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Digital Integration of Energy Management and GHG Inventories in Thermal Power Generation: A Systems-Based Systematic Mapping Review

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Abstract

Thermal power generation relies on fuel, electricity, process-performance, emissions, and operational data, yet these data are commonly held in disconnected systems. This study maps how digitalization and systems thinking are used to connect energy management with greenhouse-gas (GHG) inventories. A rapid systematic mapping review examined English-language Scopus records published in 2016-2026. Two search streams returned 156 records; one article-in-press record was removed, and 30 final-stage records were selected through pre specified title-and-abstract screening. Eighteen studies addressed digital operations and 12 used system dynamics or systems thinking for energy and carbon decisions. Most digital studies applied artificial intelligence or machine learning to boiler or turbine optimization, performance prediction, and emissions estimation. Systems studies concentrated on carbon policy, electricity markets, CCUS, and low-carbon fuels. No abstract-level evidence described one plant-level architecture combining real-time operational data, GHG-inventory governance, and system feedback. The study proposes a four-layer integration framework for traceable energy and GHG management.

Keywords: Digitalization; Energy Management; GHG Inventory; System Dynamics; Thermal Power Generation

Abstrak

Pembangkit listrik termal membutuhkan data bahan bakar, listrik, kinerja proses, emisi, dan operasi, tetapi data tersebut sering tersimpan dalam sistem yang terpisah. Penelitian ini memetakan bagaimana digitalisasi dan pemikiran sistem digunakan untuk menghubungkan manajemen energi dengan inventaris gas rumah kaca (GRK). Rapid systematic mapping review dilakukan terhadap publikasi berbahasa Inggris di Scopus pada tahun 2016-2026. Dua strategi pencarian menghasilkan 156 rekaman; satu artikel in press dikeluarkan dan 30 rekaman tahap final dipilih melalui penyaringan judul dan abstrak berdasarkan kriteria yang telah ditetapkan. Sebanyak 18 studi membahas digitalisasi operasi, sedangkan 12 studi menggunakan system dynamics atau system thinking untuk keputusan energi dan karbon. Sebagian besar studi digital menggunakan AI atau machine learning untuk optimasi boiler atau turbin, prediksi kinerja, dan estimasi emisi. Studi sistem terutama membahas kebijakan karbon, pasar listrik, CCUS, dan bahan bakar rendah karbon. Tidak ditemukan bukti abstrak yang mengintegrasikan data operasi waktu nyata, tata kelola inventaris GRK, dan umpan balik sistem dalam satu arsitektur tingkat pembangkit. Studi ini mengusulkan kerangka integrasi empat lapis untuk mendukung manajemen energi dan GRK yang dapat ditelusuri.

Kata kunci: *Digitalisasi; Manajemen Energi; Inventaris GRK; System Dynamics; Pembangkit Listrik Termal*

INTRODUCTION

Thermal power plants and their supporting functions generate several interdependent data streams: fuel receipts and consumption, electricity output, energy-performance indicators, Stack and environmental compliance measurements, GHG activity data, maintenance histories, and supply chain information. In practice, these data are frequently dispersed across logsheets, spreadsheets, laboratory records, control-room historians, environmental reports, and stand-alone applications. The result is not merely an information technology problem. Fragmented data weakens the ability to reconcile fuel use, unit performance, emissions estimates, and operational decisions within a consistent management boundary.

Recent digital studies show that data-driven methods can improve plant level decisions. Business process modelling has been used to extend energy baselines beyond core production activities, while digital simulation, digital twin modelling, and fuel-stock digitalization have been proposed for thermal-power planning and operations (Munsamy & Telukdarie, 2021; Kalmykov et al., 2025; Chen et al., 2024; Hermawan & Nurahman, 2023). Artificial intelligence and machine learning have been applied to thermal-power operational optimisation, coal-consumption modelling, boiler control, turbine efficiency, and performance prediction (Ding et al., 2018; Naveen Kumar & Gundabattini, 2022; Strušnik et al., 2016, 2021; Ashraf et al., 2023; Haddadin et al., 2024; Prokhorskii et al., 2024; Xie & Pan, 2025; Yudisaputro et al., 2023).

