Pumped Storage Hydropower Graph Model for Climate-Resilient Energy System Optimization

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Abstract: Climate change is altering weather patterns and increasing uncertainty of renewable energy availability. Energy system modelling therefore requires coherent future time series of renewables derived from weather variables such as irradiation, wind speed, and precipitation. Deriving inflows for pumped-storage hydropower schemes is particularly challenging due to the relational complexity of collection works, reservoirs, discharge pathways, turbines, and pumps. Although several studies have considered relational complexities, modelling tools that support robust and independent scenario analysis remain limited. This work addresses this gap by developing a graph-based database of Austria’s pumped-storage schemes using open-source datasets. The graph-based approach ensures the preservation of hydraulic and operational plant constraints. Coupled with a precipitation–runoff routing hydrological model, the framework generates inflow time series from spatially temporally resolved climate data, which serves as input for energy system optimization models, such as the LEGO model used in the *iKlimEt* project. The framework is tested and calibrated in numerous case studies of Austrian pumped storage schemes, demonstrating its applicability.

Keywords: Pumped-storage hydropower systems; graph modelling; climate change impacts; renewable energy integration; rainfall–runoff modelling; multi-year climate scenarios.

1 Introduction

The transition to low-carbon electricity generation involves increasingly complex and interdependent energy systems, requiring effective strategies to manage the variability of renewable energy sources and optimize system-wide performance [1]. To address these challenges, this thesis contributes to the development of a graph-based model [2] within the scope of the *iKlimEt* [3] project, which aims to create an energy optimization framework that enhances the resilience and efficiency of future energy systems. A particular focus is placed on the role of pumped storage hydropower, evaluating its contribution as a key component for enabling flexibility, reliability, and sustainability in low-carbon energy scenarios [4]. By capturing these interactions across both temporal and spatial, the modelling supports informed planning and flexible management strategies, which are the byproducts of optimisation.

1.1 Background

Hydropower is a clean, renewable, and environmentally friendly source of energy. It produces 3930 (TW.h) and yields 16% of the world's generated electricity and about 78% of renewable electricity generation. Electricity is essential for human life, welfare, and sustainable development. However, about 20% of the world's population remains in the dark (with no access to lighting, refrigeration, computers, good education, or running water). Light means socioeconomic development, while darkness is a major concern for sustainable development. Today, more than 1.2 billion people around the world lack access to electricity, mainly in {Asia} and Africa (about 80 % are in rural areas) [5].

In 2020, the world's installed pumped hydroelectric storage capacity reached 159.5 GW and 9000 GWh in energy storage, which makes it the most widely used storage technology, however, to cope with global warming its use still needs to double by 2050. Currently, this is the most mature, efficient, and long-term storage technology that has been developed on a large scale [6]. Hydropower plays a vital role in modern electricity systems due to its exceptional flexibility and rapid responsiveness. By modulating the flow of water through turbines, hydroelectric plants can swiftly adjust to changes in electricity demand—an ability that traditional base-load technologies such as coal and nuclear power lack. This fast-response capability makes hydropower indispensable for maintaining grid stability and balancing supply and demand in real time. Consequently, flexible hydro generation often commands a premium in energy markets, and several countries generate substantial income through hydroelectricity exports.

Among large-scale energy storage technologies, pumped hydroelectric energy storage stands out as the most widely implemented solution. Its appeal lies in the substantial potential energy that can be stored in reservoirs, the high efficiency of the energy conversion cycle, the relatively low cost per unit of power, and the operational flexibility it offers to Transmission System Operators for short-term grid management. As a result, pumped-storage hydropower plants (PSHPs) have been extensively deployed since the 1890s, with global installed capacity now approaching approximately 130 GW [7].

