Energy for Sustainable Development 90 (2026) 101886

Contents lists available at ScienceDirect

Energy for Sustainable Development

journal homepage: www.journals.elsevier.com/energy-for-sustainable-development

Predictive model for sustainable exploitation of geothermal resources in Africa: The case of Olkaria geothermal field

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ARTICLE INFO

Keywords:
Geothermal energy
African energy development
Renewable energy
Sustainable decision making

ABSTRACT

Geothermal energy is a crucial renewable resource for a sustainable future, especially in African nations cut by the Rift Valley, which holds vast untapped potential. However, high upfront costs and development risks remain key challenges. This study introduces a simplified model calibrated with real data from Kenya's Olkaria geothermal field. The model enables rapid preliminary assessments of both technical and economic performance, requiring minimal input data. Additionally, it incorporates a Life Cycle Assessment to evaluate environmental impacts, an aspect rarely explored in African geothermal studies. The research analyses various technological configurations, including Single Flash, Double Flash, and Organic Rankine Cycle (ORC) systems, aiming to improve efficiency without additional drilling. Findings show that integrating an ORC with existing flash systems can boost energy output by up to 20.1 %, with only a modest rise in the Levelized Cost of Electricity. Compared to the current Olkaria IV setup, hybrid systems demonstrated lower carbon emissions and reduced material resource use per energy output. Results confirm that ORC integration offers the most sustainable pathway for developing high-temperature geothermal resources in the East African Rift. This approach balances energy efficiency, economic feasibility, and environmental impact, providing valuable guidance for future power plant development in regulatory-constrained settings. This work is fully consistent with the objectives of Sustainable Development Goals (SDG) 7 and 13.

Introduction

Geothermal energy is recognized as a viable option for partially replacing fossil fuel-based baseload electricity generation, thereby contributing to the mitigation of energy-related greenhouse gas emissions (Sharmin et al., 2023). The African continent, where electricity demand is projected to increase substantially over the next three decades, possesses significant geothermal potential, predominantly located within the East African Rift System (EARS) (Omenda & Simiyu, 2015).

Current estimates indicate an exploitable capacity of approximately 15 GW within the EARS (Elbarbary et al., 2022); however, only 1.02 GW has been developed to date, with nearly 95 % of this capacity concentrated in Kenya (Omenda et al., 2025). This considerable underutilization is primarily attributable to the high technical and financial risks inherent to upstream development phases, specifically surface exploration and exploration drilling, which entail substantial capital expenditure and offer uncertain returns (Shortall et al., 2015).

Numerous studies have explored the wide range of technical, economic, and environmental challenges facing geothermal energy development (Kang et al., 2022; Kumar et al., 2022; Tomac & Sauter, 2018). In the African context, as in other geothermal areas located in developing countries, additional constraints hinder progress. Ethiopia is a pertinent example, where the geothermal sector faces a shortage of qualified expertise. This shortage could be mitigated through targeted capacity building, such as collaborative training partnerships with foreign institutions, engaging expert guidance and establishing dedicated institutions to strengthen local capabilities (Benti et al., 2023). Furthermore, the absence of specific laws and the government's limited focus on geothermal development result in licensing delays, underscoring the urgency of defining a clear national strategy for geothermal integration into the energy mix (Benti et al., 2023).

Similarly, the Uganda case highlights challenges related to limited awareness and information, policy and institutional challenges,

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https://doi.org/10.1016/j.esd.2025.101886
Received 28 August 2025; Received in revised form 2 November 2025; Accepted 9 November 2025
Available online 15 November 2025

inadequate research and development, and insufficient human capacity expertise (Mutumba et al., 2021).

Addressing these interconnected challenges in a coordinated manner is essential for unlocking the full potential of geothermal resources in Africa and ensuring their sustainable contribution to the continent's energy future. In this regard, ongoing international research efforts should prioritize the development of advanced, simplified, and replicable remote sensing and geoscientific modeling tools. Such tools would support early resource assessment, guide policy, enhance community acceptance, and reveal a region's true geothermal potential in the context of Africa and other developing economies.

Previously, researchers have developed software tools for evaluating the techno-economic feasibility of geothermal projects, considering factors such as resource assessment, plant design, financial modeling, and market dynamics. Geothermal Electricity Technology Evaluation Model (GETEM) is an Excel-based tool used to estimate the Levelized Cost of Electricity (LCOE) for geothermal projects, including hydrothermal and Enhanced Geothermal System (EGS). It allows users to input technical and economic parameters and uses a discounted cash flow method to calculate costs and assess different scenarios (Mines, 2016). GEOthermal techno-economic PHysics-based sImulator for Resource Evaluation and Simulation (GEOPHIRES) is a flexible and user-friendly tool for evaluating geothermal systems' technical and economic performance, including electricity generation, direct heat use, and combined heat and power (CHP). It simulates all major system components, such as reservoirs, wells, and surface plants, and calculates key metrics like LCOE and Levelized Cost of Heat (LCOH) using user inputs or default correlations (Beckers & McCabe, 2019). The Flexible Geothermal Economics Modeling (FGEM) tool is designed to assess the technical and economic feasibility of flexible geothermal operations by modeling the interaction between the subsurface, surface plant, and energy markets. It supports the evaluation of different dispatch strategies, including mass flow variation, wellhead pressure modulation, and integration with thermal energy storage (TES) and lithium-ion batteries (LiBs) (Aljubran & Horne, 2024).

Although comprehensive, these tools are best suited for later project stages, as they require extensive input data on subsurface conditions, wells, plant design, and related economic or environmental factors. Collecting this data can be difficult, especially in areas with limited data availability, as seen in most geothermal regions in Africa. Thus, the question remains whether it is possible to predict the techno-economic performance of a plant with limited available data. Solving this question could be valuable for assessing geothermal potential on a large scale. Moreover, a significant gap in the literature is the inability of these methods to evaluate the potential cascade exploitation of the resource, an issue that remains insufficiently addressed.

The primary objective of this work is to develop a techno-economic model capable of assessing the geothermal potential for electricity generation based on a limited set of input variables. The model also incorporates the evaluation of cascade uses of geothermal resources, aiming to optimize both existing and future installations. Applying this tool in developing regions, such as Africa, would offer a valuable quantitative contribution to support policymakers and guide stakeholders, providing a solid foundation for energy planning (Mohamed and Kassim (2024); Amir & Khan, 2022; Kumar et al., 2022).

Another important aspect is including environmental factors to provide a more complete and holistic analysis. In literature, the life cycle assessment (LCA) methodology is commonly employed to evaluate the environmental impacts of geothermal plants (Parisi et al., 2020; GECO project, 2020; Zuffi et al., 2022). In many studies, LCA is combined with exergy-based evaluations, leading to an exergo-environmental analysis (Manfrida et al., 2023). This approach offers a more comprehensive understanding of the environmental impact of energy systems by integrating thermodynamic efficiency with sustainability metrics.

However, despite its widespread application of LCA globally, such analyses remain notably absent in the African context (Mukoro et al., 2021), highlighting a significant gap in the literature that this work aims to begin addressing.

An additional innovative aspect of this work is the application of an LCA to an African case study, a context that has been largely underexplored in the existing literature. This allows a comparison between standard energy systems and other countries' geothermal systems. Furthermore, a novel methodology is proposed that integrates techno-economic and environmental analyses, aiming to define a decision-making approach that prioritizes the most sustainable solutions, considering energy, economic and environmental aspects.

Therefore, as part of the collaborations established within the European project LEAP-RE (LEAP – RE project, 2020), a simplified model has been developed to assess the feasibility of geothermal resource utilization for electricity generation using a minimal set of input parameters. The model is structured in a modular framework, allowing for the evaluation of different technologies individually, as well as their potential integration. This enables a cascading utilization approach, where higher-temperature resources are used first, followed by lower-temperature ones, or the enhancement of existing geothermal plants. The model is simulated using data from Kenya's Olkaria geothermal field, which is in the axial of the central Kenyan Rift. Currently, the Olkaria geothermal field is the second most productive worldwide, surpassed only by the geysers in the USA (Renkens, 2019). To support the analysis, a data collection effort was conducted to perform the first LCA of a geothermal plant in Africa, addressing a gap in the existing literature (Mukoro et al., 2021). Finally, the results of the techno-economic and environmental assessments are integrated to provide a decision-making framework for evaluating the sustainability of the proposed solutions.

