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Review Article

Perspective on Digital Technologies and Optimization Used to Improve the Management of Natural Resources

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ABSTRACT

Recent advances in digital technologies and optimization methodologies are revolutionizing how we monitor, allocate, and conserve vital natural assets such as water, energy, and arable land. This review presents a comprehensive perspective on the transformative role of digital innovations—including artificial intelligence (AI), geographic information systems (GIS), and blockchain—in enhancing the visibility, efficiency, and transparency of resource management systems. It also highlights the mathematical and algorithmic frameworks, such as Pinch Analysis or optimization approaches, that underpin modern techniques used to address complex resource allocation problems. The paper further discusses emerging directions to underscore the need for interdisciplinary collaboration and policy alignment. This article aims to inform stakeholders and researchers on the integrative potential of technology and optimization approaches in driving resilient, data-driven, and equitable resource management practices.

KEYWORDS

Resource management, Digital technology, Blockchain, Process integration, Artificial intelligence, Optimization.

INTRODUCTION

Natural resources are the foundation of human survival and economic development. However, their sustainable management is increasingly challenged by global issues such as climate variability, urbanization, and escalating industrial consumption. Traditional resource management systems, often reactive and fragmented, are insufficient in addressing the complexity and scale of today's environmental and socio-economic pressures [1]. There is a growing urgency to develop more adaptive, transparent, and efficient approaches to monitor and allocate resources in a manner that supports both ecological balance and human well-being.

Amid this backdrop, digital technologies have emerged as powerful enablers of transformation. From real-time environmental monitoring using satellite imagery and IoT sensors to data-driven forecasting powered by machine learning, these technologies are reshaping the landscape of natural resource governance. When coupled with mathematical optimization techniques—such as linear programming, heuristic algorithms, and process integration frameworks—these innovations enable more precise, responsive, and equitable allocation of limited resources.

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Industrial symbiosis (IS) refers to a collaborative strategy where the waste outputs, such as excess heat, pressure, and other by-products generated by one industry, are repurposed as input materials or alternative energy sources for another industry [2]. This exchange system fosters a closed-loop production cycle that contributes to reducing the overall consumption of raw materials and energy, while simultaneously minimizing environmental pollutants [3]. By facilitating material and energy flow across industrial boundaries, IS supports the transition toward more resource-efficient and sustainable industrial systems.

Compared to traditional energy conservation and emissions reduction (ECER) strategies, industrial symbiosis has been shown to offer superior cost-effectiveness and environmental benefits [4]. These advantages have sparked growing interest among policymakers, scholars, and industry leaders, positioning IS as a key component in the broader framework of environmental and industrial management.

Globally, numerous governments are actively supporting the development of eco-industrial parks (EIPs)—planned areas where multiple companies cooperate to optimize resource use and reduce waste—through various policy instruments. These include legislative reforms, financial incentives, subsidies, and preferential land use policies aimed at encouraging industrial collaboration and circular resource flows.

From a research standpoint, the complexity and interdisciplinary nature of IS implementation have prompted the use of advanced analytical models and decision-support tools. For example, Bacudio et al. [5] applied the Decision Making Trial and Evaluation Laboratory (DEMATEL) method to identify and analyze the barriers hindering the development of IS networks, highlighting challenges such as information asymmetry, lack of stakeholder engagement, and infrastructural limitations. In another line of inquiry, Wen et al. [4] utilized a single-objective optimization approach to evaluate and select the most effective symbiotic technologies for various types of eco-industrial parks within the iron and steel sector. Their study demonstrated how mathematical modelling can be used to systematically assess symbiosis potential and technology suitability across different industrial contexts.

These theoretical and practical efforts underscore the growing recognition of industrial symbiosis as a viable and impactful pathway toward achieving sustainable industrial development. However, successful implementation requires overcoming institutional, technological, and behavioural barriers—necessitating a coordinated effort among businesses, regulators, and researchers to design systems that are both economically viable and environmentally resilient.

In terms of technological advancements, Green innovation (GI) often is the way forward considering the increasing environment awareness [6]. GI reflects a company's ability to align environmental objectives with business growth, offering a dual advantage of ecological sustainability and economic performance [7]. Achieving GI typically requires substantial investments in eco-friendly materials, cleaner production methods, environmental surveillance, and recycling systems. While green financing—such as green loans—has been found to increase firms' motivation for technological advancement [8], the path to green innovation is often costly and carries significant supply chain risks, with returns that may not be immediately visible [9].

Despite these hurdles, advanced technologies like big data, artificial intelligence (AI), and the Internet of Things (IoT) provide transformative potential for manufacturing/processing industries, enabling firms to overhaul traditional production systems and enhance both environmental and economic results [10]. Key elements—such as IoT integration in the process to enable real-time data streaming [11], efficient energy usage and supply chain improvements [12], and the deployment of AI tools in decision-making are increasingly seen as foundational to driving GI. Tools like data mining, intelligent algorithms, and computer vision support greater efficiency, lower energy demands, and reinforce sustainable practices across operations [13].