For this thesis study the main area of interest was Europe and Austria in particular. Currently hydropower is an integral part of Europe's energy sector. As a highly efficient technology, it is characterized by (i) a high energy conversion rate, and (ii) the highest energy payback ratio – defined as the ratio between the energy output and input over the lifespan of a project – among all electricity-generating technologies. In many European countries, hydropower use has a long historical tradition. Out of all of the renewable energy sources, hydropower is the largest one, contributing 41.7% of the total electricity generation in the EU [8]. The total hydropower installed capacity in 2017 in Europe (including non-EU countries) amounts to 248.6 GW, and the electricity generated from hydropower is approximately 600 TWh [9].

Austria's topography, marked by a dense network of rivers and streams along with considerable elevation differences, creates highly favourable conditions for hydropower utilization. As a result, hydropower constitutes a fundamental component of the national energy mix, with a particularly significant contribution n to electricity generation [10] approximately 65.7% of the electricity is generated by hydropower plants. Two thirds of Austria's hydropower plants are run-of-river plants supplying energy to cover base load. The other third are storage and pumped-storage plants, which particularly contribute to meet national and European peak load demands [11] . Approximately one-third of the total installed hydropower capacity is attributed to run-of-river systems, while the remaining two-thirds originate from storage-based power plants. Among these, pumped storage facilities contribute significantly, with an installed capacity of 14,120 MW and an annual electricity production of 42,900 GWh [12].

Austria is also investing in improving energy efficiency through the modernization of transmission networks or new technologies and in hydropower [13]. This study under the *iKlimET* project can be view as an investment towards this goal.

1.2 Research objectives

To address the complex interconnectivity of the systems modelled in this study, a graph-based database was identified as the most effective approach. Graph models—commonly employed in relational databases—are well-established and have long been recognized for their efficiency in traversing relationships between nodes. Their structure allows for rapid and intuitive navigation of interconnected data, making them particularly suitable for capturing system-wide interactions. In the field of hydraulics or hydrology similar approaches such as [14] to provide a multi-stage, physics-guided machine learning framework that combines physics-based river network models with Graph Neural Networks (GNNs) for streamflow forecasting. In this study, the primary motivation for employing this method is its efficiency in modelling complex systems. Their study highlighted how recent developments, using vector-based river network models, make it possible to represent large river basins at increasingly fine spatial resolutions. However, while they offer enhanced detail, these models are also computationally intensive, posing challenges in terms of scalability and processing power.

The second layer to this approach can then be adopted to hydropower which in recent years, has required the need to develop models that integrate both spatial and temporal dimensions. This has become increasingly important—particularly in the context of climate change, where impacts vary across regions and time periods. As highlighted by [15], most traditional hydropower forecasting methods rely solely on time series predictions and often overlook the spatial topological relationships among power stations or reservoirs within a river basin or catchment area. This limitation makes it difficult to fully capture the interconnected characteristics and behaviours of spatially distributed stations, which are essential for building robust and responsive models under evolving climatic conditions.

While it could be argued that a relational database might achieve similar outcomes to those of a graph database, recent studies suggest otherwise. A comprehensive performance comparison by [16] [17] evaluated execution times between a graph database and a relational database system using a real-world dataset. The results demonstrated that the graph database consistently outperformed the relational database in most query scenarios, particularly those involving complex relationships and network traversal. Recognising these benefits is essential when shifting focus to hydropower systems, which are shaped not only by infrastructure networks but also by climate-driven hydrological patterns.

Hydropower systems rely on climate-influenced hydrological patterns, and shifts caused by climate change can significantly affect energy generation. Although hydropower is a renewable energy source it is sometimes mistaken to not have an impact on climate change. From a life cycle analysis standpoint, no method of electricity generation is entirely free from greenhouse gas (GHG) emissions. In the case of the hydropower sector, more than 80% of GHG emissions are associated with construction, for example, the production and transport of materials (especially concrete), and energy usage during the construction process [18]. When evaluating net GHG emissions from the hydropower sector—as distinct from gross emissions—it is important to account for pre-impoundment emissions from the natural water body, along with any sources of GHG emissions that were displaced as a result of reservoir construction [19].

