

CHAPTER 2 - LITERATURE REVIEW

2.1. Geothermal Power Plant

2.1.1 Geothermal Power Plant Technology

The single-flash steam plant is the cornerstone of the geothermal power sector. The initial power plant typically established in a newly-developed liquid-dominated geothermal site. As of May 2007, 159 units of this type were operational in 18 countries globally. Single-flash plants constitute around 32% of all geothermal facilities. They represent more than 42% of the global installed geothermal power capacity (Huttrer 2001, pp.1–27).

The single-flash plant is a straightforward method for converting geothermal energy into electricity when geothermal wells yield a combination of steam and liquid. The mixture is initially segregated into separate steam and liquid phases with minimal pressure loss. This occurs in a cylindrical cyclonic pressure vessel, often positioned with a vertical axis, where the two phases separate due to their significant density disparity. The placement of the separators is crucial to the overall design of the plant, and several configurations are feasible (DiPippo 2011).

The flash process can transpire in several locations: (1) within the reservoir as the fluid traverses the permeable formation, accompanied by a pressure decline; (2) in the production well, from the entry point to the wellhead, due to pressure loss from friction and gravitational effects; or (3) at the inlet of the cyclone separator, resulting from a throttling process instigated by a control valve or orifice plate. In freshly developed fields, flashing often occurs in the wellbore initially; however, as the field is exploited and reservoir pressure decreases, the flash point may descend inside the well and potentially penetrate the formation. The term "separated steam" is occasionally employed for this sort of plant due to the method by which the steam is procured for turbine utilisation (Dickson & Fanelli 2013).

The specific position of the flash point is significant for power plant operations; nevertheless, it is inconsequential for comprehending the thermodynamics of the energy

conversion process. We shall presume that the geofluid initially exists as a compressed liquid within the reservoir, undergoes a flashing process at some point, the two phases are subsequently separated, and the steam is utilised to power a turbine that, in turn, powers the electric generator. This simplification allows the thermodynamic analysis to focus on enthalpy changes and phase transitions that are most relevant to energy conversion efficiency, rather than on the spatial details of flashing within the production system (Barbier 2002, pp.3–65).

2.1.2 Environmental and Sustainability Consideration in Geothermal Power Plant

From an environmental and sustainability perspective, the control of non-condensable gas emissions (e.g., CO₂, H₂S) is essential to mitigate air quality impacts and account for greenhouse contributions. Hybrid configurations combining flash and binary cycles can achieve near-zero emissions through complete reinjection—including NCG reinjection—but often at a modest trade-off in electrical productivity (Bruscoli et al. 2015). Reinjection also helps sustain reservoir pressure, reduce thermal decline, and prevent land subsidence and water contamination. Life-cycle assessments confirm that flash plants generally emit significantly less CO₂ per kWh than fossil-fuel plants and operate with minimal land and water footprints (≤ 20 L/MWh versus $>1,000$ L/MWh for coal) (Soltani et al. 2021).

2.1.3 Economic Challenge in Geothermal Power Plant

On the **economic** side, single-flash plants are attractive due to their lower initial capital cost and simpler construction compared to double-flash or ORC systems. However, sustainability of revenue and efficiency over the reservoir lifecycle can be threatened by declining reservoir pressure. Additional costs may arise from scaling, corrosion-control measures, and environmental compliance—highlighting the need for careful lifecycle and economic planning. Capital expenses remain significant, with upfront drilling and surface infrastructure often costing between \$2,000–\$3,000 per kW, depending on plant type and size; operational expenditure must also account for mitigation of resource decline impacts (Hackstein & Madlener 2021, Soltani et al. 2021).

2.2. The Concept of Digital Transformation

Digitalisation is a fundamental component of the extensive advancement of society, economics, and industry. Digitalisation and globalization—interdependent processes—define our contemporary reality. The European Commission anticipates that a "transformative industrial and technological revolution" will be a significant worldwide trend until 2030. "Technological breakthroughs will transform all facets of society, including politics, governance, education, science, lifestyles, collective intelligence networks, the establishment of open systems, and health, encompassing the transformation of the human genome" (European Commission. 2015).