Methodology

General approach

To characterize a geothermal resource, several parameters are required (Barbier, 2002; Reed & Anderson, 2011; Di Pippo, 2008). However, four key parameters are selected in the context of developing a simplified predictive techno-economic model. The four chosen parameters include reservoir temperature, mass flow rate, well depth and ambient air temperature. The four parameters were selected because they encapsulate the dominant physical drivers that determine a geothermal system's performance, as already demonstrated in Zuffi and Fiaschi (2025). Previous research has also shown that temperature and mass flow rate primarily determine the usable energy and power capacity of a geothermal system, directly influencing the energy conversion process and system design (Beckers et al., 2017; Beckers & McCabe, 2019). Conversely, well depth and ambient temperature influence costs, efficiency and operational constraints. Together, these variables represent the most critical determinants of both technical and economic performance of a resource. Each parameter is defined as follows:

- *Reservoir Temperature* ($T_{geo,in}$). It defines the possible applications (electricity production/heat/cold) and also the potential of the selected technology;
- *Mass flow rate* (m_{geo}). It defines the capacity of the energy systems and their components, such as heat exchangers, turbines, and other mechanical components;
- *Well Depth* (L_{well}). It defines the depth of the well and thus results in a possible change in temperature at the wellhead and thus at the input to an energy system;
- *Ambient air temperature* (T_{air}). It defines the average temperature of the environment and the related interactions at the condenser and cooling tower of power plants.

These parameters are not arbitrary. They form a minimal yet sufficient set of parameters capable of reproducing the first-order dependencies that control plant performance in real systems. By centering the model on the four inputs, the framework achieves computational simplicity without compromising predictive reliability.

Predictive model framework

The predictive model, presented in this work, is divided into two main sections: the production section and the surface section. The production section represents a one-dimensional model of a geothermal well that estimates the thermodynamic state of the fluid at the wellhead. The surface section comprises the thermodynamic blocks that model geothermal energy conversion technologies, including the Flash power plant and the Binary ORC power plant.

Each section represents a simplified and independent model that receives inputs, processes them, and produces output parameters representative of the geothermal fluid characteristics. In the case of the thermodynamic blocks, the outputs also include the power generated by the turbine. These features allow each block to be connected to another in series or in parallel, adding blocks to the plant diagram like pieces of a puzzle. For each thermodynamic block, its applicability depends on the temperature classification of the input resource. Fig. 1 shows the conceptual framework of this predictive model, showing model stages and inputs and outputs.

The model is designed so that the selection of each thermodynamic block—either Flash or ORC—depends on the temperature classification of the geothermal resource. This classification follows the Lindal diagram, which defines temperature ranges suitable for different geothermal applications (Gupta & Roy, 2007; Soelaiman, 2016). By using this approach, the model ensures that the chosen energy conversion system is well-matched to the thermal characteristics of the geothermal resource, as illustrated in Fig. 2.

Meta-model development

To develop an accurate and fast predictive model, meta-models were designed. Meta-models are mathematical tools that simplify the evaluation of input-output relationships in complex systems (Palar et al., 2019). For instance, they evaluate how changes in inputs like temperature, pressure or flow rate affect outputs like power produced or efficiency. To construct this meta-model, input parameter ranges were selected for each thermodynamic block, as shown in Supplementary material A (SM.A). A homogeneous distribution was created for each parameter, organized into three-dimensional cubic matrices. Thus, the resulting matrix had three-dimensional arrays of size $N_p \, x \, N_p \, x \, N_p$, where N_p denotes the number of elements along each axis (integer greater than 1). The model was run for every combination of these input values to calculate the optimal installed power. The obtained results were organized into output matrices and subsequently interpolated using linear multidimensional interpolation (Chan et al., 1997) to create the final meta-model. The value of dimensions of input matrix N_p was carefully chosen to create a dense input grid and keep the prediction error below 0.5 %, ensuring a good balance between accuracy and computational speed. The four-step schematic representation of the meta-model development process is illustrated in Fig. 3.

This approach allows the model to predict outcomes across a wide range of conditions without running a full-time, time-consuming and costly simulation each time, hence saving time and cost while maintaining reliability. All thermodynamic blocks were implemented in Python using the CoolProp library and are described in the Thermodynamic blocks section. The approach uses a few input parameters, and the meta-model generation enables interpolation across realistic operational regimes without needing a full high-fidelity simulation for every case, thus preserving predictive power while keeping computational cost low.

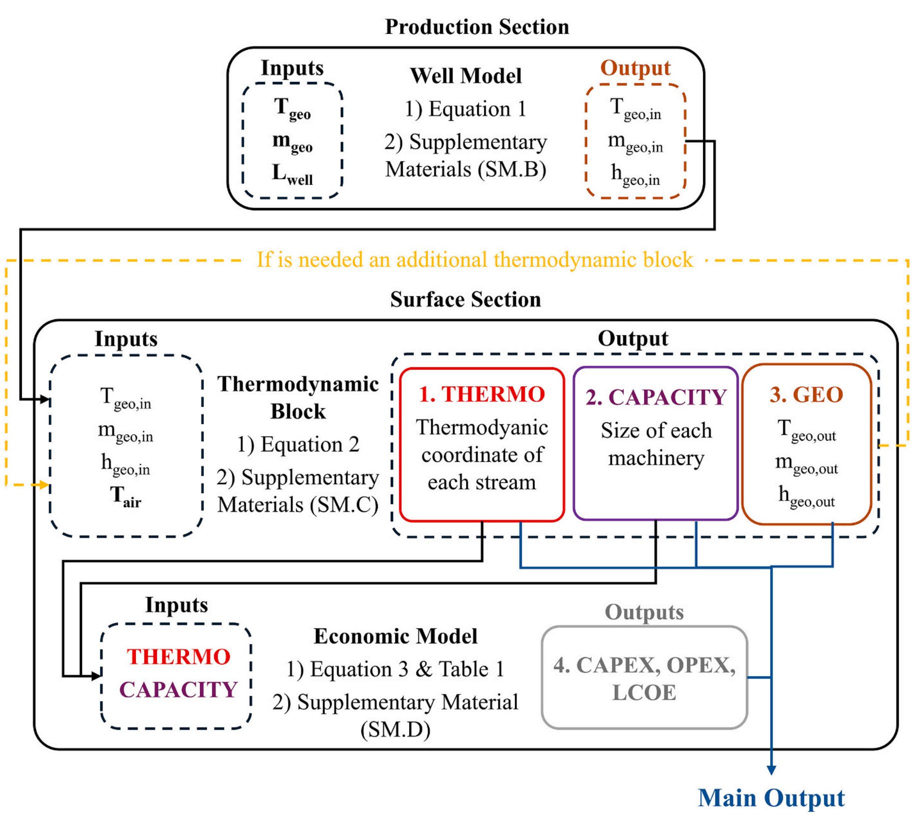


Fig. 1. Conceptual framework of the model showing the model processing stages and their inputs and outputs.

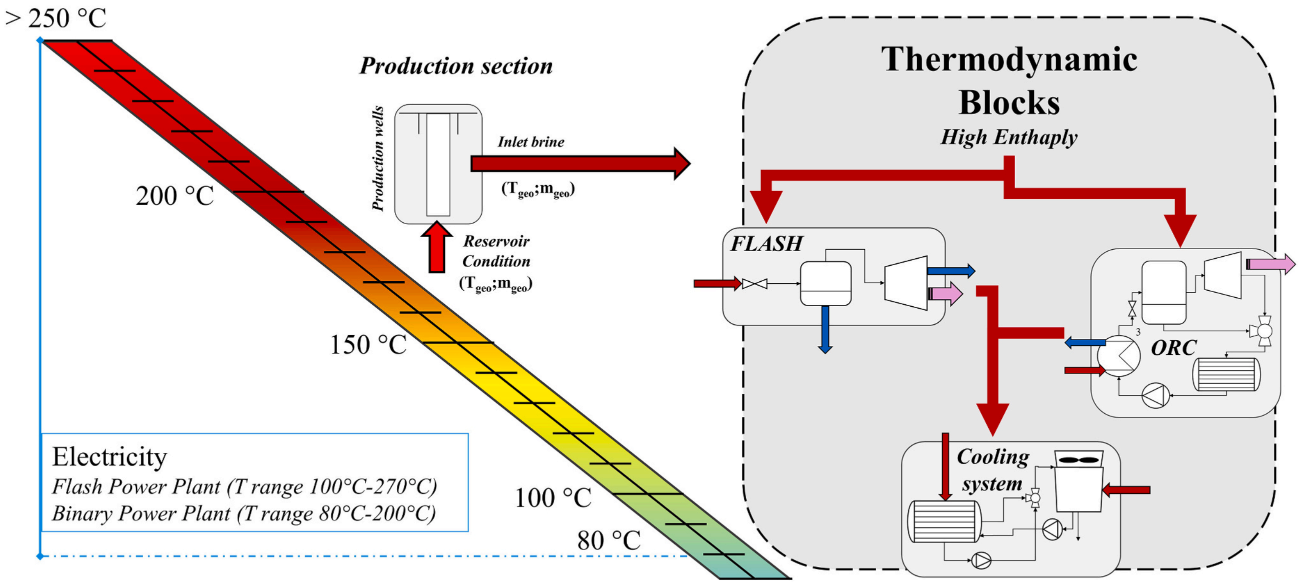


Fig. 2. Geothermal predictive model concept.