Given the context of climate-resilient energy development, it is important to highlight the relative environmental performance of hydropower. Studies have shown that hydropower exhibits notably low life-cycle greenhouse gas emissions when compared to most other energy sources. Specifically, the median emissions range between 18 and 24 g CO_2-eq/kWh—substantially lower than those associated with natural gas, coal, biomass, and geothermal energy systems [20].

When then assessing the impact of climate change on hydropower one of the main parameters of interest in inflow. Depending on the region of study the results vary. Another critical consideration is that the outcome of an impact assessment is heavily influenced by the choice of model used, as different models can produce varying estimates and sensitivities based on their structure, assumptions, and input data.

In the study by [21] the review focuses on observed precipitation and run-off. The studies reviewed can be broadly categorized into two groups: those that examine historically observed trends, and those that focus on future projections. Their review state that Reduced hydropower production is projected in many areas where precipitation is projected to decline. In other areas with increased precipitation, an increase in production is projected. Changes in timing and in seasonal inflow variability even in areas where increase in precipitation and possibly flow is projected, will affect system operation.

In the study [22] the model used address the run-off, water demand, and water systems models which then feeds into a hydropower generation is valued using annual electricity prices produced from an electric sector planning model of the U.S. to estimate economic implications with and without Green House Gase (GHG) mitigation. This Climate projections across diverse emissions scenarios enable them to assess the long-term benefits of GHG mitigation strategies and to track how those benefits change over time.

1.3 Tool application

The hydropower module within the existing modelling framework represented hydropower contributions as static inputs. Specifically, the mean annual energy production of each plant was evenly distributed across all hours of the year, resulting in a temporally uniform generation profile decoupled from hydrological and meteorological variability. This simplification limited the model's ability to capture the dynamic interactions between runoff, storage, and power generation, thereby reducing both accuracy and practical applicability.

This thesis advances the modelling framework by integrating pumped storage hydropower systems (PSHS), capturing their operational complexity and dynamic relationship with hydrological conditions. The enhancement enables a more realistic representation of reservoir operations, turbine and pump interactions, and their influence on temporal generation variability—significantly improving the adaptability and robustness of energy system simulations under changing climatic and hydrological conditions.

However, with rainfall–runoff values now routed through storage, turbine, and pump operations, several limitations remain. Factors such as environmental base flow requirements, reservoir release constraints, and plant-specific operational variability introduce complexities that are not yet fully represented. To address these challenges, the modelling approach was simplified by focusing on annual energy generation estimates *equation 1*, while maintaining daily temporal resolution for hydrological processes and annual inflow dynamics. This balance allows for meaningful analysis within current data limitations, while preserving flexibility for future refinements

Even with reliable peak flow forecasts, the implementation of flood-related shutdown logic remains difficult due to the diverseness of operational regulations across hydropower facilities. In this model, extreme flow events are represented as spillage conditions, constrained by available reservoir storage. Furthermore, all simulations were based on historical meteorological and generation data, avoiding assumptions regarding uncertain future operational behaviour. This ensures a transparent and reproducible modelling process while still supporting exploratory analysis of operational trends and optimization scenarios.

In its current form, the tool calibrates hydrological processes using observed weather data to simulate energy generation and annual inflows. Once calibrated, the tool can function as a forecasting engine for annual energy yield estimation. To further improve its temporal and operational accuracy, the integration of plant-level operational and telemetry data would be necessary. Nevertheless, this thesis establishes a flexible graph-based framework that demonstrates clear applicability to real-world pumped storage systems and provides a scalable foundation for future enhancements in energy system and hydropower modelling.

Equation 1: Annual energy generation equation and reservoir constraint equations[23].

$$Generation\ (MWh) = \frac{9.81\,\rho\,Q\,H\,\eta\,T}{3.6 \times 10^{9}}$$

where: ρ— water density, g— gravitational acceleration, $\boldsymbol{Q}$**— discharge through the turbine**, h— hydraulic head, η— overall efficiency, T= seconds per year (31,536,000).