Historically, technological revolutions have had both constructive and disruptive effects on industries [14]. On the downside, new technologies can render existing expertise or business frameworks obsolete, leaving established firms vulnerable to market newcomers. Overinvestment in innovation with a short-term mindset may lead to "technological shortsightedness," wasting resources and misaligning market expectations [15]. Disruptive digital changes—termed Digital Disruptive Events (DDEs), including AI, big data, and IoT—may lead to organizational instability, such as employee displacement and task restructuring. technological changes can lead to extreme events, and intense task changes can result in large-scale personnel turnover – see Figure 1.These disruptions, however, could also open new innovation pathways, especially in green practices within manufacturing [16]. As such, organizations should balance technological advancement with collaboration and knowledge sharing to thrive in a fast-evolving environment [17].

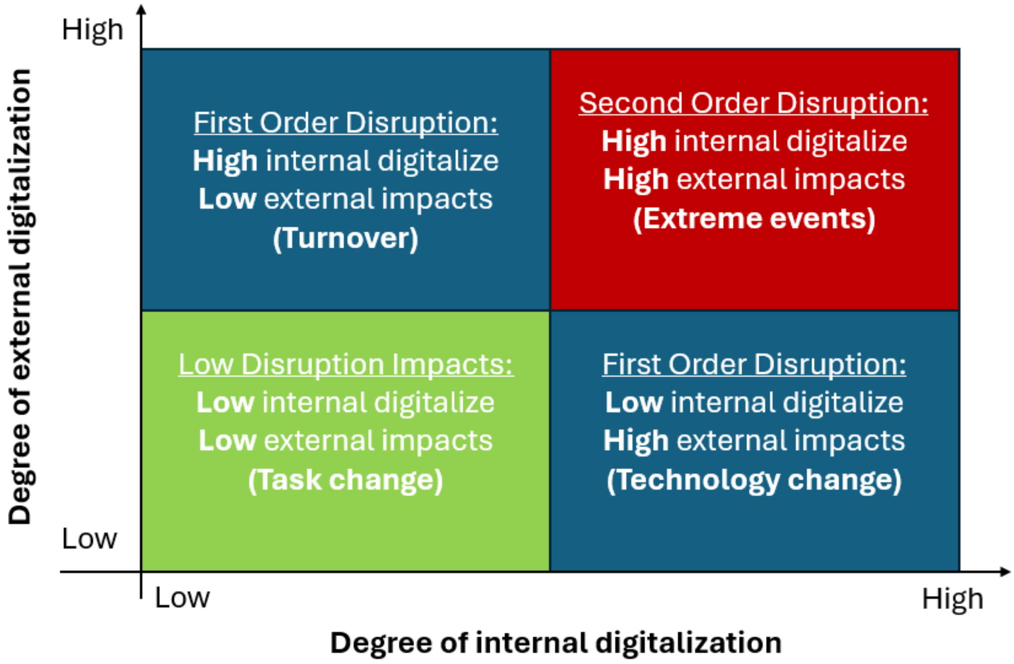

Figure 1: Disruptive events due to Digital Disruption Events on any industries, adapted from [6]

Advancing GI in the manufacturing sector often involves participation in various inter-organizational networks [18]. For instance, Rizzo et al. [19] highlighted how personal network ties influence the adoption of mobile applications for food waste reduction, while Hossain et al. [20] emphasized the distinct roles of knowledge and financial resources in fostering GI. This underscores the need to conceptualize two types of innovation-related networks in manufacturing: knowledge networks and collaboration networks. Knowledge networks capture the flow of information and expertise between entities, while collaboration networks represent cooperative efforts among inventors or professionals. Understanding how these two networks individually and jointly shape green innovation is especially important amid growing digital disruptions. However, the degree of interaction and overlap requires still a need for more empirical inquiry into their combined influence on innovation during digital transformation processes [21].

Prior studies have investigated precursors to GI—such as green strategy adoption [22], environmental learning, and sustainable supplier involvement [23]. Xiao et al. [6] had examined the relationship between DDEs and GI, clarifying how firms could organize and leverage their collaboration and knowledge assets in volatile, rapidly changing environments. As manufacturing firms evolve to embrace GI, they often integrate into multiple inter-organizational networks [24].

Summarizing the literatures review above, this review article aims to explore the intersection of digital technologies and optimization approaches in enhancing natural resource management. It provides an examination of tools such as remote sensing, big data analytics, geospatial systems, and blockchain, illustrating their practical applications towards natural resources managements. This paper delves into the role of optimization models in resolving resource allocation challenges and introduces future directions including digital twins and decentralized computing. By presenting a cross-disciplinary perspective, the article aims to highlight the potential of integrated technological solutions in achieving sustainable resource use for current and future generations.

ROLE OF DIGITAL TECHNOLOGY

The role of Artificial Intelligence (AI)

Efficient resource utilization, risk mitigation, and early anomaly detection are essential for the smooth operation of process industries such as chemicals, pharmaceuticals, oil and gas, and food processing. The integration of Artificial Intelligence (AI) and remote sensing technologies offers new opportunities to monitor assets, identify inefficiencies, and optimize decision-making processes in real-time. By leveraging machine learning (ML) algorithms and high-resolution imaging data, industries can detect deviations, classify materials, and forecast system failures more accurately and cost-effectively. This section briefly explores three key areas—classification, early detection, and decision-making—where AI-driven tools are being adapted to manage resources more intelligently in industrial settings.

