical role in determining optical behavior. As thickness increases, absorption increases and transmittance decreases, while the band gap may show slight variation due to changes in grain size and internal stress. Surface roughness and morphology further influence light scattering and overall optical response.

Electrical Properties of CoS Thin Films

The electrical properties of CoS thin films are of considerable importance for their application in electronic, optoelectronic, and electrochemical devices. These properties are strongly dependent on factors such as phase composition, crystallinity, grain size, defect concentration, and deposition conditions. CoS thin film typically shows semiconducting to quasi-metallic behavior. The electrical conductivity (σ) of CoS thin films generally lies in the range of 10^{-3} to 10^{2} S/cm, depending on synthesis conditions and stoichiometry. Films with poor crystallinity or high defect density tend to show lower conductivity values (10^{-3}–10^{-1} S/cm), whereas well-crystallized films or those with slight non-stoichiometry can exhibit higher conductivity, approaching 1–10^{2} S/cm. This relatively high conductivity compared to many other metal sulphides is attributed to the presence of partially filled cobalt 3d orbitals, which facilitate charge transport.

The resistivity (ρ), being the inverse of conductivity, typically falls in the range of 10^{-2} to 10^{3} Ω·cm. The resistivity decreases with increasing temperature, confirming the semiconducting nature of CoS thin films. This temperature dependence of conductivity follows the Arrhenius relation, indicating thermally activated conduction. The activation energy for CoS thin films is typically found in the range of 0.1–0.4 eV, suggesting that charge carriers can be thermally excited with relatively low energy [14]. The conduction mechanism in CoS thin films varies with temperature and structural disorder. At higher temperatures, conduction is dominated by band conduction, where electrons (or holes) are thermally excited

across the band gap. At lower temperatures or in films with higher disorder, conduction may occur via hopping mechanisms, such as nearest-neighbor hopping or variable range hopping, where charge carriers move between localized states. The carrier concentration (n or p) in CoS thin films is typically in the range of 10^{16} to 10^{20} cm^{-3}, depending on defect levels and stoichiometry. The mobility (μ) of charge carriers generally lies between 0.5 and 20 $cm^2/V \cdot s$. The relatively moderate mobility is mainly limited by scattering at grain boundaries, lattice defects, and impurities. CoS thin films often exhibit p-type conductivity, which is primarily attributed to the presence of cobalt vacancies or sulphur interstitials that create hole carriers. However, under certain synthesis conditions, n-type behavior may also be observed due to sulphur vacancies acting as donor states. The type of conductivity can be confirmed using Hall effect measurements, where the sign of the Hall coefficient indicates the dominant charge carriers. The electrical properties of CoS thin films are highly sensitive to deposition parameters. Increasing the deposition temperature or applying post-deposition annealing (in the range of 200–400°C) improves crystallinity, reduces defect density, and enhances grain size, leading to increased conductivity and carrier mobility. Similarly, optimization of pH and precursor concentration ensures uniform film growth and improved electrical performance. Film thickness also influences electrical behavior. Thicker films generally exhibit lower resistivity due to improved connectivity between grains, while thinner films may show higher resistivity due to increased grain boundary scattering. Additionally, surface morphology and roughness can affect charge transport by introducing scattering centers.

Surface Morphology of CoS Thin Films

The surface morphology of CoS thin films is typically analyzed using techniques such as scanning electron microscopy (SEM), atomic force microscopy (AFM), and occasionally transmission electron microscopy (TEM). These techniques provide detailed insights into grain size, surface roughness, porosity, uniformity, and film coverage. CoS thin films deposited by CBD generally exhibit a uniform and continuous surface morphology with good adhesion to the substrate. SEM images commonly reveal that the films are composed of closely packed nanocrystalline grains forming a dense microstructure. The grain size observed from SEM typically lies in the range of 30–150 nm, which is often larger than the crystallite size 20–70 nm estimated from XRD due to agglomeration of smaller crystallites into larger grains.