Numerous definitions are offered by scholars, governmental entities, and business professionals. Several are included in Table 2.1.

Table 2.1 Definitions of the term "Digital Transformation" (Verina & Titko 2019)

Source	Definition
European Commission (2019)	"Digital transformation is characterized by a fusion of advanced technologies and the integration of physical and digital systems, the predominance of innovative business models and new processes, and the creation of smart products and services."
OECD (2018)	"Digital transformation refers to the economic and societal effects of digitization and digitalization. Digitization is the conversion of analog data and processes into a machine-readable format. Digitalization is the use of digital technologies and data as well as their interconnection which results in new or changes to existing activities."
Ismail, Khater, and Zaki (2017)	[Digital transformation is a] "process through which companies converge multiple new digital technologies, enhanced with ubiquitous connectivity, with the intention of reaching superior performance and sustained competitive advantage, by transforming multiple business dimensions, including the <i>business model</i> , the <i>customer experience</i> (comprising digitally enabled products and services) and <i>operations</i> (comprising processes and decision-making), and simultaneously impacting <i>people</i> (including skills talent and culture) and <i>networks</i> (including the entire value system) "
Schwertner (2017)	"the application of technology to build new business models, processes, software and systems that result in more profitable revenue, greater competitive advantage, and higher efficiency."
Deloitte (2018)	"Digital transformation is the use of technology to radically improve the performance or reach of an organization. In a digitally transformed business, digital technologies enable improved processes, engaged talent, and new business models."
Bloomberg (2018)	"Digital transformation requires the organization to deal better with change overall, essentially making change a core competency as the enterprise becomes customer-driven end-to-end. Such agility will facilitate ongoing digitalization initiatives but should not be confused with them."

Refer to Deloitte and Schwertner, the application of technology can improve process and business models. According to the study analysis on digital transformation by Natalja Verina and Jelena Tito (2019), three areas have been identified: technology, processes and management, and people. This study revealed that significant advancements in digital transformation are driven not by technology, but by people, who must be matched accordingly. (Verina & Titko 2019)

Pattharin Tangwaragorn (2024) defined and analysed the primary drivers of digital transformation utilising 19 established readiness metrics. This paper analyses the dimensions and indicators utilised in these indices, emphasising their significance and prevalence to identify the principal elements driving digital transformation. Digital transformation encompasses strategic initiatives wherein organisations adjust to the evolving digital landscape, utilising technologies such as mobile computing, Artificial Intelligence (AI), cloud computing, Blockchain, and the Internet of Things (IoT) to innovate their value creation processes. This report provides clear insights into the effective implementation of digital transformation within an ecosystem, based on a thorough examination of data from digital transformation indexes, encompassing both broad categories and particular indications as shown on Figure 2.1 (Tangwaragorn et al. 2024, pp.93–108).