However, a prediction of an emission or an efficiency variable is not automatically a complete GHG inventory. An inventory also needs a defined organizational and operational boundary, traceable activity data, documented calculation assumptions, quality checks, and a reporting trail. The digital literature includes carbon-emission prediction, life-cycle carbon assessment, remote CO2 observation, and fuel-activity models (Yin et al., 2025; Liu et al., 2025a, 2025b; Hobbs et al., 2023; Herawati et al., 2024), but these applications do not necessarily connect to an auditable inventory process or managerial feedback loop.

Systems-thinking research provides a complementary view. System dynamics and causal-loop studies model feedback among carbon prices, electricity markets, carbon trading, CCUS, co-firing, investment incentives, and power-sector transitions (Bao et al., 2021; Ye et al., 2023; Wang et al., 2023; Handayani et al., 2024; Feng et al., 2025; Haowei, 2025; Zhang et al., 2025; Lu et al., 2023; Du et al., 2025; Wang et al., 2026; Widhiantoro et al., 2025; Qu et al., 2026). Yet this work commonly operates at policy, market, or strategic levels rather than connecting real-time plant data to energy-management and GHG-inventory governance.

This study therefore maps the intersection of digitalization, energy management, GHG inventories, and systems thinking in thermal power generation. Its contribution is a transparent evidence map and a proposed systems-based integration framework. The review is deliberately a rapid systematic mapping review: it synthesises bibliographic metadata and abstracts, and it does not claim a full-text effectiveness meta-analysis.

- **RQ1.** Which digital technologies and functions support energy management and GHG-related activities in thermal power generation?
- **RQ2.** How are fuel, energy-performance, emissions, environmental-compliance, and operational data integrated or represented?
- **RQ3.** How are system boundaries, feedback, interdependencies, and trade-offs treated in energy and carbon decisions?

RQ4. What maturity gaps and implementation priorities emerge for integrated energy and GHG management?

RESEARCH METHODS

Review design and information source

The review used PRISMA 2020 as a reporting guide (Page et al., 2021). A working protocol was documented and refined after pilot scoping searches and before title-and-abstract screening. Scopus was the sole bibliographic source because the review aimed to generate one reproducible, time-bounded mapping dataset. Searches were completed on August 2026 and covered publication years 2016-2026. The unit of analysis was a Scopus record with its bibliographic metadata and abstract. No proprietary plant reports, operational datasets, or confidential documents were used as review evidence.

Table 1. Search Strategy and Selection Protocol

Protocol	Applied rule	Outcome
Database and date	Scopus; August 2026	One reproducible public bibliographic source
S01 digital stream	Thermal-power terms AND digitalization, digital twin, IoT, AI/ML, data integration or EMIS AND energy/GHG-management terms	118 records
S02 systems stream	Thermal-power terms AND systems thinking, system dynamics, causal loop, stock-flow or socio-technical terms AND energy/carbon terms	38 records
Limits	English; 2016-2026; article, review, or conference paper; final publication stage	One article-in-press record was removed before screening
Include	Direct thermal-power relevance plus eligible digital-energy/GHG function or explicit systems-thinking energy/carbon analysis	Title and abstract reviewed against fixed criteria
Exclude	Non-thermal context; generic power, digital, or emissions work; electrical-control-only studies; pollutant-only studies without energy/GHG-management connection	Reasons recorded during screening
Synthesis	Descriptive evidence mapping and thematic coding; no effect-size meta-analysis	30 final-stage records included

The two search streams were intentionally complementary. S01 retrieved operational and digital evidence; S02 retrieved systems-level evidence. A record did not need to address every concept simultaneously, but it had to contribute to the specified integration problem. The 156 exported records were retained in the raw dataset. One article-in-press record was removed under the pre-specified final-stage rule, leaving 155 records for screening.

Screening, coding, and synthesis

Titles and abstracts were screened using the eligibility criteria in Table 1. A structured AI-assisted preliminary coding pass was used only to organise candidate labels and reasons. The author checked the final decision for every included record, and AI did not generate references or access confidential data. For included records, the review coded publication year, document type, digital technology, data type, energy or GHG-management function, system boundary, systems-thinking method, and stated limitation or implication. The

analysis compared process-level digital work with policy- and market-level systems work to identify missing integration links.
This design has a deliberate limitation. Findings represent what authors reported in Scopus metadata and abstracts, rather than a full-text validation of technical performance or GHG accounting quality. Accordingly, the paper reports mapped patterns and design implications, not pooled quantitative effects or verified plant emission reductions.