Previous storage: $S(t)$; **Provisional storage:** $S^*(t) = S(t) + I(t) - E(t)$

Inflow definition: $I(t) = I_n(t) + P(t)$, $P(t) = 0$ if $S(t) < S_{\min}$

Spillway calculation: $\text{Spill}(t) = \min\left(\max\left(S^*(t) - S_{\max}, 0\right), C_{\text{spill}}\right)$

Final storage: $S(t+1) = S^*(t) - \text{Spill}(t)$

2 Methodology

It should be noted that the hydropower model used in this study is one-dimensional: it represents flow and storage dynamics along a single spatial dimension while explicitly accounting for temporal variability in inflows, releases, and generation. This section outlines the complete workflow, beginning with data capture and progressing through the construction of the graph-based model. It then describes the development of a climate-driven runoff routing tool, which integrates hydrological and operational inputs to simulate inflows and ultimately estimate energy generation.

2.1 Workflow for Data collection to Energy Simulation

Transforming raw input data into a reliable energy optimization tool involves a multi-stage workflow that includes several layers of data processing and transformation. *Figure 1* illustrates the key components of this process:

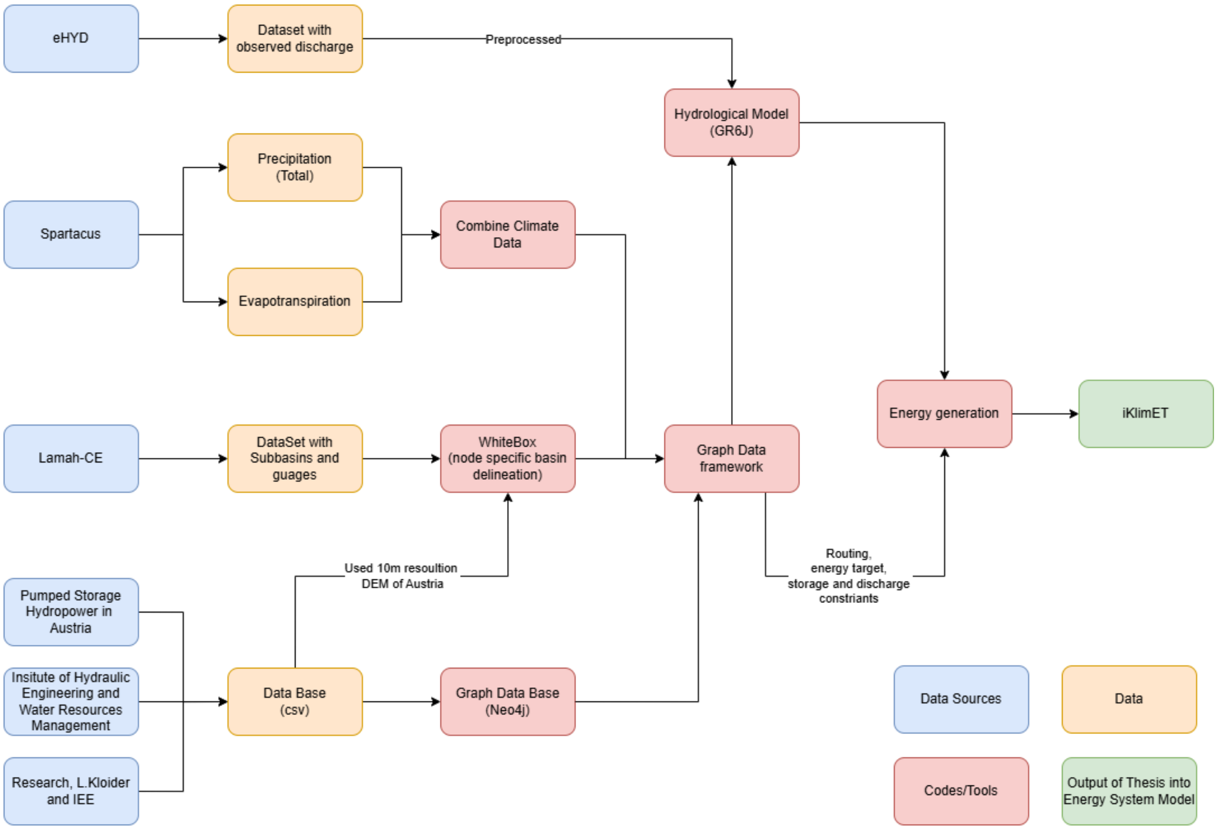

Figure 1: Summary of the overall workflow.

On the left side of the diagram, the primary data sources used in this thesis are listed, including meteorological records, hydrological observations, and technical specifications of power plants, collection works, reservoirs and dams. The adjacent yellow boxes highlight the specific data types extracted from these sources—such as temperature, precipitation, observed discharge, and sub-basin information.

These raw datasets undergo a series of processing steps, including aggregation, conversion, and calibration, to align with the input requirements of the hydrological model, system routing and energy conversion routines. The final output is a set of consistent, high-resolution time series that represent the potential discharge or energy production of each hydropower plant, ready for integration into energy system optimization models.

The calibration strategy focused on using annual energy generation targets as the primary objective, evaluated using Random Mean Square Error (RMSE). Within the graph-based model, each power plant or turbine is assigned a fixed annual generation value. The simulation then attempted to match these targets using the available reservoir storages, the available inflow and discharge derived from the GR6J output.