Classification

In process industries, accurate identification of raw materials, intermediate products, or waste streams is vital for efficient resource management and quality control. Traditionally, laboratory-based spectral analysis has been used to differentiate between materials, but real-time implementation in industrial settings has been limited due to the lack of high-resolution imaging, robust machine learning (ML) algorithms, and reliable sensor data.

Recent advancements in data fusion techniques—especially combining hyperspectral imaging with LiDAR—have shown promise for on-site material classification. Convolutional Neural Networks (CNNs) can analyze hyperspectral signatures and incorporate spatial characteristics using LiDAR inputs **[25]**. For example, a custom CNN model trained on hyperspectral and RGB images, along with LiDAR data collected using aerial platforms, demonstrated significant accuracy in classifying different tree species based on field-verified data **[26]**. When applied to process industries, similar methodologies could be used to classify different materials on conveyor belts, detect contamination in pipelines, or identify corrosion in storage tanks.

Notably, the hyperspectral CNN model in that forestry study outperformed the RGB-based model by a margin of 23%, with overall classification accuracy reaching 87% **[27]**. This suggests that integrating high-resolution multisensor data with ML algorithms could form a repeatable and scalable approach for material identification in industrial environments.

Early Detection

Timely identification of equipment faults, chemical leaks, or microbial contamination is crucial in process industries to prevent costly downtime and ensure product integrity. In high-value sectors such as food processing or pharmaceuticals, early detection can prevent widespread product recalls and protect consumer safety.

Drawing parallels from agriculture, where hyperspectral drone imaging has been used to detect diseases like citrus greening with up to 99.7% accuracy, similar ML-based monitoring systems can be adopted in industrial settings [28]. These systems rely on multi-feature fusion—combining vegetation indices (analogous to spectral or thermal indicators in industrial equipment) and physical attributes (e.g., heat signatures, surface area changes)—to distinguish between healthy and compromised components or batches.

Implementing such AI-driven inspection frameworks using drones, robots, or mounted sensors can significantly reduce inspection time and costs [29]. Moreover, integrating them into predictive maintenance systems could allow facilities to quarantine affected sections, reduce risks of large-scale failures, and optimize resource use by targeting interventions more precisely.

Decision-Making

Strategic investment and resource allocation are fundamental to efficient operations in process industries, especially when balancing safety, environmental compliance, and production goals. Artificial Intelligence (AI) can support these decisions by automating risk assessments and optimizing maintenance schedules [30].

For instance, a decision-tree model applied to urban forestry successfully assessed the collapse risk of trees using just 14 out of 36 initially measured variables [31]. In process industries, similar methodologies could assess the risk of equipment failure or production bottlenecks using a reduced set of critical indicators—such as vibration, temperature fluctuations, or pressure variances—collected through sensors and analyzed using decision-tree or other classification algorithms [33].

A case study from Brazil used mobile data collection tools to evaluate tree risks and achieved a 73% accuracy rate in prioritizing interventions [30]. Translating this approach, plant managers can develop AI-based protocols to rank and address the most pressing operational hazards. Though current models may struggle with edge cases, ongoing refinement using larger and more diverse datasets will improve accuracy and applicability over time [33].

Geospatial tools for resource management

In the field of remote sensing and geospatial data analysis, the efficient management of massive datasets is crucial. To address the growing demand for large-scale data processing, several specialized platforms have been developed. These tools not only enable researchers and professionals to analyze spatial information effectively but also support a wide array of applications ranging from environmental monitoring to disaster management. This section explores five prominent geospatial software tools—Google Earth Engine, ENVI, ERDAS IMAGINE, Global Mapper, and others—highlighting their features, strengths, and relevance in managing complex geospatial resources.

GIS tools

Launched in 2010, Google Earth Engine (GEE) is a cloud-based geospatial processing platform built upon Google's computational infrastructure. It provides researchers with free access to an extensive data catalog—including Landsat, Sentinel, MODIS, and climate datasets—and supports JavaScript, Python, and R for algorithm development [34]. Tailored for educational and research purposes, GEE provides free access to a powerful suite of tools designed for the large-scale analysis of spatial data. Its core mission is to support scientific advancement by facilitating unrestricted access to a vast array of datasets and computational tools, particularly for addressing global-scale challenges in environmental monitoring and big data analytics.

GEE hosts an extensive data catalog, featuring petabytes of satellite imagery and geophysical datasets, including those from Landsat, MODIS, and Sentinel missions. Users can interact with the platform through a JavaScript-based code editor or utilize the Python and R APIs for advanced scripting. For those unfamiliar with programming, GEE offers a simplified interface known as “Explorer” to perform essential operations. Additionally, GEE allows for both importing local data and exporting results for further analysis in desktop GIS tools such as QGIS and ArcGIS Pro [35].

Widely used in remote sensing and geoscience, GEE supports a diverse range of applications—from crop monitoring [36] and vegetation tracking [37] to land cover classification and forest fire analysis [38]. It has played a key role in academic and practical research, especially when supported by bibliometric studies that trace evolving trends and uncover knowledge gaps [39]. The integration of AI technologies—such as machine learning (ML), deep learning (DL), and computer vision—has further expanded its capabilities, particularly in high-impact domains like natural disaster assessment and healthcare analytics. The emerging field of GeoAI, which combines geospatial science with AI and high-performance computing, demonstrates how GEE is central to extracting valuable insights from geospatial big data.