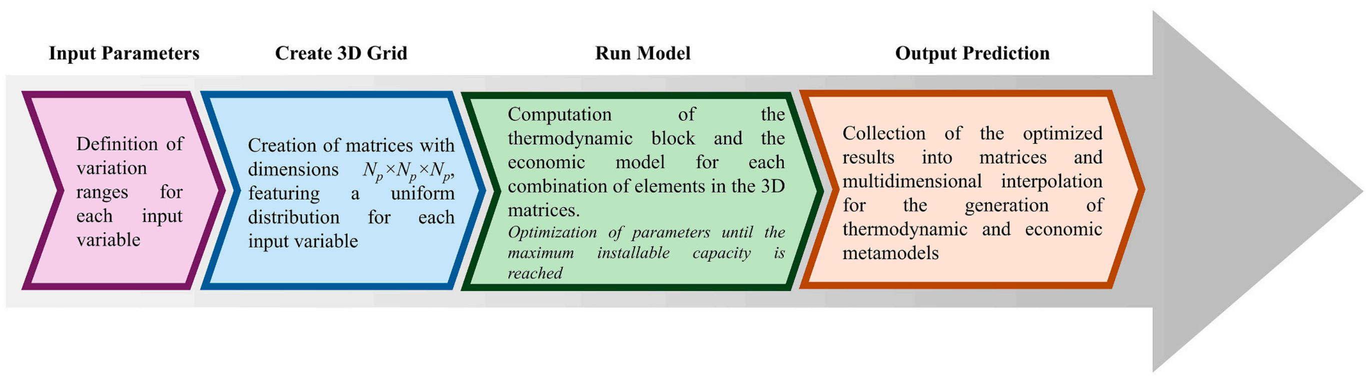


Fig. 3. Four-step schematic meta-model development.

Thermodynamic blocks

The thermodynamic blocks developed in this study form the analytical foundation for assessing the technologies and their performance. The models were validated against published correlations and operational data (Karimi & Mansouri, 2018; Shamoushaki et al., 2022), ensuring consistency with established geothermal system behaviour. Quantitatively, the models reproduce the expected hierarchy of performance, where double-flash systems exhibit 10–15 % higher conversion efficiency than single-flash, while binary systems, though less efficient, enable better recovery of low-enthalpy heat.

Production section – geothermal well

The first thermodynamic block represents the geothermal well. It describes the upward flow of geothermal fluid from the deep reservoir to the surface, considering pressure losses and corresponding temperature changes, which in turn determines whether the fluid reaches the surface in liquid phase or liquid and vapor phase. It represents a simplified version of the Boiling Point Depth (BPD) Model (Di Pippo, 2008; Grant & Bixley, 2011), assuming one-dimensional, vertical, and adiabatic flow within the well. Initial condition: The geothermal fluid starts as a subcooled liquid at the bottom of the well. As the fluid rises, pressure decreases due to both gravity and dynamic flow effects. When the pressure drops to the saturation pressure corresponding to the fluid's temperature, flashing occurs, part of the liquid turns into vapor, and a two-phase flow begins. Eq. (E.1) estimates the **boiling depth** L_f—the depth in the well where geothermal fluid first starts to boil (i.e., flashing begins).

$$L_f = \frac{P_1 - P_{sat}(T_{geo})}{\rho g + C_2 \dot{m}^2} \tag{E.1}$$

where: P_1: Pressure at the bottom of the well (deep reservoir pressure); $P_{sat}(T_{geo})$: Saturation pressure of the geothermal fluid at reservoir temperature T_{geo}; ρg: Hydrostatic pressure gradient (gravity + density term); $C_2 \dot{m}^2$: Additional dynamic pressure loss due to flow and friction effects.

Eq. (E.1) represents the final outcome of a series of mathematical steps that are extensively described and applied in the literature. For this reason, and due to space limitations in the article, only the relevant references are provided here, while the full derivation and detailed explanation are available in the Supplementary material B (SM.B).

Eq. (E.1) estimates the boiling depth L_f, which is critical in determining the phase state of the geothermal fluid at the wellhead. If L_f exceeds or equals the total well depth (L_{well}), the fluid remains in liquid phase up to the surface, and an Organic Rankine Cycle (ORC) technology is adopted. Conversely, if $L_f < L_{well}$, flashing occurs within the wellbore, producing a two-phase mixture suitable for the flash technology. Thus, Eq. (E.1) provides the first decision criterion for selecting the appropriate power conversion technology based on reservoir pressure, temperature, and flow conditions. The results of this phase feed into the surface section phase of the modeling framework.

Surface section – flash and binary power plant

The Flash system model is divided into two main blocks, representing the two fundamental phases of the thermodynamic cycle in a geothermal power plant: steam production and separation and cooling and reticulation.

- *Steam production and separation:* This block covers the initial part of the cycle, from the wellhead to the turbine inlet. The high-pressure geothermal fluid passes through an expansion valve, causing a pressure drop that partially flashes the liquid into vapor. The resulting two-phase mixture enters a separator, where the vapor and liquid phase are separated. The vapor fraction is directed to drive the turbine, while the liquid is directed for secondary use. The separator regulates the pressure to ensure the proper operation of the turbine. The amount of separated steam is managed to maximize energy production without dropping below the minimum pressure required by the condenser.

  To ensure stable operation between the valve outlet and condenser pressure, a control parameter x_{rel} is introduced, defined by Eq. (E.2).

$$x_{rel} = \frac{x_{sep}}{x_{max}} = \frac{x_{sep}}{x(h_{1'}; P_{cond})} \tag{E.2}$$

  It represents the ratio between the actual vapor fraction x_{sep} and the maximum allowable vapor fraction x_{max}. The x_{sep} represents the real operating value of the system and corresponds to the unknown variable calculated during the simulation. Conversely, the x_{max} denotes the highest attainable value, defined as the condition where the fluid has the same enthalpy (h_1)as the geothermal inlet but at the condenser pressure (P_{cond}). This definition ensures that, for any value of x_{rel} within the 0 and 1 range, the separator pressure remains higher than the condenser pressure, thereby allowing the turbine to extract power from the fluid efficiently. Such an approach enhances the numerical stability during simulation and simplifies the formulation of the metamodel by providing consistent control parameters for various geothermal conditions.

  Ultimately, this method identifies the optimal operating conditions that maximize turbine output without compromising system pressure balance.
- *Cooling and recirculation:* After passing through the turbine, the steam is condensed by a cooling system consisting of a condenser, two pumps, and a cooling tower. Part of the cooled water is reinjected into the system, while the remaining part is used as cooling fluid in the condenser. The system ensures that operating temperatures remain within safe limits, adapting to the external ambient air temperature.

A key feature of the model is its modular structure, which allows the output from the first block to be used as input for additional thermodynamic cycles, such as in double flash systems or in ORC to heat the secondary fluid.

The ORC binary thermodynamic block includes the main heat exchanger (MHE), turbine, condenser, and pump, with an additional fictitious separator used only for metamodel development. Unlike flash systems, the ORC uses a secondary working fluid, allowing flexibility in fluid choice based on thermodynamic and environmental performance.