In schemes where observed gauge data was available, these measurements were incorporated as a secondary objective, assessed using RMSE. In the absence of gauge data, calibration relied solely on the energy targets. While this is not the most ideal approach, it was the most viable given the nature of available open-source data. The model's strong performance when using both energy targets and gauge data together provided confidence in the reliability of results, even when only energy targets were used.

Additionally, natural inflow data reported for some reservoirs aligned well with the simulated inflows when scaled to match reported catchment areas versus model catchment areas, further validating the approach.

This methodology did not require turbine and pump activation thresholds to be set as calibration parameters. Since the goal was to match annual generation totals rather than daily operational dynamics, the simulation could abstract away from time-step-specific pump–turbine interactions.

A calibration approach using the Génie Rural à 6 paramètres Journalier (GR6J) [24] [25] rainfall runoff model was calibrated individually for each valid node, and unknown discharge amounts between interconnected nodes were treated as calibration variables to account for unmeasured flow exchanges within the graph-based network.

The simulation was conducted over a continuous 11-year period, with the first year designated as a warm-up to stabilize model states. Calibration was then performed across six years, followed by validation over the remaining three years. This structured approach ensured effective use of all available data, yielding robust parameter estimates and reliable model performance across diverse hydrological conditions.

The approach introduced several new methodological refinements. Initial reservoir conditions were recognized as influential, and simulations were initialized with reservoir volumes set to 50% of their maximum capacity to reflect a neutral starting point. Additionally, spillage routing logic was enhanced to ensure that spillage from individual nodes was either explicitly directed out of the system or retained appropriately. This prevented artificial loss or misallocation of water within the scheme and improved the accuracy of water balance calculations across the network.

3 Results

A central component of this thesis was the development of a graph database to represent the hydrological and operational structure of pumped storage schemes. The graph model served as the backbone for simulation workflows, enabling flexible routing, constraint enforcement, spatial and relational association of nodes.

The graph database was built using Neo4j [26], where connections and node details were defined using Cypher queries. Each node stands for a real-world or operational component—such as reservoirs, turbines, pumps, intake structures, or dams—while the connections between them represent flow directions, system dependencies, or spatial arrangements.