RESULTS AND DISCUSSION

Study selection and profile

Figure 1 presents the selection process. The final mapping set contains 30 records: 18 digital-operations studies from S01 and 12 systems-thinking studies from S02. The corpus includes 22 journal articles and 8 conference papers. Publication activity is concentrated in 2023-2026, with 24 of 30 records published in that period. The distribution indicates a recent acceleration in digital and low-carbon thermal-power research, but it also makes the distinction between operational prediction and inventory governance especially important.

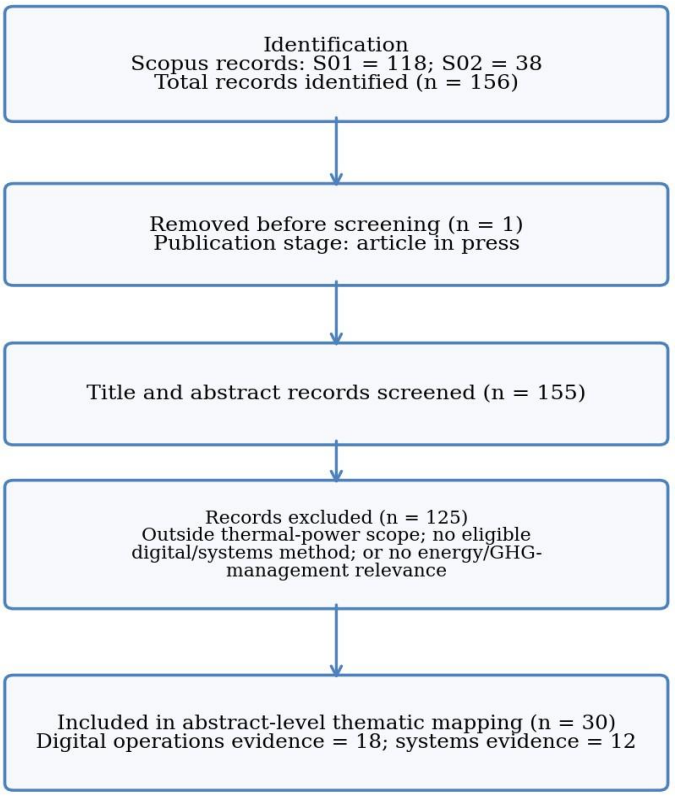


Figure 1. PRISMA-Style Record Selection for The Rapid Systematic Mapping Review

Figure 2 shows the publication profile of the included records. The 2025 peak and the concentration of 24 records in 2023-2026 indicate a recent expansion of work at the

intersection of digital operations, energy management, and low-carbon thermal-power transitions. This pattern reflects the defined Scopus search scope and should not be interpreted as a census of the entire field.

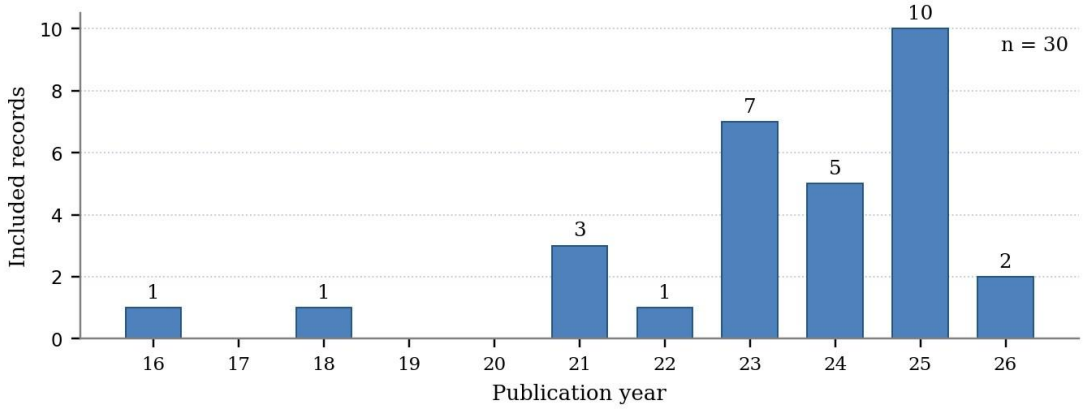


Figure 2. Publication-Year Distribution of The 30 Included Records

Digital evidence: strong on optimisation, limited on inventory governance

Fifteen of the 18 digital-operations records use AI, machine learning, or data-driven regression. Their dominant application is prediction or optimisation of thermal performance, boiler operation, coal consumption, turbine efficiency, or load response. The studies demonstrate a practical path from historian or operational data to decision support, including real-time boiler control, hybrid turbine models, and digital-twin representations (Ding et al., 2018; Chen et al., 2024; Yin et al., 2025; Xie & Pan, 2025). This body of work is operationally useful because it connects measurable conditions to an energy-performance decision.