Global Mapper is another user-friendly GIS software package, released in 2001, and recognized for its versatility in handling a wide range of spatial data. Supporting over 300 file formats, it offers robust functionality for managing vector, raster, elevation, and point cloud data. Its real-time reprojection capabilities and integration with online data services—such as aerial and satellite imagery—make it a highly adaptable tool for geospatial analysis [40].

The software provides a powerful set of tools for vector digitization, spatial operations (like intersection and union), and attribute editing. Global Mapper also features scripting and batch processing, allowing users to automate routine GIS tasks and streamline workflows. Its “Pixels-to-Points” tool is particularly useful for UAV users, enabling the conversion of aerial imagery into high-resolution 3D models and dense point clouds using photogrammetry techniques [41].

Image processing tools

Introduced in 1994, The Environment for Visualizing Images (ENVI) is a remote sensing software suite designed for users at all skill levels, offering a blend of usability and advanced analytical capabilities. Its interface simplifies the image processing workflow by organizing tasks into guided steps, covering operations such as calibration, atmospheric correction, orthorectification, and image registration [42]. A typical spectral workflow in ENVI includes data preparation, creating spectral libraries, target detection, mapping unique materials, and visualization

ENVI is compatible with a wide variety of data formats, including HDF, CDF, GeoTIFF, and NITF, and supports multiple sensor types—radar, LiDAR, SAR, multispectral, hyperspectral, thermal, and more. The platform integrates data from modern satellite and airborne systems such as Sentinel, AVIRIS, WorldView, and Planet Dove. Its spectral analysis capabilities allow for accurate material detection, vegetation monitoring, and environmental assessment.

Recent research underscores ENVI's strength in hyperspectral image processing [43]. Studies have used the software to detect bruises on fruits, monitor quality in agricultural produce, and identify contaminants. ENVI's flexible workflows support tasks such as anomaly detection, feature extraction, and terrain modeling, making it a versatile solution in both scientific and applied geospatial contexts.

Another tool: ERDAS IMAGINE is another comprehensive software suite focused on remote sensing data analysis and image classification. Its intuitive interface supports a broad spectrum of geospatial workflows, such as orthorectification, mosaicking, terrain categorization, and LiDAR editing. Designed for both beginners and experts, it emphasizes ease of use while offering powerful backend algorithms for efficient processing [44].

The software includes tools for supervised and unsupervised image classification, terrain modeling, and spatial analysis. ERDAS IMAGINE also provides scripting capabilities through its Macro Language (EML) and supports AI-based workflows with tools for training and deploying ML and DL models. These features are especially useful for feature extraction and land cover classification [45].

The “Advantage” edition of the software builds upon the core functionalities by offering more advanced mapping tools, point cloud editing, and radar analysis. It has been effectively employed in environmental monitoring, natural resource management, and defense applications, and its image enhancement capabilities—such as histogram equalization and Gaussian filtering—help improve image clarity and detail [45]

BLOCKCHAIN TECHNOLOGY

Blockchain technology is increasingly recognized as a powerful tool for fostering trust among distributed stakeholders, particularly in decentralized energy systems [46]. The foundational concept, introduced by Nakamoto [47], presents a decentralized computational framework known as Blockchain, which offers transformative capabilities in managing data and energy transactions. This system is based on a cryptographically secure and distributed ledger, maintained through consensus protocols and cryptocurrency mechanisms. Central to this framework are smart contracts—self-executing code that enables automated, real-time energy trading, transparent data exchange, and collaborative decision-making across multiple participants. These contracts ensure fair and optimized resource distribution while reducing inefficiencies and operational waste.

The term "blockchain" refers to a data structure where digital records, or "blocks," are sequentially linked to form a secure and immutable "chain." Each block contains a cryptographic hash, a timestamp, a batch of verified transactions, and a reference to the preceding block’s hash, thereby making any unauthorized alteration evident. Once data is added, consensus protocols—like those based on proof of work—ensure that only validated transactions are recorded, with agreement required from all participating nodes. This consensus mechanism eliminates the need for centralized authorities and establishes trust through decentralized validation. The integration of cryptographic elements such as digital signatures, hashing, and public-private key encryption makes blockchain one of the most secure data systems currently available [48]. Example of a blockchain adjustment when new data comes in is illustrated in Figure 2.

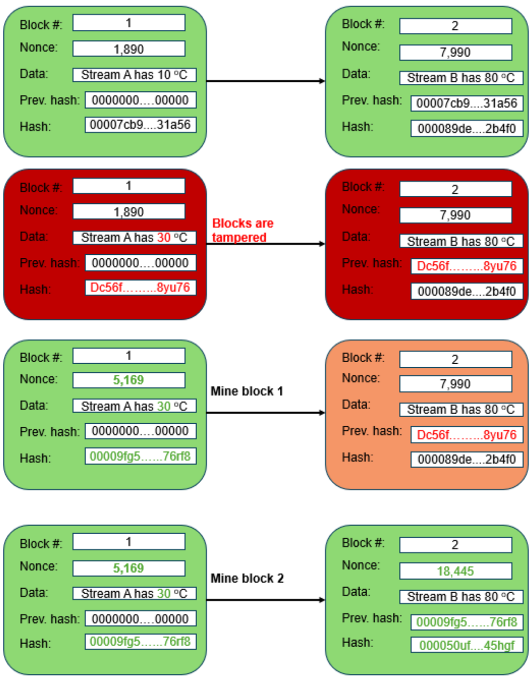

Figure 2: Illustration of blockchain adjustment when new data comes in, adapted from [49]