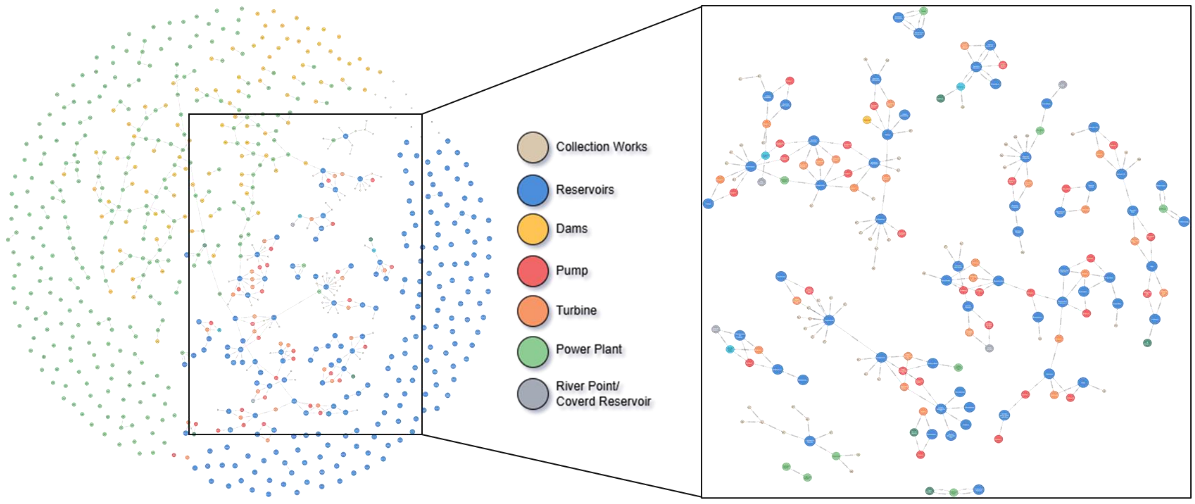

Figure 2: Graph model database of Austrian hydropower Infrastructure, with focus on pumped storage.

Energy targets were met by calibrating catchment parameters using run-off routed inflows derived from climate data. This approach enabled simulation of annual inflow volumes as well to each viable node within the scheme and the overall annual inflow to the scheme. The corresponding plot are shown for each case study. Below are the systematic layout, graph model, and results for the benchmark scheme. Hintermuhr was selected as the benchmark due to the availability of gauge data within its catchment.

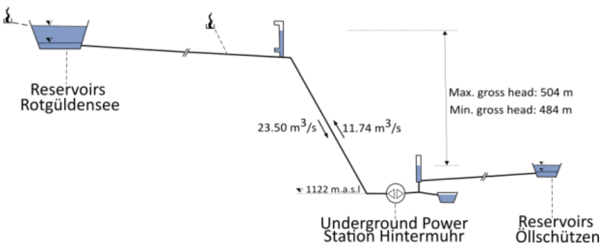

Figure 3: Systematic layout of Hintermuhr scheme.

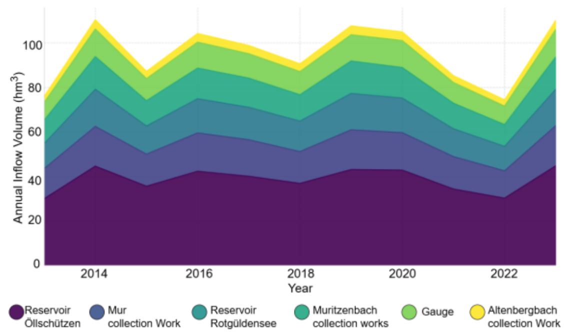

Figure 5: Inflow simulation results for the Hintermuhr scheme.