Selected fluids (R1233zd(E), R1234ze(Z), isopentane) were chosen because of their subcritical behaviour and low Global Warming Potential (GWP), and their suitability for medium enthalpy geothermal systems consistent with geothermal resources within the African Rift (Di Pippo, 2008; DiPippo, 2016; Tammone et al., 2021). Another key reason for selecting these fluids lies in the computational nature of the model, which evaluates a very large number of geothermal resource combinations. To ensure reasonable computation times and, most importantly, consistent model convergence across all simulations, it was necessary to maintain the cycle under subcritical conditions. The selected fluids fully meet this requirement, providing numerical stability and reliable performance throughout the modeling process. The model determines optimal working fluid pressure and mass flow through an iterative process. Heat exchange is governed by the geothermal temperature difference (ΔT_{geo}), adjusted to prevent supercritical conditions. If the working fluid becomes superheated, it all enters the turbine; if not, only the vapor portion does. The entire cycle is solved respecting mass and energy balances, ensuring realistic sizing and compatibility with market-available heat exchangers.

The extended description and the equations of flash and binary blocks are reported in the Supplementary material C (SM.C).

In terms of technological benefits for design, the main advantage of the proposed model lies in its pre-implemented and adaptable structure, which can be easily applied to different geothermal contexts. The model automatically evaluates the optimal operating parameters of the plant according to the characteristics of the geothermal resource. A representative example is the x_{rel} parameter used in Flash systems, which allows the model to set appropriate values as the geothermal resource conditions change or under off-design operating scenarios.

Economic modeling

The economic evaluation of the system is carried out in two stages. The first stage involves performing a cost analysis of the individual plant components, utilizing thermo-economic correlations as those proposed in Turton et al. (2008). Key parameters necessary for these correlations, such as the surface area of the condenser and evaporator, the flow rates managed by the compressor, and the volume of the separator, are derived from the thermodynamic blocks. For the separator, the cost estimation employs the thermo-economic correlation provided by Mosaffa et al. (2017). The specific components and the corresponding equations used for each are detailed in Supplementary material D (SM. D). Economic estimations for geothermal wells typically rely on linear, exponential, or logarithmic correlations. In this study, we adopted the correlation tailored for African applications as proposed by Shamoushaki et al. (2021). The cost of the well can greatly affect the total cost of the plant, both in terms of initial investment and LCOE (Karimi & Mansouri, 2018; Shamoushaki et al., 2021), and therefore special attention is put on the number of well and their depth. The number of wells in the analysis depends on the specific case. If known, it can be directly input into the economic model. Otherwise, two options are available: assume one production and one reinjection well, or estimate the well count using an empirical correlation based on plant capacity, as derived from literature data see equation and reference in the SM.D. With the economic model described above, the initial investment costs and total operation and maintenance (O&M) costs are evaluated to determine the Levelized Cost of Electricity (LCOE). The LCOE represents the full cycle costs (both fixed and variable) of a generation technology per unit of energy, enabling comparisons across different technologies irrespective of their size, cost structure, or lifespan (Ueckerdt et al., 2013). In the context of renewable energy systems, the value of produced energy is influenced by the resource availability and by the intermittent nature of the energy source. Consequently, the LCOE is intrinsically linked to the variability patterns that define the energy generation profile (Tran & Smith, 2018). This parameter is particularly important in this study, as it serves as a significant economic indicator (de Simón-Martín et al., 2022). By consolidating these costs into a single economic indicator, LCOE effectively quantifies the cost of electricity unitary production cost ($/kWh), as discussed by de Simón-Martín et al. (2022).

$$LCOE = \frac{C_{TCI} + C_{WD} + \sum_{i=1}^{n} \frac{C_{pr}}{(1+r)^i}}{\sum_{i=1}^{n} \frac{E_i}{(1+r)^i}} \tag{E.3}$$

The equation's parameters in Eq. (E.3) are as follows: C_{TCI} is the total capital investment cost; C_{pr} for power plant is the Total Production Cost

(C_{TPC}) (Shamoushaki et al., 2022) for other application is the annual operating and maintenance cost ($C_{O\&M}$) (de Simón-Martín et al., 2022); E_i is the annual electricity produced; r is the discount rate; n is the lifetime of the energy system; C_{WD} denotes the cost of wells drilling. For the calculation of C_{TCI}, the method and parameters used in this work were taken from Karimi and Mansouri (2018), Shamoushaki et al. (2022). For the evaluation of LCOE with the integration of geothermal wells Hackstein and Madlener (2021) have been adopted, and it allow to consider the wells drilling cost. While for the evaluation of C_{TPC}, Shamoushaki et al. (2022) was followed. For $C_{O\&M}$, literature reference values were taken (Beckers et al., 2021). The discount rate was set for each application at 7 % (Beckers et al., 2021) and the lifetime varies between power plant and other application is fixed to 30 years (IRENA, 2020; Shamoushaki et al., 2021; Beckers et al., 2021; GEOENVI project, 2020). A discounting rate of 7 % was adopted to reflect the financing conditions for geothermal projects in developing economies supported by concessional funding. Empirical data from global reports indicate that publicly financed projects operate within a 6–10 % range, depending on country risk and access to low-interest capital. Thus, 7 % was selected as a midpoint. Research shows that a geothermal plant can sustain operation for 25–40 years with proper plan maintenance and servicing. To ensure comparability with previous techno-economic analysis and international standards, the lifespan used in this study was set at 30 years. All correlations used and the general expression of the thermo-economic model are shown in Table 1. The model described in this paragraph was implemented in the Python environment.

Case studies

Olkaria geothermal field

The case study to which the model developed in this work is applied in the Olkaria geothermal field, focusing on data from wells that feed steam to Olkaria IV. The selection of the Olkaria geothermal field illustrates the progressive understanding of geothermal systems through sustained research-industry collaboration. Partnership between KenGen and learning institutions has fostered continuous understanding and advancements in reservoir modeling and optimisation, well design and related studies. The previous studies focused on sub-surface reservoir characterisation (Musonye, 2015; Wanyonyi et al., 2024; Omollo et al., 2022). This study advances research on steam characteristics, applicable energy conversion technologies, and their economic and environmental implications. The operational data for the Olkaria IV power plant, covering well performance, reservoir conditions, steam intake data, and plant configuration, provides a reliable basis for model validation. Further, its single-flash technology has the potential for hybridisation, making it ideal for assessing the techno-economic performance of advanced energy conversion schemes for geothermal resources found in the East African Rift. The power plant is a single flash with an installed capacity of 150 MW_e, featuring two turbines, each with a rated capacity of 75 MW_e. The net output capacity is 140 MW_e and exploits a liquid-dominated resource hosted in Trachyte formation between 1.2 and 3 km below the surface (Musonye, 2015). The plant is served by 21 wells: 18 production wells and 3 re-injections wells. Each turbine is fed by a steam line with an intake flow rate of 135 kg/s, 180 °C temperature, and pressure between 9 and 12 bar. Several scenarios were analyzed, which are briefly described below and discussed in more detail in the following section:

- Scenario Base case: This scenario represents the case study of Olkaria IV, thus using the data regarding the wells, a Single Flash system was calculated
- Scenario Double Flash (FII): In this scenario, another flash is added to the results obtained for a single flash by connecting two thermodynamic blocks
- Scenario Triple Flash (FIII): In this scenario, an additional thermodynamic block is added to the FII case to simulate a third level of power generation
- Single Flash and Binary cycle (FI - ORC) scenario: here an ORC-type thermodynamic block is added to the basecase scenario
- Double Flash and Binary cycle (FII - ORC) scenario: Here, however, a thermodynamic block is added to the FII scenario ORC.

Table 1
Economic correlations for thermo-economic model.