In exploring its industrial adoption, Bruel and Godina [50] examined both challenges and enablers of Blockchain integration in industrial park ecosystems. They proposed an architectural model for smart contracts aimed at enhancing inter-organizational communication in industrial symbiosis (IS) settings. Kröhling et al. [51] demonstrated a functional prototype utilizing smart contracts for peer-to-peer (P2P) trading of electricity and thermal energy in industrial environments, facilitating improved financial outcomes for individual prosumers through autonomous negotiations.

Lin et al. [52] carried out a comparative evaluation of auction-based models for localized solar energy trading among neighbors, while Padghan et al. [53] leveraged Ethereum Blockchain infrastructure to develop a cooperative and equitable trading mechanism for distributed energy assets. Abdo and Zeadally [54] introduced a Blockchain-centric framework designed for multi-utility exchanges, emphasizing modularity and transparency. Ramos et al. [55] proposed a utility optimization model using a multi-leader–follower game theory approach to ensure stable and fair transaction equilibria. In the context of industrial automation, Zhou et al. [56] designed a smart contract agent capable of processing feedback during autonomous trading operations, validated through simulation using the J-Park platform.

Expanding on cooperative strategies, Luo et al. [57] proposed decentralized trading protocols that support energy reimbursement among prosumers in microgrids with integrated renewable sources and storage capabilities. Yang et al. [58] focused on developing incentive models to boost participation in surplus energy markets. Building on this, Yang et al. [59] also introduced a pricing system grounded in a proof-of-stake consensus tailored to enhance fairness in traditional grid-connected prosumer trading.

Several studies have emphasized innovative Blockchain solutions, including alternative consensus algorithms for renewable energy coordination and mechanisms to ensure equitable energy trade [60]. The use of Blockchain has been explored in chemical processing, particularly for optimizing heat exchange systems in eco-industrial parks [61], marking a significant expansion of its industrial relevance. Chin et al. [49] also introduced the concept of using blockchain to broadcast streams data among site and using smart transaction methods to identify the optimal energy resources exchange between sites.

Blockchain networks can vary significantly depending on how access, control, and operations are structured. Based on access governance, blockchains can be public, private, consortium-based, or federated. In terms of data access rights, platforms are categorized into permissionless (open to all participants) and permissioned (restricted to authorized users) systems [62]. Token-based models offer economic incentives within blockchain ecosystems, while non-tokenized frameworks operate without such mechanisms [63]

Despite its vast potential, blockchain technology still faces substantial hurdles that limit its widespread commercial implementation. Key challenges span technological, organizational, economic, and legal dimensions. Technologically, blockchain's relative immaturity brings concerns related to scalability, performance, and user-friendliness. Adoption is further constrained by limited technical expertise, infrastructure costs, and system complexity. On an organizational level, barriers include insufficient top-level support, cultural resistance to change, and financial limitations [64].

While practical applications are still emerging, real-world use cases of blockchain have been identified across a range of sectors. These include supply chain management and logistics [65], the fashion and retail industry [66], Internet of Things (IoT), healthcare systems, finance, governance, digital identity management [67], and social impact initiatives.

Industrial symbiosis and blockchain technology

Supply chains are intricate systems made up of numerous interdependent business relationships focused on the creation and delivery of value. Traditional supply chains often lack transparency and trust. The exchange of information, especially between geographically dispersed partners, typically demands significant resources, intermediaries, and time. Many transactions are still conducted on paper, making the system vulnerable to fraud, asymmetric information, and operational inefficiencies. Another pressing challenge is coordinating effectively among supply chain stakeholders. Even though tools like enterprise resource planning (ERP) systems and digital tracking technologies are employed, issues related to complexity and errors persist [68].

In light of these challenges, blockchain has emerged as a particularly promising tool for transforming supply chain operations. By enabling complete auditability across the supply chain and reducing reliance on intermediaries, blockchain simplifies the process of tracking goods and transactions [67]. Through its capacity to consolidate data from various sources, blockchain fosters better communication among companies, encouraging the adoption of standardized protocols that facilitate strategic and mutually beneficial partnerships. As a result, blockchain significantly enhances supply chain mapping, auditing, and certification, helping companies build greater trust with end consumers [62].

Blockchain supports supply chain management through three key functionalities:

1. **Transparency** – The decentralized nature of blockchain ensures that the distributed ledger is visible to all participants.
2. **Traceability** – All actions and transactions are recorded in an immutable format, making it easy to track the origin and movement of goods.
3. **Authentication** – All network participants participate in verifying and storing transaction data (Wang et al., 2020).

In some systems, supply chain transactions are logged automatically using smart contracts or Internet of Things (IoT) sensors. Smart contracts offer a way to digitally enforce agreements and procedures, blending user interfaces with secure protocols to facilitate automated, trustworthy operations. In recent years, major global corporations such as Carrefour, Walmart, Nestlé, and Alibaba have started incorporating blockchain into their supply chain processes [66].