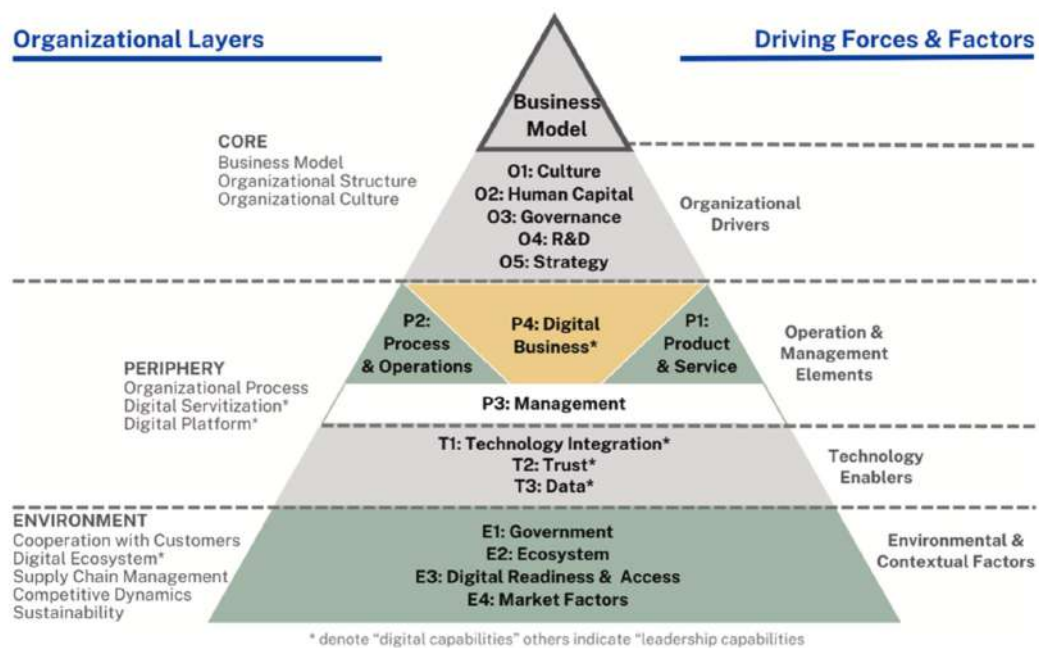


Figure 2.1 A Framework for Digital Transformation (Tangwaragorn et al. 2024, pp.93–108)

Frank Jordan established key performance indicators for digital transformation (2020). Key Performance Indicators (KPI) are not inherently integrated into the control cycle of corporate or operational management through a computerised business model. Generally, they are at a high level and do not delve into the nucleolus of the manufacturing process and operational plant equipment. Consequently, data simplicity and reduction are essential for facilitating decision-making. In the era of cloud

computing, deep learning, and artificial intelligence, it is feasible to assess the performance of infinitesimal components of a processing plant. The resultant data may be synthesised from the ground up to yield accurate outcomes, facilitate immediate action, and enable the identification of the underlying causes of any problems. This research aims to provide prospective solutions for utilising KPIs in the digital transformation of various industries to enhance operations and commercial prospects. The objective is to establish a KPI with corresponding features that can be assessed for a business model. The KPI properties can be inputted into a computational model that simulates the company's operations. The business model is exclusively a mathematical framework that requires the input of all known parameters or key performance indicators (KPIs). By comparing rules and formulas against a knowledge base, the output will direct the corporation on the appropriate course of action at any given moment to avert business deterioration. In order to accurately represent a company from the ground up, a business model will necessitate the input of numerous parameters and attributes as shown on Figure 2.2 (Jordan 2020, pp.45–52).