Cost type	Relation
Total cycle cost	$TC_B = \sum_{i=1st\ component}^{i-th\ component} C_i$
Cost of site preparation	$C_{site} = 0.05{*}TC_B$
Cost of service facilities	$C_{serv} = 0.05{*}TC_B$
Allocated cost	$C_{alloc} = 0$
Total direct permanent investment	$C_{DPI} = TC_B + C_{site} + C_{serv} + C_{alloc}$
Cost of contingencies and contractor's fee	$C_{cont} = 0.18{*}C_{DPI}$
Total depreciable capital	$C_{TDC} = C_{DPI} + C_{cont}$
Cost of plant startup	$C_{startup} = 0.1{*}C_{TDC}$
Permanent investment	$C_{TPI} = C_{TDC} + C_{startup}$
Working capital	$C_{WC} = 0$
Total capital investment	$C_{TCI} = C_{TPI} + C_{WC}$
Cost of wages and benefits	$C_{WB} = 0.035{*}C_{TDC}$
Cost of salaries and benefits	$C_{SB} = 0.035{*}C_{TDC}$
Cost of materials and services	$C_{TPI} = C_{WB}$
Cost of maintenance overhead	$C_{MO} = 0.05{*}C_{WB}$
Direct manufacturing costs	$C_{DMC} = C_{MO} + C_{TPI} + C_{SB} + C_{WB}$
Fixed manufacturing cost	$C_{FIX} = 0.02{*}C_{TDC}$
Total annual cost of manufacture	$C_{COM} = C_{DMC} + C_{FIX}$
General expense	$C_{GE} = 0$
Total production cost	$C_{pr} = C_{COM} + C_{GE}$

Life Cycle Assessment

Data collection was carried out to calculate the environmental impact of a sustainability analysis. The approach followed was Life Cycle Assessment (LCA), per the framework established by ISO 14040 and ISO 14044. The objective is to determine the environmental impact of the Olkaria IV power plant, identify the most significant ecological indicators and compare them to other systems. The approach used for this analysis is a cradle-to-gate type. The system boundaries encompass all processes related to the construction, operation, and maintenance phases of the power plant. The end-of-life phase is not considered due to the lack of a disposal program. The functional unit selected is the electrical energy produced by the power plant in kWh, considering a useful 30-year lifetime and a capacity factor of 0.94, corresponding to 8234 h/year of operation.

Environmental model

The processes for the construction phase which were modeled in this settlement are the geothermal wells and wellheads; the building hosting the powerplant, and the collection pipelines. The average geothermal wells depth is 3000 m each. The collection pipelines are divided into 28 km of production and 5 km of re-injection pipe. The machinery and power plant have not been modeled with primary data from KenGen because of lack of data. Consequently, machinery and plant data were adopted from the model proposed by Karlsdóttir et al. (2015). For the scenario analysis involving the ORC plant, the reference inventory for the machinery was taken from Zuffi et al. (2024).

The operation phase consumes 40.4 m^3 of water per day for plant operation and approximately 126 MWh of electricity for heat distribution. Of this electricity, 16 % is taken from the national grid and 84 % from plant production. Direct emissions to the atmosphere are mainly CO_2, H_2S, H_2 and CH_4. Six make-up wells are expected to be built in 25 years to maintain the geothermal steam flow rate at the required level. In addition, lubricant oil is consumed for the machinery, while Sodium Carbonate is used for anticorrosion and anti-scaling of the pipes. All inventory data are reported in Supplementary materials F (SM.F). The results shown in this paper refer to the single score. The contribution analysis of the main indicator analyzed is reported in the Supplementary material F (SM.F.) The environmental model is realized using OpenLCA 2.4, and the background data comes from Ecoinvent 3.10. It is imperative to state that the LCA analysis relies on the European-based databases and inventory due to the limited availability of local data. For this reason, representative providers from the Ecoinvent database were used, selecting processes labeled “market - GLO,” which denote the global market, in order to best reflect global average conditions, as is widely done in the literature (Blanc et al., 2020; GEOENVI project, 2020; Douziech et al., 2021). While this may introduce some regional bias, the selected dataset ensures methodological consistency and compatibility across the analyzed scenarios. This assumption may slightly affect absolute impact values, but does not alter the overall environmental trends and conclusions derived from the analysis.

Results

Validation techno-economic

Results metamodels

The validation of the thermodynamic model, performed by comparing several power plants reported in the literature, has been included in Supplementary materials G (SM.G) due to space limitations in the main text. The general results of the metamodels are reported in the following paragraph.

Thermodynamic metamodels – power production

Fig. 4 compares three geothermal technologies, by analyzing installed power as a function of flow rate and geothermal fluid temperature, with an external temperature fixed at 30 °C. The meta-models estimate power output, highlighting significant differences in operational temperature ranges. The Single Flash system achieves high power output at geothermal temperatures above 250 °C, where the Binary ORC is ineffective. The Double Flash outperforms the Single Flash, particularly between 100 °C and 150 °C, increasing power by 6–7 %, and above 200 °C, where gains exceed 20 %. However, in high ambient temperatures, rising condensation temperatures reduce efficiency, limiting power gains to 0.5–1 %, making the system less viable.

Comparing Fig. 4A and B, the Double Flash expands the installed power area beyond 50 MW and shows steeper power growth with increasing flow rate (m_{geo}) and geothermal temperature (T_{geo}). The Binary ORC, within its operational range, enables slightly larger plants than the flash systems at the same geothermal conditions. For example, at 200 °C and 400 kg/s, the ORC reaches 20.9 MW, Single Flash 20.1 MW, and Double Flash 23.6 MW. For lower flow rates (<200 kg/s) at maximum T_{geo}, installed capacities remain moderate: Single Flash (~37 MW), Double Flash (~46 MW, +24 %), ORC (~12 MW).

A key distinction lies in operational temperature ranges: ORC functions between 80 and 200 °C, while flash systems extend from 100 °C to >350 °C, allowing greater energy exploitation at high temperatures. While power output is similar when operating at the same temperature, the flash systems leverage higher temperature resources for greater efficiency. Prediction uncertainty varies, being lowest for Single Flash, higher for ORC, and highest for Double Flash. These findings clarify each technology's capacity and optimal conditions based on flow rate and temperature parameters.

Economic metamodels – power production

This section presents the results of the economic metamodels. Validating the model requires a similar approach to the thermodynamic model but with actual LCOE values for specific cases, which are rarely provided alongside necessary thermodynamic and economic parameters in literature. Thus, the model's predictions can only be compared to known reference values.

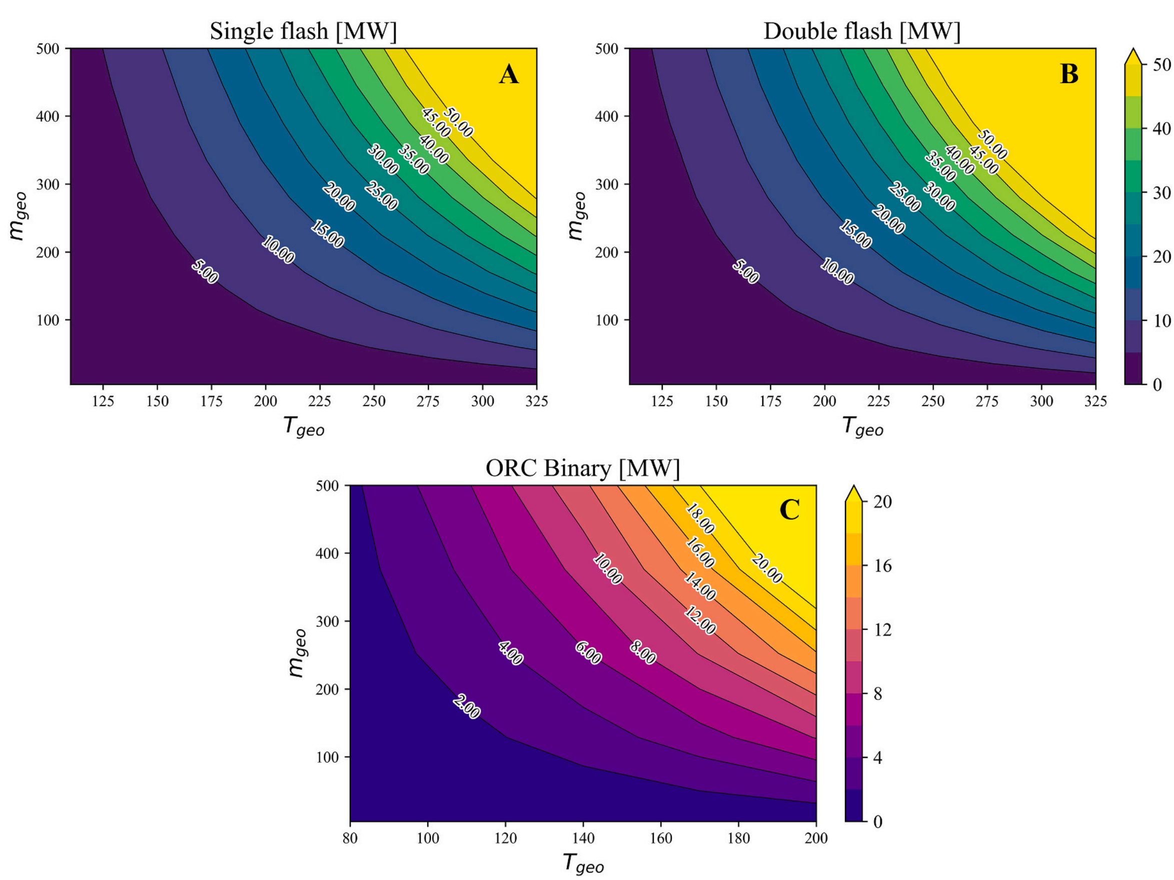


Fig. 4. Metamodel surface representing the power installed for single (A), double flash (B) and ORC binary (C).