The morphology of CoS thin films can vary significantly depending on deposition parameters such as precursor concentration, pH, temperature, and deposition time. Under optimized conditions, the films exhibit a smooth, crack-free, and pinhole-free surface, which is essential for device applications. However, at higher precursor concentrations or longer deposition times, the films may show agglomerated

clusters or cauliflower-like structures, indicating a transition from uniform growth to cluster-by-cluster deposition.

AFM analysis provides quantitative information about surface roughness. The root mean square (RMS) roughness of CoS thin films is typically found to be in the range of 10–80 nm, depending on growth conditions. Lower roughness values like 10–30 nm correspond to smoother and more uniform films, while higher values indicate increased surface irregularities and grain clustering. Surface roughness plays an important role in light scattering, charge transport, and electrochemical activity. The film thickness, which usually ranges from 100 to 700 nm, also influences the surface morphology. Thinner films tend to have smaller grains and smoother surfaces, whereas thicker films often exhibit larger grains and increased roughness due to prolonged growth and coalescence of particles. The growth mechanism in CBD, involving both ion-by-ion and cluster-by-cluster processes, contributes to the observed morphological features. Porosity is another important characteristic of CoS thin films. Moderate porosity is often observed, especially in films prepared at higher pH or lower temperatures. This porosity enhances the surface area, which is beneficial for applications such as supercapacitors and electrocatalysis, where a large active surface area improves performance. However, excessive porosity can reduce electrical conductivity and mechanical stability. The surface morphology is also strongly affected by post-deposition annealing. Annealing at temperatures between 200°C and 400°C generally leads to grain growth, improved crystallinity, and reduced surface defects. As a result, the films become denser and more uniform, with a slight increase in grain size and a reduction in surface roughness. In addition, substrate type plays a role in determining film morphology. Films deposited on conductive substrates such as FTO or ITO often show better uniformity and adhesion compared to those deposited on plain glass, due to differences in surface energy and nucleation behavior.

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Advances in Engineering Research and Applications

ISBN: 978-81-69492-09-6 | Year: 2026 | pp: 99 - 109

Engineering Microbial Consortia for Environmental Remediation: Design Principles, Construction Strategies and Field Application

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Article DOI Link: https://zenodo.org/uploads/22080864

DOI: 10.5281/zenodo.22080864

Abstract

Single-strain bioaugmentation often fails to fully mineralise complex or mixed environmental pollutants, since one organism rarely encodes the complete enzymatic repertoire required and is vulnerable to competition and fluctuating field conditions. Engineered microbial consortia — rationally assembled multi-species systems that distribute catabolic labour, exploit syntrophic and cross-feeding interactions, and combine complementary environmental tolerances — offer a more robust and versatile alternative. This chapter reviews the ecological rationale for consortium-based remediation and contrasts top-down (enrichment-based) and bottom-up (synthetic biology-based) design strategies, including the use of genome-scale metabolic modelling and orthogonal genetic circuits to guide assembly. Representative applications are examined across major pollutant classes, including petroleum hydrocarbons, heavy metals, PET microplastics, azo dyes, and pharmaceuticals and personal care products, alongside the omics-based tools used to monitor consortium performance in situ. Key barriers to field-scale translation — compositional instability, loss of engineered function, poor establishment, and regulatory constraints around genetically modified organisms — are discussed together with corresponding mitigation strategies. The chapter concludes by outlining emerging directions, including machine-learning-guided consortium design, programmable synthetic ecologies, and bioelectrochemical integration, that are expected to accelerate the transition of engineered consortia from laboratory proof-of-concept to regulator-approved environmental application.