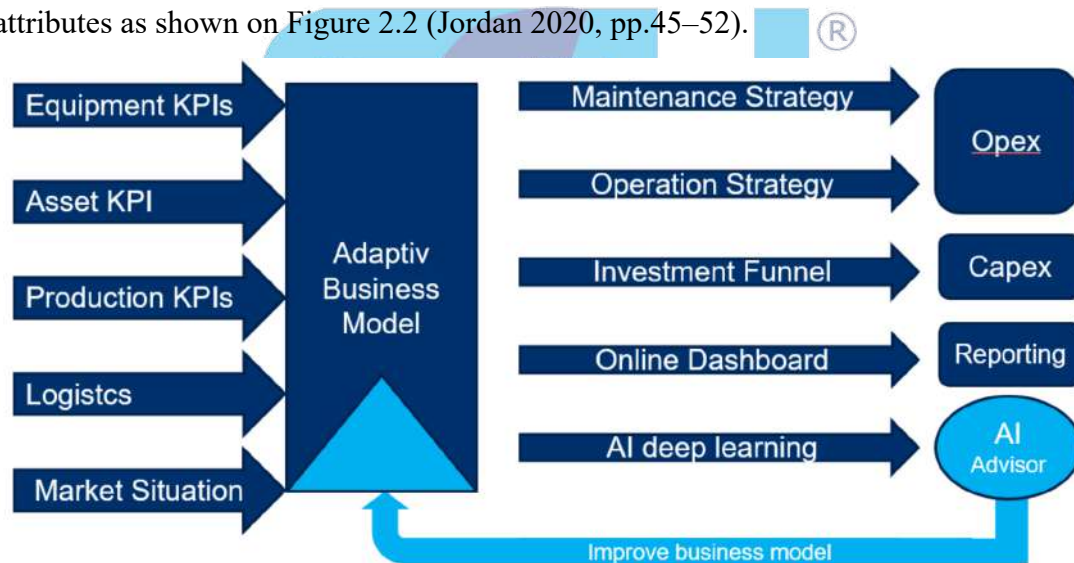


Figure 2.2 KPI Controlled Business Model (Jordan 2020, pp.45–52)

The Object KPI of each instrument or equipment will encompass all characteristics necessary for a computer system to comprehend the significance of this equipment to the organisation refer to Figure 2.3. With its comprehensive perspective on the situation (access to all data), it will automatically select the optimal solution that has been predetermined by specialists for this specific equipment. The plant's response and the object KPI will be analysed throughout time, allowing for ongoing adjustments to the

particular object KPI based on real-time data from the plant. Therefore, there is no delay, no HSSE infringement, and no error in the execution. The AI system will augment its knowledge and refine its predictive capabilities, along with revenue potential, with each occurrence.

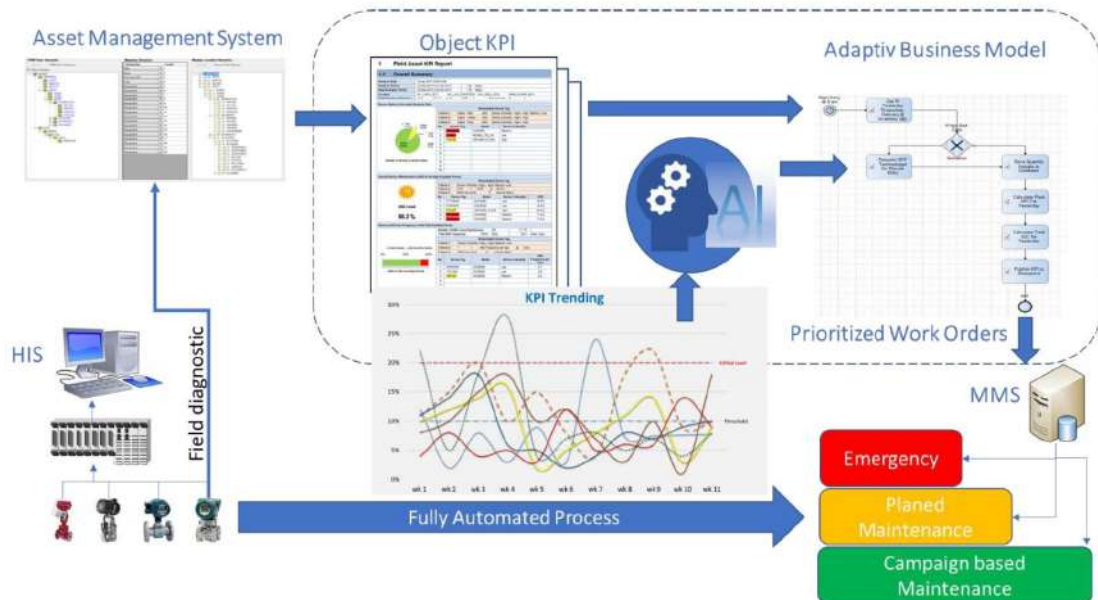


Figure 2.3 Digitized Work Process for AI Controlled Maintenance

Also, Jordan's research identified several possible benefits that may be realised, including:

1. Reduced OPEX
 - a. significant reduction of operators and experts over the lifetime of the plant
 - b. personnel is focused on maintenance and assisted by an AI system
 - c. predictive maintenance is based on real-time data and not statistical benchmarks.