A major contributor to total plant cost and LCOE is the cost of wells, primarily influenced by their number and depth. To assess this impact, four scenarios with well depths of 1000 m, 2000 m, 3000 m, and 4000 m were analyzed. Fig. 5 illustrates the LCOE (c$/kWh) as a function of geothermal resource flow rate (1–80 kg/s) and temperature, with reference values for photovoltaic (8.7 c$/kWh, yellow), wind (8.4 c$/kWh, purple), and gas turbine (18 c$/kWh, red) from Trinomics B.V. (2020). The maximum cost threshold is 30 c$/kWh, beyond which the technology is not viable.

For low flow rates and temperatures, the LCOE is high but decreases rapidly as conditions improve. However, increasing well depth shifts the low-LCOE area significantly to the right, reducing cost-effectiveness. Reference LCOE ranges from IEA (2023) and IRENA (2017) stand at 12–8.8 c$/kWh and 14–4 c$/kWh, respectively. Additionally, the analysis considers a maximum flow limit of 140 kg/s, focusing on intermediate-sized plants (20–30 MW). Larger plants, capable of handling higher flow rates, remain cost-effective even at lower temperatures, particularly when flow rate and temperature increase significantly.

Case studies: Olkaria IV

Fig. 6 presents the tool's predictions for both energy and economic analyses in a comprehensive manner. In the energy analysis (Fig. 6A), the red bar represents the original Olkaria IV plant data, which features a turbine rated at 150 MW and a net output of 140 MW. In comparison, the Basecase prediction calculates a net power of 137.9 MW, only 1.7 % lower than the actual value, based on an evaluated liquid flow of approximately 721 kg/s at 179 °C from the separator. Building on this, the "F II" scenario introduces a second flash turbine that adds 26 MW to yield a total output of 163.9 MW, utilizing a secondary flow of 626 kg/s at 111 °C from a second separator. Further, the "F III" scenario contributes an additional 4.5 MW (total 168.4 MW), corresponding to installed capacity increases of 16.9 % for F II and 20.1 % for F III relative to the Base case. When integrating an ORC system, the "F I – ORC" scenario—using the same input data as F II—achieves an increase of approximately 29.2 MW (about 19.2 %), while the "F II – ORC" scenario, which builds on the F II output, adds an extra 5.6 MW for a total increase of 20.89 %. A relevant aspect that should be highlighted when comparing geothermal energy with other renewable sources concerns the capacity factor. The increase in installed power obtained in this study may appear modest when compared to that of wind or photovoltaic systems. However, it is important to note that the capacity factor, which is defined as the ratio between the actual annual operating hours and the total hours in a year, it is significantly higher for geothermal power plants, typically ranging between 85 % and 95 % (IRENA, 2025). In contrast, the capacity factor of wind and photovoltaic (PV) systems strongly depends on the geographical location, with global averages of approximately 34 % for wind and 15–22 % for PV systems (IRENA, 2025). This, of course, has a significant effect on the total amount of energy generated by such systems. Consequently, for an equivalent installed capacity, a geothermal power plant produces substantially more energy than wind or PV systems. The economic analysis (Fig. 6B) shows that the base scenario is estimated at roughly $517 million in total costs (CAPEX plus OPEX over a 30-year lifespan), with OPEX accounting for 31.3 % and CAPEX for 68.7 % of this value. The F II scenario incurs a cost increase of approximately 19.8 % compared to the base case, and the F III scenario sees a 27.3 % increase. Scenarios incorporating an ORC system generally lead to higher costs for a modest power gain of about 3 MW, with the "F I – ORC" and "F II – ORC" scenarios showing cost increases of 24.1 % and 27.3 %, respectively—findings that align with literature reports (IRENA, 2017; Sigfússon & Uihlein, 2015) attributing

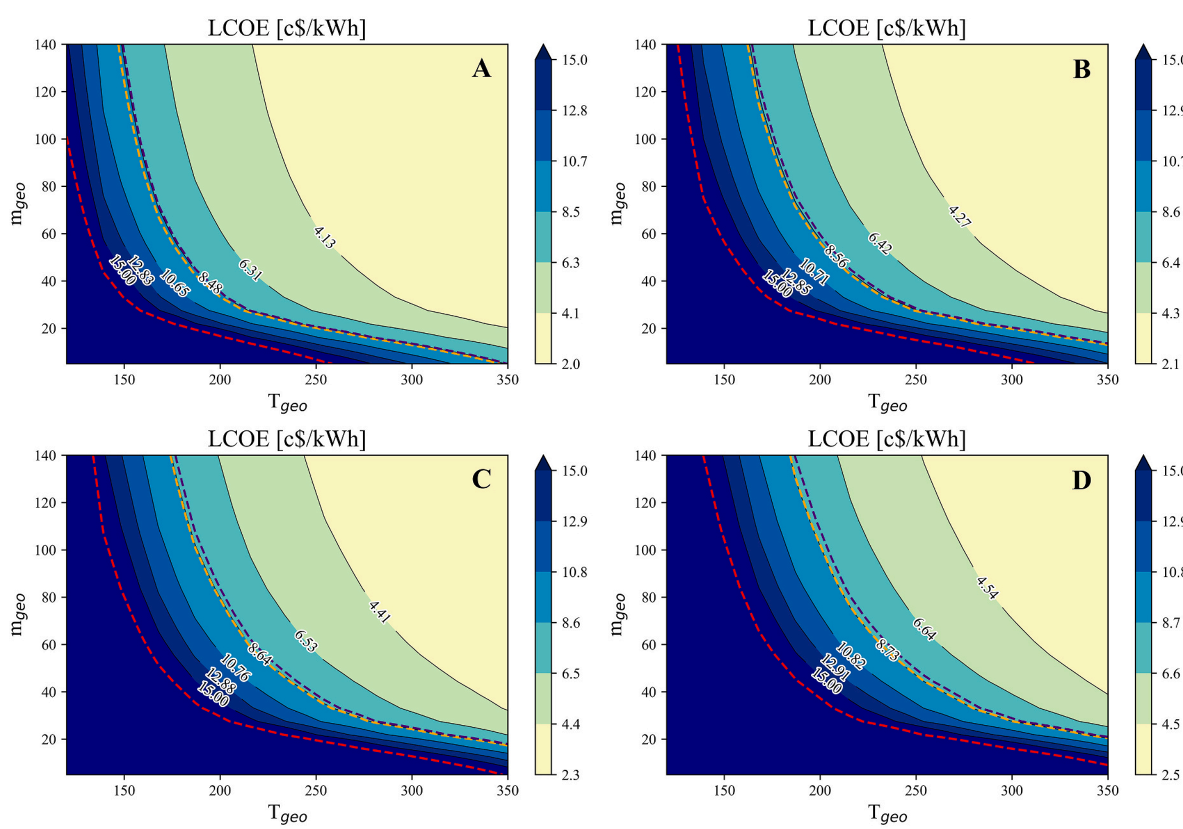
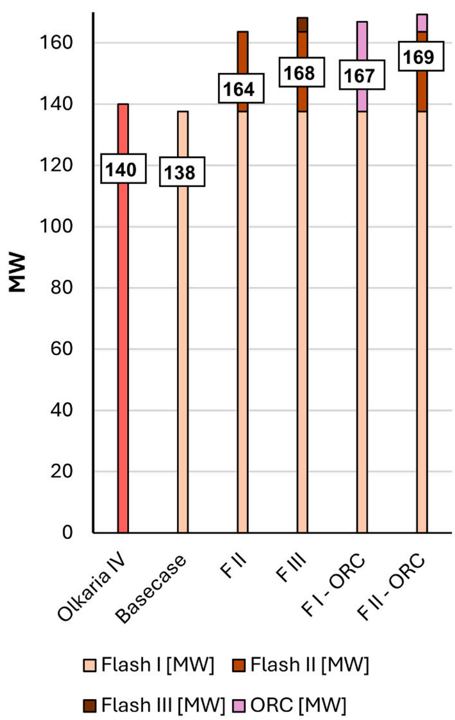