Keywords: microbial consortia; bioremediation; synthetic ecology; synthetic biology; syntrophy; cross-feeding; metabolic engineering; bioaugmentation; environmental biotechnology; genome-scale metabolic modelling

Introduction

Environmental contamination by petroleum hydrocarbons, heavy metals, synthetic dyes, pesticides, and emerging pollutants such as microplastics and pharmaceuticals continues to challenge ecosystem health and human wellbeing worldwide. Bioremediation — the use of living organisms to degrade, transform, or immobilize pollutants — has long been favoured over physicochemical remediation because it is comparatively low-cost, low-energy, and environmentally benign [1,2]. Historically, this field relied heavily on single-strain bioaugmentation, in which one well-characterized microorganism (e.g., Pseudomonas putida for hydrocarbon degradation) is introduced into a contaminated site. However, single strains rarely possess the complete enzymatic repertoire required to mineralize complex or mixed pollutants, and they are frequently outcompeted by indigenous microbiota or inhibited by fluctuating environmental conditions [3].

Natural microbial communities, in contrast, achieve remediation through division of metabolic labour, cross-feeding, and syntrophic cooperation among diverse taxa. This recognition has driven a paradigm shift toward engineered microbial consortia — rationally designed or selectively assembled multi-species systems that combine complementary metabolic capabilities, exhibit greater robustness to environmental perturbation, and can be tuned for specific pollutant profiles [4,5]. This chapter reviews the ecological rationale, design principles, construction strategies, and applications of engineered consortia in environmental remediation, and discusses the technical and regulatory challenges that must be resolved for field-scale deployment.

Why Consortia Outperform Monocultures

Microbial consortia offer several functional advantages over axenic (single-species) cultures in remediation contexts:

- **Metabolic Complementarity:** Complex pollutants such as polycyclic aromatic hydrocarbons (PAHs) or lignin-derived aromatics require sequential enzymatic transformations that are rarely encoded within a single genome; different community members can specialise in successive degradation steps [3,6].
- **Division of Labour and Reduced Metabolic Burden:** Distributing a biosynthetic or catabolic pathway across multiple strains reduces the metabolic load on any one organism, improving pathway flux and genetic stability relative to engineering the entire pathway into a single chassis [7].
- **Resilience and Functional Redundancy:** Diverse consortia can maintain function even if particular members decline due to stress, predation, or competition, since functionally redundant taxa can compensate [4,8].

- **Enhanced Tolerance to Toxicity:** Detoxification of an intermediate by one partner can protect co-occurring degraders from product inhibition, sometimes described as "division of chemical labour" [9].
- **Broader Environmental Adaptability:** Consortia comprising strains with different optimal pH, temperature, or salinity ranges can operate effectively across the physicochemical gradients typical of real contaminated sites [2,10].

Design Principles for Engineered Consortia

1. Top-Down Versus Bottom-Up Design

Two broad strategies are used to assemble remediation consortia. Top-down (community-level) approaches start from natural or enriched communities — e.g., contaminated soils, activated sludge, or biofilms — and use selective enrichment, dilution-to-extinction, or directed evolution to enhance desired remediation traits while retaining native ecological interactions [11]. This approach benefits from pre-existing, evolutionarily optimised interactions but offers limited control over final community composition. Bottom-up (synthetic) approaches assemble consortia de novo from individually characterized, often genetically engineered, strains chosen for complementary functions, such as pairing a hydrocarbon-oxidizing strain with a surfactant-producing strain and a nitrogen-fixing strain [5,7]. This offers precise control and reproducibility but requires deep mechanistic understanding of strain compatibility and interaction dynamics. Hybrid strategies — for example, bioaugmenting an enriched native consortium with one or two engineered specialist strains — are increasingly used to balance robustness and control [12].

2. Ecological and Metabolic Modelling

Genome-scale metabolic models (GEMs), when combined into multi-species community models, allow in silico prediction of cross-feeding interactions, resource competition, and emergent community stability prior to experimental assembly [13]. Flux balance analysis (FBA)-based tools such as COMETS and OptCom have been used to predict which strain pairings maximise pollutant flux while minimising competitive exclusion [13,14]. These predictions are increasingly validated and refined using multi-omics data (metagenomics, metatranscriptomics, metabolomics) from pilot-scale bioreactors [15].