Therefore, it is best-practice for the specific plant and not just for an average plant.

 - d. knowledge is machine-based and continuously available over the lifetime of the plant
 - e. improved uptime of the plant's business
2. Clear facts and priorities for the investment funnel.
3. Best practice for the plant with the lowest possible CAPEX.

4. Optimally adjusted business model to ensure the best profit.
5. Leading indicators which come directly out of the process ensure the fastest possible reaction times.

Only firms who can fully leverage the new object-oriented KPIs and incorporate them into their business strategy will succeed with this technology. Experts and innovative minds are essential for its success (Jordan 2020, pp.45–52).

2.3. Machine Learning in Industrial and Energy System

Machine learning (ML) has emerged as one of the most influential tools in modern industrial and energy systems, as it allows computers to learn from data rather than being explicitly programmed with rules. This flexibility is especially critical in energy systems, where nonlinear interactions, variability, and uncertainty complicate conventional modelling approaches. By leveraging historical and real-time data, ML models provide insights for prediction, anomaly detection, and optimization that enhance both reliability and efficiency (Bishop 2006, Heaton 2018).

In geothermal applications, ML is increasingly applied to production forecasting, anomaly detection, and resource characterization. For instance, anomaly detection in geothermal operations has been demonstrated using **Locality Sensitive Hashing (LSH)**, which efficiently identifies abnormal operational states in large, high-dimensional datasets. Similarly, clustering approaches such as **OPTICS** enable the identification of density-based patterns in steam production and reservoir behavior, allowing operators to group wells with similar characteristics and detect deviations that might indicate equipment faults or reservoir changes (Ankerst et al. 1999, pp.49–60). These approaches help engineers move from reactive to proactive maintenance strategies.

Regression-based models have also gained prominence, particularly for forecasting geothermal well performance and deliverability. A key metric used in validating these models is the **Root Mean Square Error (RMSE)**, which measures the average magnitude of prediction errors and is especially sensitive to large deviations. RMSE provides a quantitative benchmark to evaluate the alignment between field sensor readings and model projections, ensuring that updated deliverability curves or reservoir

simulations reflect actual performance (Hyndman & Athanasopoulos 2018). In geothermal plants, this helps bridge the gap between simulation tools and real-world operations.

Recent studies further illustrate the integration of ML in geothermal reservoir and exploration work. For example, clustering techniques such as **K-means** have been used for electro-facies classification to improve permeability and reservoir characterization (Koray et al. 2025, Okoroafor et al. 2022). Likewise, temperature forecasting models in Western Yemen demonstrate how ML-based regression enhances subsurface predictions, thereby reducing exploration risk and uncertainty in resource estimation (Al-Fakih et al. 2025). These studies confirm that ML contributes not only to operational optimization but also to improved exploration and reservoir management.

Beyond geothermal, ML is widely applied in the energy industry for tasks such as wind turbine fault detection, solar power forecasting, and energy demand prediction. Predictive models, including support vector machines (SVM), neural networks, and ensemble learning methods, have consistently demonstrated improvements in accuracy and decision-making speed (Colmenar-Santos et al. 2013, pp.42–49, Bloess et al. 2018, pp.890–907). The successful application of these techniques in other renewable sectors underscores their potential to address geothermal-specific challenges, particularly where nonlinear reservoir dynamics make traditional methods inadequate.

The integration of ML within geothermal operations reflects the broader **Industry 4.0** paradigm, emphasizing cyber-physical systems, digital twins, and smart data ecosystems. Combining historian systems with ML enables real-time anomaly detection and predictive simulation, allowing operators to anticipate failures and optimize operational parameters dynamically. This transition to proactive decision-making ensures long-term reliability, reduces downtime, and strengthens cost-efficiency in geothermal power production (Lee et al. 2015, pp.18–23).