Five digital records directly address carbon or CO2 estimation, carbon-footprint analysis, or fuel-activity-based emission reduction. These models expand the evidence base for GHG management, particularly where direct measurements are limited (Liu et al., 2025a, 2025b; Hobbs et al., 2023; Herawati et al., 2024). Nevertheless, the mapped abstracts generally emphasise prediction accuracy, optimization benefit, or emission intensity. They rarely describe the inventory boundary, emission-factor governance, recalculation rules, approval workflow, and audit trail needed for an organization-level GHG inventory. The key implication is that a predictive model should feed, rather than substitute for, controlled GHG-inventory processes.

Systems evidence: rich on feedback and policy, distant from plant data

All 12 systems-stream records use system dynamics, causal-loop reasoning, dynamic business modelling, or a closely related method. They examine the feedback structures that arise when carbon pricing, energy quotas, electricity markets, CCUS incentives, co-firing, and investment decisions interact. For example, plant- and technology-oriented studies model CCUS, biomass, green-ammonia co-firing, carbon pricing, and business-model evolution for coal-fired generation (Ye et al., 2023; Wang et al., 2023; Handayani et al., 2024; Widhiantoro et al., 2025; Qu et al., 2026; Wang et al., 2026).

Market- and policy-oriented studies capture trade-offs across electricity and carbon markets, carbon-trading policy, renewable portfolio standards, and energy quotas (Bao et al., 2021; Lu et al., 2023; Feng et al., 2025; Haowei, 2025; Zhang et al., 2025; Du et al., 2025). This literature is particularly valuable for identifying reinforcing and balancing feedback loops. Yet it usually relies on aggregate parameters and scenarios, whereas digital operational

studies rely on unit-level or plant-level variables. The separation of these analytical scales is the central integration gap found by this mapping.

Table 2. Thematic Evidence Map of The 30 Included Records

Evidence theme	n	Typical data or focus	Interpretation for integration
AI/ML performance optimisation	15	Boiler and turbine variables, coal consumption, thermal efficiency, load response	Strong process-level prediction and control; limited inventory governance
Digital integration, simulation, and twin approaches	3	Business-process energy baseline, fuel allocation, hybrid steam-turbine model	Shows how data can be structured across plant functions
Digital carbon and CO2 estimation	5	Carbon intensity, life-cycle footprint, satellite CO2, fuel-activity emissions	Extends measurement capability but does not by itself establish a GHG inventory
Systems dynamics and systems thinking	12	Carbon pricing, markets, CCUS, co-firing, business models, policy scenarios	Makes feedback, trade-offs, and boundary choices explicit

Theme counts overlap because several studies contribute to more than one category. The dominant evidence stream is identified by the study purpose reported in the abstract.

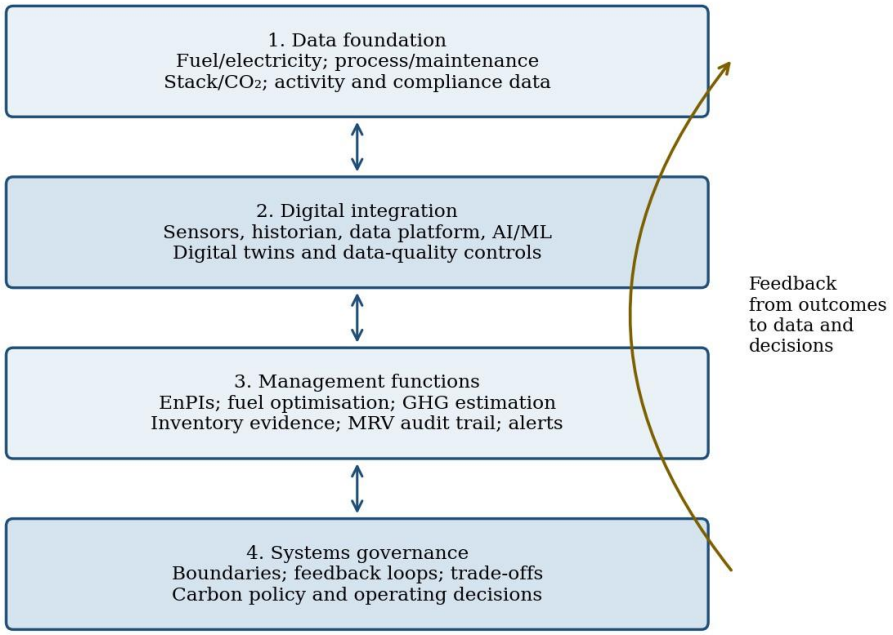
Table 3. Systems-Based Maturity Gaps and Priority Actions