3. Genetic and Regulatory Tools

Bottom-up consortium engineering draws on synthetic biology toolkits, including:

- Orthogonal quorum-sensing circuits to coordinate gene expression across species [7]
- CRISPR-based genome editing for pathway insertion or auxotrophic "kill-switch" containment [16]

- Division-of-labour pathway partitioning, where a catabolic pathway is split across two or more engineered strains to reduce enzyme burden and enable independent strain-level optimisation [7,9]
- Biocontainment strategies (auxotrophy, synthetic auxotrophic cross-feeding, xenobiotic nucleic acids) to prevent uncontrolled environmental persistence or horizontal gene transfer of engineered constructs [17]

Consortium Assembly Workflow

Figure 1 summarises a generalised workflow for engineering a remediation consortium, moving iteratively from problem definition through to field deployment and monitoring, with continuous feedback from field performance data back into strain screening and community modelling stages.

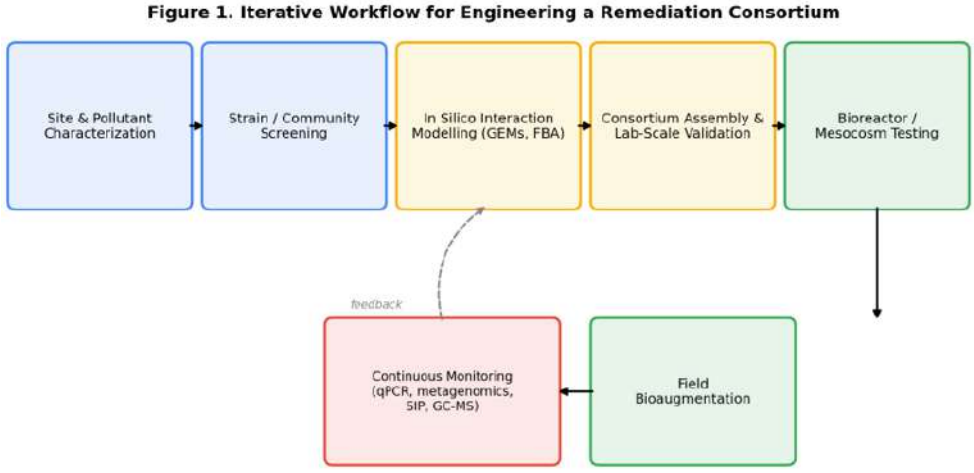


Figure 1. Iterative workflow for engineering a remediation consortium.

Interaction Architectures within Consortia

Consortia are typically organised around one or more ecological interaction motifs, summarised in Table 1. Figure 2 illustrates a representative syntrophic hydrocarbon-degrading consortium built around these motifs.

Table 1. Common ecological interaction motifs exploited in remediation consortia

Interaction type	Description	Example in remediation	Ref.
Sequential catabolism (metabolic handoff)	Product of one strain's degradation pathway becomes substrate for the next	PAH ring-opening by Mycobacterium spp. followed by mineralisation of intermediates by Pseudomonas spp.	[3,6]

Syntrophy	Mutual dependency, often via interspecies electron/hydrogen transfer	Anaerobic degradation of chlorinated solvents by Dehalococcoides supported by fermentative H2-producing partners	[8,18]
Cross-feeding of growth factors	One strain supplies vitamin, amino acids, or siderophores that another cannot synthesise	Co-culture of hydrocarbon degraders with vitamin-B12-producing partners in oil-contaminated soils	[9]
Competitive exclusion of pathogens/weeds	Engineered strains outcompete undesirable or non-degrading organisms for niche space	Biosurfactant-producing strains suppressing competitors in contaminated groundwater	[10]
Detoxification support	One partner neutralises a toxic intermediate, protecting co-culture members	Consortium detoxification of chlorophenol intermediates during pesticide bioremediation	[9,19]