2.4. Related Work

Previous studies on geothermal operations have explored a range of approaches, from wellbore simulations to advanced machine learning techniques. Allan et al. (2019) focused on modeling calcite deposition in the Ngatamariki geothermal field in New

Zealand, using wellbore simulations to predict scaling behavior and assess cleaning interventions such as broaching and acidizing. While effective for field-specific management, this work did not integrate digital or machine learning frameworks, limiting its broader applicability. Broader reviews of machine learning applications in geothermal energy have emphasized its role in advancing both exploration and operational efficiency. Okoroafor et al. (2020) examined two decades of ML use in subsurface modeling, noting its effectiveness in seismic interpretation, well logging, and reservoir property prediction. However, the review concentrated primarily on exploration, leaving surface-level operational optimization largely unaddressed. Yamin et al. (2023) had used one software to analyse the operation integrated field management effectively helps to ensure “Readiness to Operate”. This program offers data processing system, real time analysis, and collaborative decision-making process.

Siratovich et al. (2023) extended this perspective by outlining opportunities for ML in geothermal operations, identifying clustering, regression, and anomaly detection as promising tools for optimization and reliability enhancement. Yet, their work remained largely conceptual, without quantitative validation in real operational settings. Koray et al. (2025) studies about machine learning in geothermal reservoir and exploration work, such as clustering techniques have been used to improve permeability and reservoir characterization. Collectively, these studies illustrate the growing recognition of ML’s potential in geothermal systems while highlighting the gap in fully integrated, real-time digital frameworks.

In contrast to these prior studies, the Geothermal Operation Optimisation, Reliability, and Efficiency using Machine Learning (GOOREMALE) initiative advances geothermal digitalization by directly integrating machine learning with real-time operational data. Unlike simulation-only approaches or conceptual reviews, GOOREMALE employs Locality Sensitive Hashing (LSH), OPTICS clustering, and Root Mean Square Error (RMSE) analysis to detect anomalies, validate deliverability curves, and simulate operational scenarios. By combining machine learning with a structured digital workflow—from business intelligence dashboards to historian systems—GOOREMALE provides a comprehensive framework that bridges the gap between field agility and enterprise-level decision-making.

Table 2.2 Comparison of Related Work

Authors/Year	Focus Area	Methodology/Tools	Key Findings	Limitations
<i>Allan et al., 2019</i>	Wellbore performance & scaling (Ngatamariki, NZ)	Wellbore simulation for calcite deposition; interventions (broaching, coil tubing, acidizing)	Simulation supported prediction of scaling location	Limited to field-specific conditions; does not integrate ML approaches
<i>Siratovich et al., 2022</i>	Digital transformation and ML for geothermal operations	Review of ML opportunities (clustering, regression, anomaly detection)	Identified potential of ML in reliability, optimization, anomaly detection	Conceptual review; lacks case-specific quantitative validation
<i>Okoroafor et al., 2022</i>	Subsurface geothermal modelling	Review of ML in geothermal exploration & reservoir characterization	Highlighted ML in seismic, well logging, reservoir property prediction	Focused on subsurface, not integrated with production optimization
<i>Yamin et al., 2023</i>	Integrated Field Management	Real time analysis the integrate field management using software	Fit-for-purpose workflow improve decision making	Perform heat & mass balanced and power models
<i>Koray et al., 2025</i>	Subsurface geothermal modelling	Review of ML in geothermal reservoir use clustering techniques	Electro-facies classification to improve permeability	Focused on Subsurface, not production
<i>Meliala, E., 2025</i>	Operations, Reliability, & Efficiency	ML in geothermal using LSH and Optics Algorithms	ML uses to achieve production target & predictive analytics	Operations optimization, probability of failure & efficiency