Beyond supply chains, blockchain also offers valuable benefits for the Circular Economy (CE) and waste management sectors [69]. Blockchain enhances CE practices by enabling seamless information flow along supply chains, which is essential for materials and by-products exchange. It secures data management, ensures shared access to key information among stakeholders, and strengthens collaborative efforts. Within waste management, programs aimed at waste exchange often suffer from fraud, data inaccuracy, and inefficient manual handling. Blockchain can address these issues by ensuring the reliability and availability of data.

Similarly, the Industrial Symbiosis (IS) framework—which focuses on collaboration among firms to share resources, such as energy, materials, and waste—stands to benefit significantly from blockchain integration. Both IS and blockchain operate as decentralized ecosystems: blockchain is a peer-to-peer network where information is securely stored and shared, while IS is a platform for inter-firm collaboration, often aligned with CE principles. Each involves multiple actors working together to create synergies beyond what individual firms can achieve alone – see **Figure 3** where the concept of resource exchange can be managed by a smart transaction framework, namely either Pinch Analysis or some allocation methodology, through an internal cryptocurrency between the entities in the region/sites [49].

However, both IS and blockchain still face several shared barriers, including a lack of robust information systems, technical difficulties in data gathering, and challenges in encouraging collaboration, trust, and willingness among participants [70]. Sensitive data—such as waste quantities, production volumes, and pricing—often remain undisclosed due to competitive concerns, further complicating IS data collection efforts[69].

Integrating blockchain into IS platforms could mitigate many of these issues. With its secure, transparent, and immutable structure, blockchain can enhance data infrastructure, promote trust, and streamline collaboration. Despite growing academic interest in the potential of blockchain within CE and IS contexts, there remains a notable gap in research specifically linking blockchain to IS frameworks.

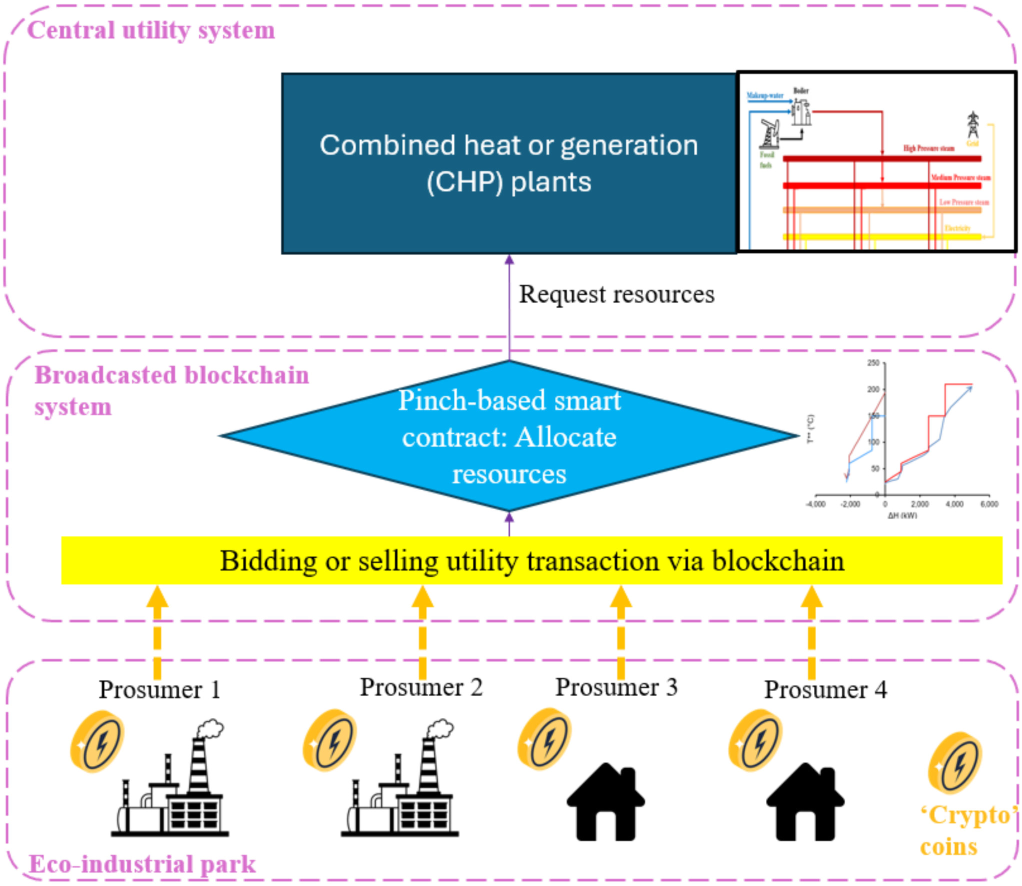

Figure 3: Concept of using blockchain in managing resource exchange between sites, adapted from [49]

RESOURCES PLANNING/ALLOCATION METHODOLOGY

Pinch Analysis

Originally developed for thermodynamic systems, Pinch Analysis has been effectively adapted for various supply chain applications, including optimization, performance evaluation, and environmental impact analysis. The technique was initially used to improve energy efficiency by optimizing the heat exchange between industrial processes requiring heating and cooling. In this context, Pinch Analysis identifies opportunities to recover and reuse heat across processes [71].