Fig. 5. Metamodel surface representing LCOE (c$/kWh) for different scenarios well-depth. Wells depth (WD): A. 1000 m; B. 2000 m; C. 3000 m; D. 4000 m. (Red line = Gas turbine; yellow line = Photovoltaic; purple line = Wind.) (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



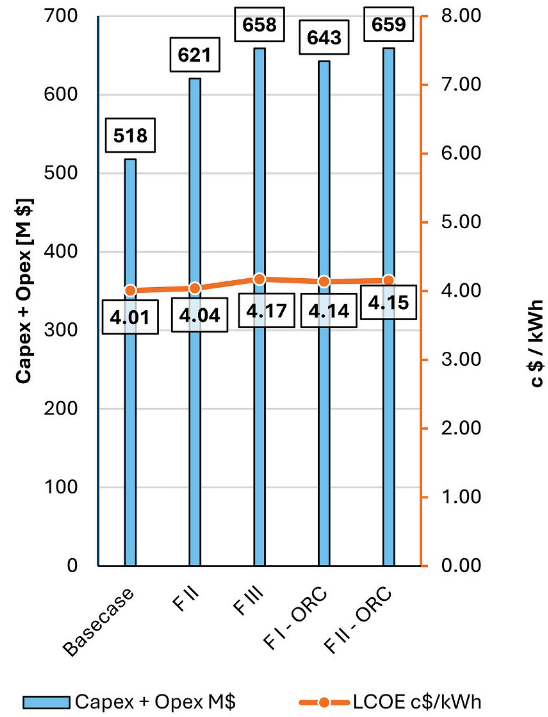


Fig. 6. Bar graph for installable power (left) and bar graph for economic cost (right) for different scenarios of Olkaria IV.

higher installation and maintenance expenses to binary ORC systems compared to flash systems. Notably, the LCOE, represented by the orange line and dots, exhibits minimal variation across the scenarios, increasing slightly from approximately 4.01 c$/kWh in the Basecase to 4.17 c$/kWh in the most economically disadvantageous scenario.

Life Cycle Assessment

The single score for the analyzed scenarios, evaluated using the

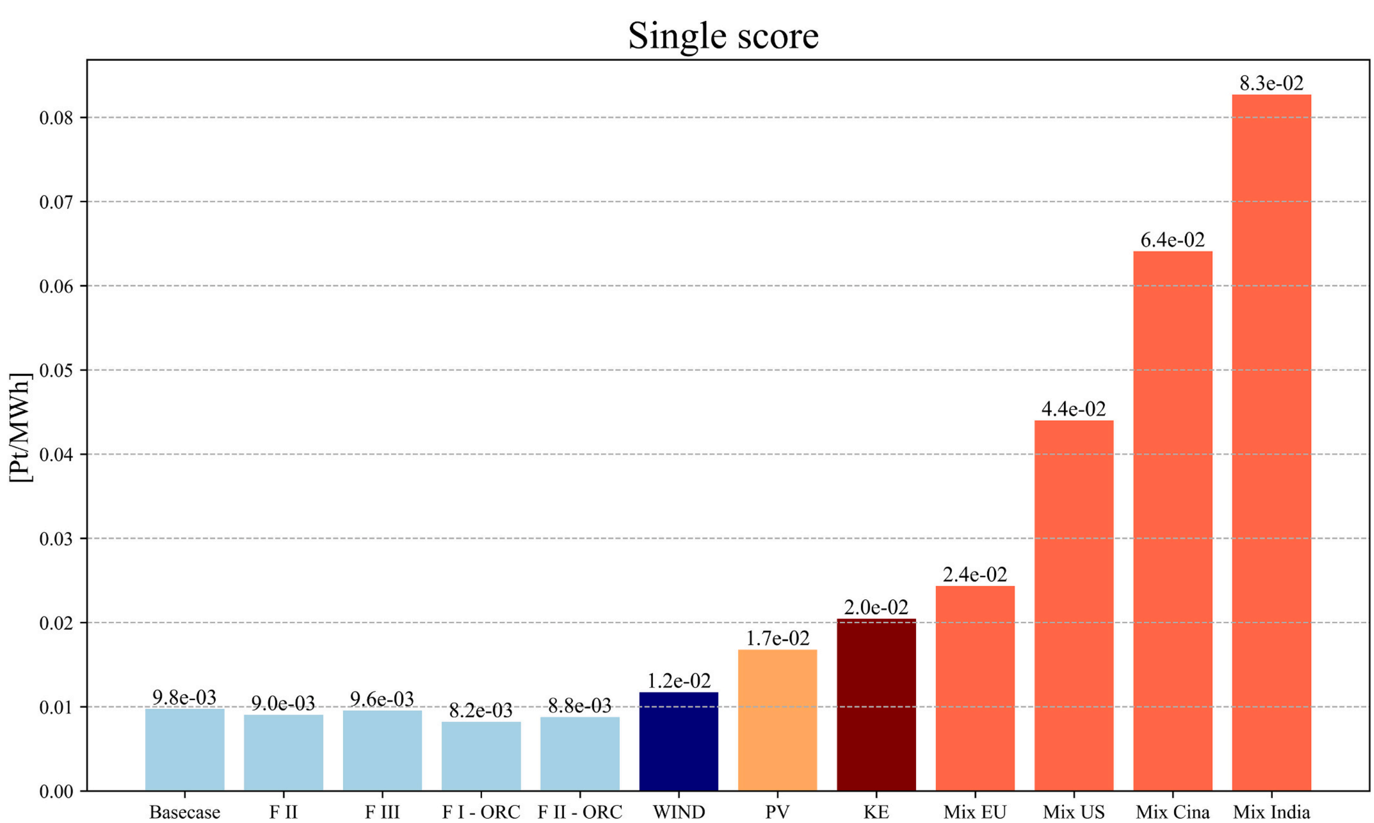


Fig. 7. Single score comparison of all geothermal Scenarios and other energy sources.

European normalization and weighting set from the EF3.1 methodology. This assessment also incorporates renewable energy systems from the Ecoinvent 3.10 database—namely, wind (WIND), photovoltaic (PV), the Kenyan (KE) national mix, and an averaged EU mix (Mix EU) derived from national high-voltage electricity production data in countries such as Italy, Spain, France, and Germany. Furthermore, to extend the comparison to both Western and Eastern contexts, the average environmental impacts from countries such as the United States (Mix US), China (Mix China), and India (Mix India) were also included.

As shown in Fig. 7, all geothermal scenarios exhibit a markedly lower environmental impact compared to other renewable energy sources, specifically about 16–29 % lower than WIND and 40–50 % lower than PV. Similarly, when considering Western energy mixes, and in particular the EU energy mix, with reductions exceeding 60 %. In particular, when compared to the baseline case, the geothermal scenarios demonstrate significant improvements: the FI–ORC scenario achieves the greatest reduction at 15.9 %, followed by reductions of 7.33 % for F II, 2.08 % for F III, and 9.95 % for F II–ORC. These findings underscore the potential of geothermal exploitation technologies to enhance environmental performance and suggest that, relative to established renewable sources like wind and PV, geothermal systems offer a more sustainable alternative.

Sustainability analysis

Based on the results from the various analyses conducted, the information is integrated to determine the most sustainable scenario. Using the base case as a reference, the relative percentage difference of each analyzed indicator, considering of absolute values, is evaluated. For each parameter, a score ranging from 1 to 4 to the scenarios is assigned, where a lower score indicates poorer outcomes.

Specifically, a low score is assigned whenever a scenario exhibits a smaller plant size, higher economic costs, or greater environmental impacts. Conversely, a high score indicates a larger plant size, lower economic costs, and reduced environmental impacts.

Four parameters were defined to compare and rank each scenario: plant size (MW), the sum of investment and operational costs (CAPEX + OPEX), Levelized Cost of Electricity (LCOE), and environmental impact (Single Score). In Fig. 8, on the left, the table displays the relative difference of each scenario compared to the base case, calculated from absolute values. Each value is assigned a corresponding score on the adjacent color scale: a dark purple cell represents the highest score (4), while a white cell represents the lowest score (1). Subsequently, potential preference approaches for selecting the scenarios are defined. In this framework, weighting factors are defined (in Table 2) and applied to the scores assigned to each scenario across the individual parameters (in Fig. 8 on the left). The resulting weighted scores are then aggregated to produce a final value, which serves as an overall indicator of the sustainability of each scenario (In Fig. 8 on the right).