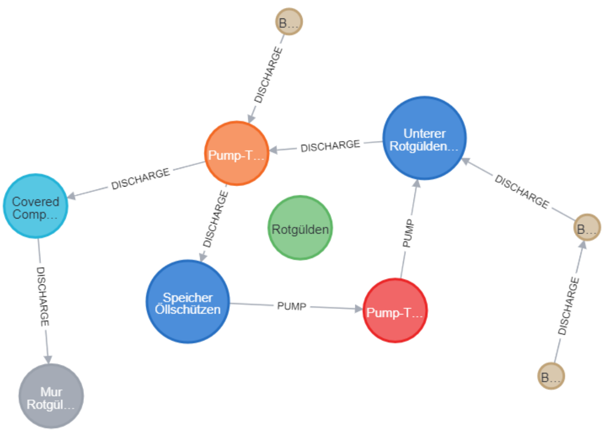

Figure 4: Graph model of Hintermuhr scheme.

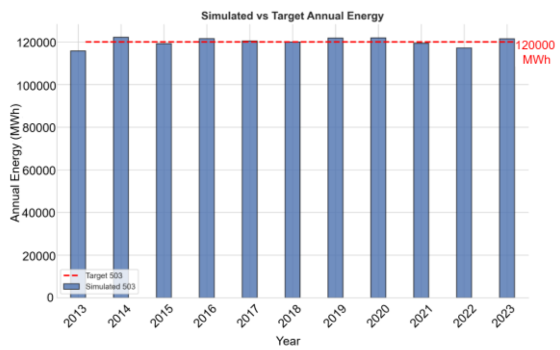

Figure 6: Energy simulation results for the Hintermuhr scheme.

Table 1 presents a summary of the performance metrics for hydrological calibration and energy simulation across all PSHPs cases examined in this thesis; Hintermuhr, Koralpe, Nassfeld, Feldsee, and Limberg I. For each case, the RMSE is reported alongside its corresponding relative error. These metrics offer a quantitative evaluation of the model's accuracy in simulating both discharge and energy generation, serving as key indicators of calibration quality and predictive reliability.

Table 1: RMSE performance across the simulation scheme case studies.

Scheme	**Energy** [MWh]	**RMSE** [MWh]	**Error** [%]
Hintermuhr	120,000	7,067.79	**1.66**
Koralpe	121,000	544.65	**5.85**
Nassfeld	36,000	658.95	**1.51**
Feldsee	240,340	2,682.50	**0.27**
Limberg I	150,400	658.95	**1.78**

The 2018 annual inflow reported in [6] was used as the benchmark for comparison. A consistency check was then performed to compare the simulated inflow values with the reported data for the schemes discussed above. This evaluation applied a scaled inflow approach; whereby expected inflows were estimated by proportionally adjusting volumes according to catchment area.

This method is used due to the lack of clarity regarding the reported catchment boundaries, making it difficult to determine which contributing areas were considered in the reference values. Despite this uncertainty, the scaled inflow check offers useful insight into the hydrological performance of the model—particularly its ability to reproduce annual average volumetric patterns under climate-driven forcing. The results are summarized in table 2 where CA_{ref}: reference catchment area [km²], CA_{mod}: modelled catchment area [km²], I_{sim}: simulated inflow [hm³], I_{ref}: reference inflow [hm³] and I_{sc}: scaled inflow [hm³].

Table 2: Scaled inflow consistency assessment for the scheme case studies.

Scheme	CA_{ref} [Km^2]	CA_{mod} [Km^2]	I_{sim} [hm^3]	I_{ref} [hm^3]	I_{sc} [hm^3]	**Error** [%]
Hintermuhr	67.34	64.83	98.64	98.47	94.96	**3.56**
Koralpe	67.67	53.25	64.09	50.31	50.43	**-0.24**
Nassfeld	63	61.95	130.64	127.1	128.46	**-1.07**
Feldsee	69.84	61.12	125	143.4	109.39	**23.71**
Limberg I	209.1	96.16	172.84	147	79.48	**45.93**

Overall, the model reproduces inflow magnitudes reasonably well across most schemes, with deviations largely attributable to differences in delineated catchment area and data resolution.