In supply chain management, a similar principle is employed by plotting supply and demand curves separately and analyzing their interactions over time. These curves help to visualize inventory levels at different points in a planning horizon, making it easier to detect imbalances such as surpluses or shortages. This graphical approach provides decision-makers with insights into energy usage and stock availability, allowing timely adjustments [72].

The first known application of Pinch Analysis to supply chain planning was introduced in 2002 [73]. This approach used a combinatorial graph with product quantity on the horizontal axis and time on the vertical, to identify the minimum production levels needed to meet demand while revealing inventory fluctuations. The "Pinch Point" marks the point of zero inventory, guiding adjustments in production, storage, and logistics to optimize profitability while satisfying demand requirements. Later, Singhvi et al. [74] validated this method using case studies and compared it with solutions generated by the GAMS software. The pinch-based approach significantly reduced computational time—up to six times faster than directly solving the mathematical model.

Further innovations extended Pinch Analysis to cost minimization in resource allocation problems [75]. By developing prioritization criteria and applying the analysis, researchers proposed efficient methods for internal and cross-regional resource management, balancing the use of dedicated and shared assets.

The methodology has also been adapted to address environmental concerns, such as reducing carbon emissions. For example, Carbon Pinch Analysis provides a visual tool for understanding how changes in energy sources affect emissions, helping regions to meet carbon reduction goals [76]. Li et al. [77] applied this approach to plan regional electricity and biomass supply chains under carbon constraints. Adjustments in biomass supply were mapped against energy demands and emission targets to identify the minimal requirement for external electricity sources.

Hwangbo et al. [78] introduced a hybrid Pinch Analysis combining carbon dioxide and hydrogen metrics, allowing comparative assessments of environmental impacts in hydrogen energy systems. Their graphical analysis displayed CO_2-equivalent emissions for different hydrogen production processes. Similarly, another study [79] used Pinch Analysis to assess greenhouse gas emissions across different bioenergy supply chain configurations.

As Pinch Analysis matured, it was further extended to handle complex, real-world challenges like uncertainty and multiple objectives. For instance, Priya and Bandyopadhyay [80] developed a multi-objective version of the analysis that balanced cost and resource quality in supply planning. Bandyopadhyay [81] explored uncertain environments by introducing interval-based representations of unknown parameters and applying the approach to develop feasible planning solutions without precise input data.

Jalanko and Mahalec [82] applied a supply-demand pinch method for optimizing gasoline blending over multiple time periods under component quality uncertainty. Their evaluation of this technique against comprehensive models demonstrated its potential for producing quality solutions efficiently.

Overall, the key strength of Pinch Analysis lies in its ability to deliver intuitive and visual solutions – see Figure 4. It facilitates energy savings, cost reductions, and more efficient supply chain operations by streamlining heat integration and resource allocation. Through straightforward calculations, planners can quickly outline preliminary supply-demand scenarios. Additionally, adjusting supply curves allows for effective comparison of different planning scenarios. Importantly, the method offers a robust starting point for mathematical programming, improving convergence speed and solution quality. Despite its growing versatility—spanning uncertain and multi-objective optimization—further research is needed to refine the method's reliability and broaden its applicability across diverse planning contexts.

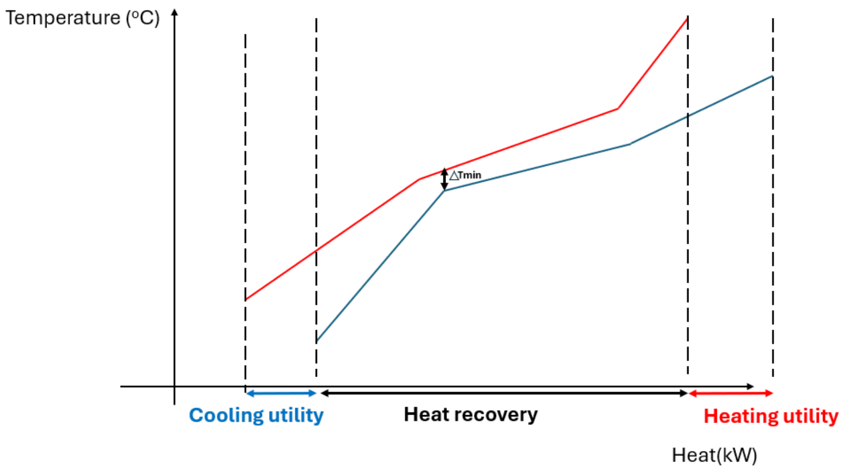

Figure 4: Classic Pinch Analysis diagram to visualize resources allocation

Advanced resource allocation methodologies

Recent studies have expanded the application of the Pinch-based approach to various forms of material integration. Chin et al. (2020a) investigated the foundational principles in resource conservation networks and developed a Pinch-based targeting methodology for networks involving multiple types of contaminants. Yanwarizal et al. (2020) proposed a framework that separates limiting Composite Curves at the stream level instead of aggregating them, enabling more precise targeting and design. Oladosu et al. (2020) introduced an algebraic method that addresses different stream splitting configurations within this problem domain. For comprehensive reviews on advanced Pinch-based methods, readers may refer to Klemeš et al. (2018) on mass-based and heat-based integration applications.