Specifically, these weighting approaches include an *Equal* approach that equally considers energy, economic, and environmental parameters, assigning each of them a weight of 0.33. In addition, three further approaches are defined: Energy, Economic, and Environmental. Each of these prioritizes its respective reference parameter by assigning it a weight of 0.5, while the remaining two parameters are each assigned a weight of 0.25. Table 2 outlines the weights assigned to each indicator.

Finally, by multiplying the scores assigned to the scenarios by the weights of each approach, it is obtained a table displaying the total weighted score for each scenario, reported in Fig. 8 on the right. A lower score means a lesser level of sustainability, whereas a higher score corresponds to greater sustainability. This principle is also reflected in the color scale shown in the table: a dark green cell indicates a high level of sustainability, whereas a light yellow cell represents a low level of sustainability.

The results indicate that the FI-ORC scenario emerges as the optimal solution for both the equitable and environmental approaches. Regarding the energy approach, FI-orc and FII-orc exhibit the same maximum score. Conversely, for the economic approach, scenario FII is identified as the best option, followed closely by FI-orc in the second position. It can be observed that the FII and FII-ORC scenarios consistently exhibit an intermediate level of sustainability across all approaches, without ever outperforming the others, as their sustainability indicator values remain within a mid-range level.

At the same time, it can be inferred that the FIII scenario is the least favorable option under all approaches, since it consistently shows the lowest indicator values.

Table 2
Weighting Approach.

Parameter	Equal	Energy	Environmental	Economic
Energy [MW]	0.33	0.5	0.25	0.25
Economic [$ or $/kWh]	0.33	0.25	0.25	0.5
Environmental [Pt/kWh]	0.33	0.25	0.5	0.25

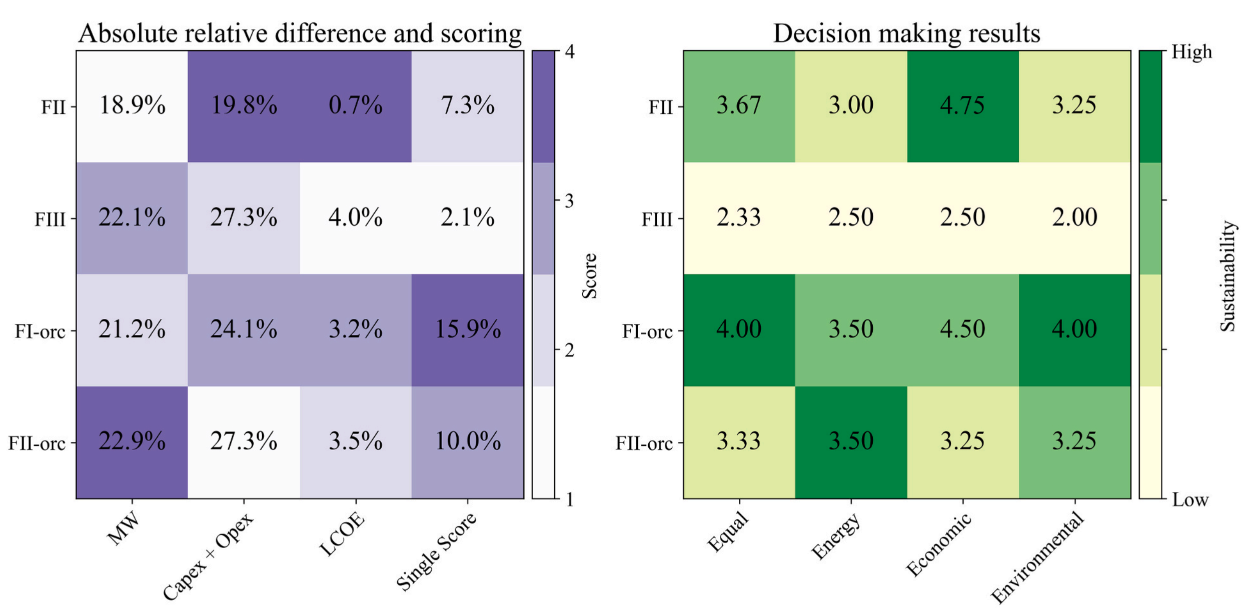


Fig. 8. Score matrix of relative difference and score level (on the left) and decision-making results (on the right).

In conclusion, by summing the values obtained in the decision-making table for each scenario, the FI-ORC scenario achieves the highest overall score. This finding confirms, as previously discussed, that the most sustainable solution for the Olkaria IV plant is integrating an ORC system alongside the existing single flash system.

Overall, the results of this study provide valuable insights for aligning geothermal development with the broader global sustainability objective. The demonstrated performance improvements across single-flash, double-flash and optimal energy extraction under the ORC highlight viable pathways for efficient utilization of geothermal resources while reducing life-cycle environmental impacts. Thus, the developed model can be directly used to assess the viability of optimising geothermal energy resources to meet power demand while keeping low greenhouse gas emissions.

It is important to emphasize that this approach, as well as the overall model, could be applied to other African regions by modifying the geothermal input data and developing an LCA for a different case study. The straightforward interpretation of the numerical result, expressed through such a sustainability indicator, can support stakeholders and policymakers in identifying and selecting the most appropriate geothermal solution. Finally, this approach addresses Sustainable Development Goal 7, which emphasises affordable and clean energy, and the climate action Sustainable Development Goal 13.

Conclusion

A simplified model has been developed to assess the feasibility of geothermal resource utilization for electricity generation using minimal input parameters. The model is structured in a modular framework, based on a metamodel approach, allowing for the evaluation of different technologies individually and their potential integration. The results obtained from the metamodels are the following:

- Double Flash technology demonstrates superior performance over Single Flash, particularly in the 100–150 °C range and above 200 °C, achieving power gains exceeding 20 %.
- While Binary ORC operates effectively between 80 and 200 °C and enables slightly larger plants under certain conditions, flash systems exploit higher temperature resources more efficiently, making them more suitable for high-temperature geothermal applications.
- Well depth significantly impacts total plant costs and LCOE, with deeper wells shifting cost-effective operation to higher flow rates and temperatures, reducing overall economic feasibility.
- While geothermal LCOE decreases with improved flow rate and temperature conditions, larger plants (20–30 MW) remain cost-effective even at lower temperatures, particularly when high flow rates are available.

The model is applied to a real case study, the Olkaria IV power plant case study. The analysis integrates energy, economic, and environmental factors to determine the most sustainable scenario for geothermal power plant optimization. A comparative evaluation is performed by assigning scores to different scenarios based on relative percentage differences in key indicators. The results indicate that the FI-ORC scenario consistently ranks as the most sustainable option under equal-weighted and environmental approaches. Under the energy-focused approach, FI-ORC and FII-ORC achieve the highest scores, while the economic approach favours the FII scenario, with FI-ORC as a close second. Conversely, all evaluation criteria consistently identify the FIII scenario as the least favorable. Ultimately, the findings highlight that the most sustainable solution is integrating an Organic Rankine Cycle (ORC) system with the existing single flash system at the Olkaria IV plant. This approach optimizes energy production while balancing economic and environmental considerations, reinforcing the benefits of a hybrid geothermal system. The developed model can be used to evaluate the most viable technological applications for harnessing geothermal resources in underdeveloped geothermal fields in Kenya and other African countries. The model can guide decision makers on the appropriate geothermal investment pathways. Future developments will focus on the creation of a parametric environmental model, which can be integrated into the existing metamodels and will no longer be case-specific, but applicable to any geothermal context, both within Africa and beyond, similar to the already established energy and economic models. Furthermore, the economic model will be enhanced with predictive inflation adjustment models to provide a more accurate assessment of economic feasibility. Finally, a variable model will be implemented to perform sensitivity analyses on the discount rate and plant lifetime, thereby improving the robustness and reliability of the overall economic evaluations.

CRediT authorship contribution statement

C. Zuffi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **D. Fiaschi:** Writing – review & editing, Resources, Project administration, Investigation, Funding acquisition. **X.S. Musonye:** Writing – review & editing, Supervision, Resources, Data curation. **H.S. Mukhongo:** Supervision, Resources. **M. Nafula:** Supervision, Project administration. **I.P. Da Silva:** Project administration, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the readability of the article and for English grammar correction. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The work came out of a collaboration between the various entities through the European project LEAP-RE [H2020 No 963530] (https://www.leap-re.eu/) specifically under Working Package 9 Geothermal Atlas for Africa (https://www.leap-re.eu/geothermal-atlas-4-africa/).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esd.2025.101886.

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