Secondary to overall performance metrics RMSE and the scaled inflow, the calibrated GR6J parameters offered insight into the hydrological behaviour of individual nodes within the scheme. The calibrated parameter values for selected nodes reveal distinct hydrological and operational characteristics across the network. However, this should not be viewed as a fixed interpretation but rather as a general guideline. Hydrological conditions vary across catchments, and parameter behaviour may differ depending on local characteristics. Moreover, in the tool, GR6J model outputs are also influenced by the routing logic of each scheme, where storage and discharge constraints are processed dynamically at each time step. This interaction between infrastructure type and routing behaviour adds further nuance to how parameters manifest in different parts of the network.

PARAMETERS	RESERVOIR NODE	RIVER / COLLECTION NODE
X1: Maximum soil water storage capacity (**Soil Storage**)	Medium to High	Medium to Low
X2: Groundwater exchange coefficient (**Water loss**)	Low to Medium	Medium to High
X3: Routing store capacity (**Water retention**)	Medium to High	Medium to Very Low
X4: Unit hydrograph time constant (**Runoff response**)	Low (slow response)	Medium to High (flashy response)
X5: Inter-catchment exchange coefficient (**Inter-catchment flow**)	Low	Medium to High
X6: Baseflow drainage time constant (**Drainage Speed**)	Low (slow drainage)	Medium to High (rapid drainage)

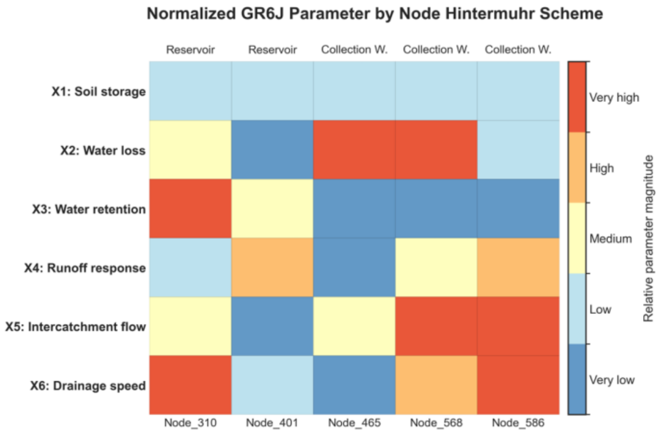

Figure 7: GR6J interpretation table based on viable nodes (left), Hintermuhr GR6J simulation parameters (Right).

4 Conclusion

The goal of this thesis was to develop a graph-based model representing the relationships among hydropower elements, derived from existing hydropower plants. In addition to constructing the model, the thesis explored how simulations of this framework could be implemented, leading to the development of a dedicated tool. Using an annual scale, the tool can be integrated into the energy module of the *iKlimEt* project to enhance the existing energy optimisation framework.

One of the most time-intensive tasks was georeferencing the dataset and constructing the graph model. While further refinements are possible, achieving operational functionality and reliable results already represents a significant accomplishment. The primary objective—establishing a foundational architecture and extensible modelling framework—has been successfully met.

The greatest limitation affecting model accuracy is the scarcity of temporal and operational data. Although RMSE analysis indicates satisfactory performance, inflow consistency checks revealed discrepancies between reported and simulated values.

The thesis outputs provide energy, and inflow estimates for pumped-storage hydropower, extending the module developed by [27]. As highlighted in that study, the generated hydropower time series can be applied across the energy sector, including:

- Energy system optimisation models (e.g., LEGO [28]), where weather-dependent generation is critical for balancing and scheduling supply.
- Long-term energy production forecasts, to assess seasonal or scenario-based impacts of climate change on hydropower availability and grid stability.
- Planning support for new hydropower projects, by extending the model with hypothetical plants to evaluate site-specific potential or system-wide effects.

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