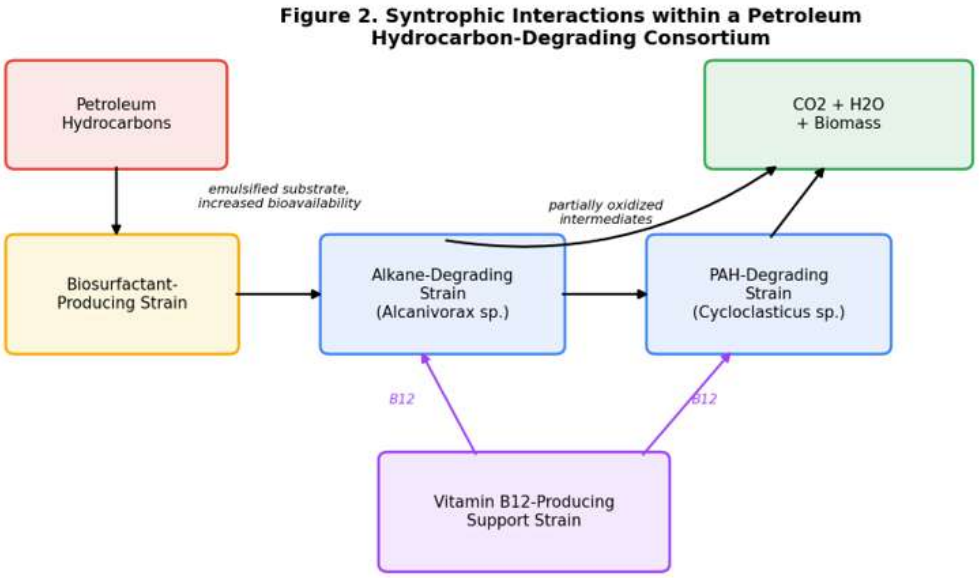


Figure 2. Syntrophic interactions within a petroleum hydrocarbon-degrading consortium.

Case Studies

1. Petroleum Hydrocarbon and Oil-Spill Remediation

Following major spills such as the 2010 Deepwater Horizon event, studies confirmed that indigenous marine microbial communities — dominated by successive blooms of Alcanivorax, Marinobacter, Cycloclasticus, and other hydrocarbonoclastic genera — naturally self-assemble into functionally structured consortia that sequentially degrade alkanes and then aromatic fractions [20]. This observation has informed the design of synthetic analogues combining alkane-degrading and PAH-degrading specialists with biosurfactant producers to accelerate oil dispersal and uptake [2,20].

2. Heavy Metal and Metalloid Bioremediation

Because metals cannot be degraded, consortia for metal-contaminated sites are typically engineered for biosorption, bioprecipitation, or biotransformation to less toxic/mobile forms. Sulfate-reducing bacteria (SRB) consortia precipitate metals as insoluble sulfides, while co-cultured metal-resistant biofilm formers enhance retention and prevent re-mobilisation [21]. Combining SRB with plant growth-promoting rhizobacteria has also been used in phytoremediation-assisted systems to improve metal uptake efficiency in constructed wetlands [22].

3. Plastics and Microplastic Degradation

Engineered consortia combining PETase/MHETase-expressing strains (derived from Ideonella sakaiensis) with strains capable of assimilating the resulting monomers (terephthalic acid and ethylene glycol) have demonstrated improved PET depolymerisation rates relative to single-strain systems, by relieving product inhibition on the PETase-expressing strain [23].

4. Azo Dye and Textile-Effluent Decolourisation

Anaerobic-aerobic consortia are used to first reductively cleave azo bonds (anaerobic step, often via redox mediators) and then aerobically mineralise the resulting aromatic amines, a task no single strain can accomplish under one set of redox conditions [19].

5. Pharmaceuticals and personal care products (PPCPs)

Fungal-bacterial consortia — pairing white-rot fungi (e.g., Trametes versicolor) that produce extracellular ligninolytic enzymes with bacteria able to mineralise resulting metabolites — have shown promise for removing recalcitrant PPCPs such as diclofenac and carbamazepine from wastewater [24].