CONCLUSION

Addressing the complex challenges of modern resource management demands the integration of advanced digital technologies, innovative resource allocation strategies, and secure data frameworks. Geographic Information Systems (GIS) and Artificial Intelligence (AI) tools enable comprehensive spatial-temporal analysis and predictive capabilities, allowing stakeholders to better understand resource distribution patterns, forecast demand fluctuations, and optimize utilization in dynamic environments. These technologies provide non-trivial advantages such as real-time data assimilation, adaptive decision-making, and scenario simulation, which are essential for effective resource stewardship in increasingly uncertain and interconnected systems.

Simultaneously, blockchain technology introduces unprecedented levels of transparency, traceability, and security in resource transactions, facilitating trust among diverse actors and enabling decentralized coordination without reliance on central authorities. The inherent immutability and smart contract functionality of blockchain help mitigate risks of fraud, misallocation, and data tampering, which are often overlooked but critical factors in ensuring equitable and efficient resource management.

Complementing these digital tools, resource allocation methodologies such as Pinch Analysis and mathematical programming provide rigorous frameworks for identifying optimal pathways to minimize waste, balance competing objectives, and enhance system-wide efficiency. These approaches address non-trivial challenges including multi-contaminant integration, conflicting stakeholder priorities, and complex network interactions that conventional heuristic or ad hoc methods cannot resolve effectively.

The convergence of GIS, AI, blockchain, and advanced resources allocation methodologies forms a multidisciplinary foundation essential for tackling resource management's multifaceted issues. Harnessing their synergistic potential empowers decision-makers to design resilient, sustainable, and adaptive resource systems capable of meeting evolving socio-economic and environmental demands. The ideal digital technology framework on resource allocation framework is illustrated in **Figure 5**.

Technological advancements facilitate the seamless streaming of essential data for process planning across various scales, while also enabling the integration of multiple advanced analytical approaches to support diverse decision-making models. This combination provides industrial practitioners with high-confidence solutions tailored to different strategic performance indicators (SPIs), such as minimizing cost or reducing pollution. This article aims to inspire both academic researchers and industry professionals to advance efforts towards developing comprehensive digital frameworks for process systems operating at multiple scales.

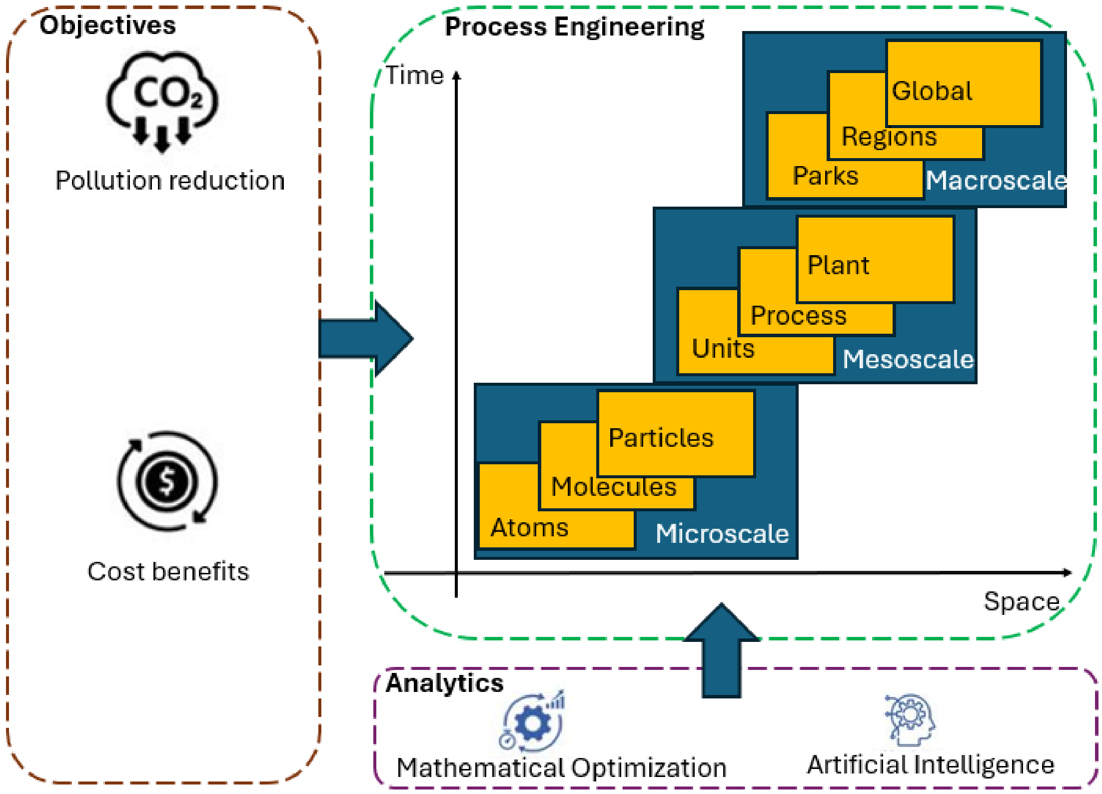

Figure 5: Proposed illustration showing the integration of digital technologies and optimization approves in addressing full-scale process industries, adapted from [87]

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