Layer	Mapped evidence	Main maturity gap	Priority action
Data foundation	Fuel, electricity, process, stack, and maintenance variables are available across the corpus.	Shared identifiers, timestamps, units, and source-to-report data lineage are rarely explicit.	Establish a controlled data model and reconciliation rules.
Digital integration	AI/ML, historians, digital twins, and simulation support operational decision-making.	Interoperability with procurement, laboratory, maintenance, and environmental systems is underreported.	Connect source systems through governed interfaces and quality controls.
Management functions	Strong evidence for EnPIs, optimisation, and emissions estimation.	GHG boundaries, calculation governance, factor control, approvals, and MRV audit trails are seldom detailed.	Implement an auditable digital GHG-inventory workflow.
Systems governance	System dynamics covers feedback, policy, markets, and long-term trade-offs.	Few studies connect systems models to real-time unit-level data and energy-carbon decisions.	Couple scenarios to validated operational and inventory outputs.

Table 3 clarifies why the evidence streams should be combined rather than treated as alternatives. Digital studies provide operational responsiveness, whereas systems studies make delayed feedback and cross-boundary consequences visible. An integrated energy-carbon management system requires both capabilities and explicit inventory governance between them.

Proposed systems-based integration framework

Figure 3 synthesises the evidence into a four-layer framework. The first layer establishes a common data foundation linking fuel, electricity, process, maintenance, stack, and GHG activity data. The second layer integrates those data through operational technology, historian or platform services, data-quality controls, AI/ML models, and digital twins. The third layer converts data into management functions: energy-performance indicators, fuel optimisation, GHG calculations, monitoring-reporting-verification evidence, and alerts. The fourth layer uses systems thinking to define the boundary, expose feedback, and test trade-offs before operational or investment decisions are made.



Proposed synthesis framework. It is a design implication from the mapped literature, not a validated plant model.

Figure 3. Proposed Systems-Based Integration Framework for Energy Management and GHG Inventories

The framework should not be interpreted as a finished software architecture. It is a design implication from the mapped literature. For implementation, a plant should first establish controlled identifiers, timestamps, units, ownership, and data-quality rules. It should then define the GHG boundary and calculation governance before using predictive analytics. Finally, scenario models should use the validated operational and inventory outputs to evaluate rebound effects, fuel-switching consequences, carbon costs, and maintenance or dispatch trade-offs. This order reduces the risk of treating a technically accurate model as a complete management system.

Limitations and research agenda

The review is limited to English Scopus records and an abstract-level mapping design. It does not assess the quality of full-text methods, perform a meta-analysis, or validate reported effects against confidential plant data. Future research should test the proposed framework in a documented plant setting, specify GHG boundaries and uncertainty procedures, compare digital models with measured and calculated inventory results, and incorporate causal feedback from policy and operating decisions. These steps would move the field from isolated optimizers and sector scenarios toward integrated, auditable energy-carbon management.

CONCLUSION

This rapid systematic mapping review identified 30 final-stage Scopus records at the intersection of thermal-power digitalization, energy management, GHG-related activities, and systems thinking. The evidence is strongest for AI and machine-learning applications that improve boiler or turbine performance, predict energy variables, and estimate emissions. Systems approaches contribute a different but necessary capability: they model boundaries, feedback, policy, and market trade-offs. The mapped literature does not yet show a plant-level architecture that combines real-time operational data, controlled GHG-inventory governance, and systems feedback in one management loop. The proposed four-layer framework therefore offers a practical research and implementation direction: build a controlled data foundation, integrate it with digital tools, convert it into energy and GHG management functions, and govern decisions through explicit systems boundaries and feedback. This conclusion is limited to abstract-level evidence and should be tested through full-text and plant-level research.

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