Table 2. Summary of representative remediation case studies

Pollutant class	Representative consortium	Mechanism	Outcome	Ref.
Petroleum hydrocarbons	Alcanivorax + Cycloclasticus + biosurfactant producers	Sequential alkane → PAH oxidation	Accelerated oil-slick dispersal and mineralisation	[2,20]
Heavy metals (Cd, Cr, Pb)	Sulfate-reducing bacteria + biofilm-forming metal-resistant strains	Bioprecipitation/ biosorption	Reduced bioavailable metal fraction in sediments	[21,22]
PET microplastics	PETase-expressing strain + TPA/EG-assimilating strain	Depolymerisation + monomer assimilation	Higher PET mass loss vs monoculture	[23]
Azo dyes	Facultative anaerobes + aerobic aromatic-amine degraders	Reductive cleavage then aerobic mineralisation	>90% decolourisation in sequential bioreactors	[19]
PPCPs (diclofenac, carbamazepine)	White-rot fungi + bacterial consortium	Ligninolytic oxidation + downstream mineralisation	Enhanced micropollutant removal in constructed wetlands	[24]

Monitoring and Performance Evaluation

Consortium performance in the field is typically tracked using a combination of complementary analytical approaches:

- Chemical analytics (GC-MS, LC-MS) to quantify pollutant and metabolite concentrations over time [1]
- Quantitative PCR / digital PCR targeting functional marker genes (e.g., alkB, nahAc, pcbC) to track degrader abundance [15]
- Amplicon and shotgun metagenomic sequencing to monitor community composition shifts and detect invasion by non-degrading opportunists [15]
- Stable isotope probing (SIP) to link taxonomic identity directly to in situ degradation activity [6]

Challenges and Mitigation Strategies

Despite strong laboratory-scale evidence, translation of engineered consortia to field conditions remains constrained by several interacting challenges, summarised in Table 3.

Table 3. Key challenges in field deployment of engineered consortia and mitigation strategies

Challenge	Underlying cause	Mitigation strategy	Ref.
Compositional instability	Differential growth rates and competitive exclusion over time	Genetic circuits enforcing mutualistic cross-feeding; periodic re-inoculation	[7,25]
Loss of engineered function	Horizontal gene loss, plasmid instability, negative selection pressure	Chromosomal pathway integration; auxotrophic strain coupling	[16,17]
Poor establishment in situ	Competition/predation by indigenous microbiota, unfavourable abiotic conditions	Encapsulation/immobilisation carriers; biostimulation with nutrients	[10,25]
Regulatory and biosafety concerns	Use of genetically modified organisms (GMOs) in open environments	Biocontainment systems; use of non-GMO enriched consortia where feasible	[17,26]
Incomplete mechanistic understanding	Complexity of multi-species metabolic networks	Multi-omics-informed community metabolic modelling	[13,15]
Scale-up unpredictability	Lab-to-field differences in mixing, heterogeneity, and bioavailability	Mesocosm/pilot-scale intermediate testing; adaptive field monitoring	[1,25]

Future Directions

Emerging directions likely to shape the next generation of remediation consortia include: (i) machine-learning-guided consortium design that integrates multi-omics datasets to predict optimal strain combinations and inoculation ratios [15]; (ii) programmable synthetic ecologies using engineered quorum-sensing "social" circuits to dynamically stabilise community composition in response to pollutant concentration [7]; (iii) integration of consortia with bioelectrochemical systems (microbial fuel/electrolysis cells) to couple pollutant degradation with energy recovery [18]; and (iv) development of standardised biosafety and regulatory

frameworks specific to engineered environmental consortia, distinct from those governing contained industrial GMO use [26].

Conclusion

Engineering microbial consortia represents a maturing and increasingly indispensable strategy for environmental remediation, offering functional advantages — metabolic complementarity, resilience, and adaptability — that single-strain bioaugmentation cannot match. Progress in synthetic biology, community metabolic modelling, and multi-omics monitoring is steadily closing the gap between laboratory proof-of-concept and field-scale, regulator-approved deployment. Continued interdisciplinary collaboration among microbiologists, ecologists, synthetic biologists, and environmental engineers will be essential to realise the full potential of designer consortia for sustainable pollution management.

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Nature- 128

ISBN: 978-81-69492-09-6
9 788169 492096
Price- 750/-