- IoT Emulator: Emulates IoT devices and plays historical or synthetic data.
- AI Models: We can plug in AI models to produce predictive telemetry, optimise performance, perform real-time monitoring, run simulations, and support decision making.

As shown on the high-level architecture diagram (Figure 1), we can populate on demand our digital twin with relevant entities based on a geocoordinate bounding box and date. The entities' models come from twin meta-models based on the NGSI-LD ontology developed for smart cities. During provisioning, the orchestrator triggers data pipelines to retrieve entities (physical assets or simulated ones) and store relevant telemetry data from models built by domain experts, AI models, or real datasets. Each entity is then instantiated in our Dynamic Digital Twin, where it can have its own interfaces and trigger events based on its properties and telemetry. We can interact with the digital twins through APIs or the user interface to run "what-if" scenarios or send commands to IoT devices. Moreover, our goal is now to further explore different technologies. For instance, we aim to replace components like Microsoft's Azure Digital Twin and the Digital Twins Definition Language (DTDL) based on the NGSI-LD ontology with other open-source solutions.

The pilot experimentation conducted through the project CitCom.ai shows the great potential of digital twins in terms of planning, simulation and prediction. It demonstrates that rapid experimentation in city-wide LDTs is possible, notably by allowing to:
- test and experiment with technologies to build a modular LDT architecture
- derive models to emulate telemetries in the digital twin
- collaborate with cities to understand their needs and leverage their data.

Beyond electromobility, we aim to expand the digital twin toolbox for various applications and for making them replicable. Future activities include refining the toolbox's capabilities, enhancing scalability, and integrating more advanced AI models for predictive analytics. We will continue exploring technologies incrementally, and building a multipurpose tool for cities to connect data, models and services, following advancements in LDTs, AI and data analytics.

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Link:
[L1] https://citcom.ai

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Predicting Energy Prices Using Cloud Forecasting Services

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The energy sector is essential for economic development, and the liberalisation of the electricity market has made energy pricing dynamic, influenced by supply and demand. Accurate energy price forecasting is crucial for supply planning and investment decisions, offering security and risk minimization for producers and traders. We propose a cloud-based AI prototype that predicts energy prices using historical data. It details our method for assessing model accuracy by comparing actual to predicted prices, demonstrating how cloud technology can streamline data-intensive tasks in energy forecasting.

The energy market is a complex and volatile system that is influenced by many internal and external factors. Until now, the ability to accurately predict energy prices has been limited, in part due to limited technological forecasting capabilities. The use of cloud technology represents a new approach, which is described in this article. To illustrate this, Figure 1 shows the development of electricity prices in the German-Austrian energy market between 2003 and 2021.

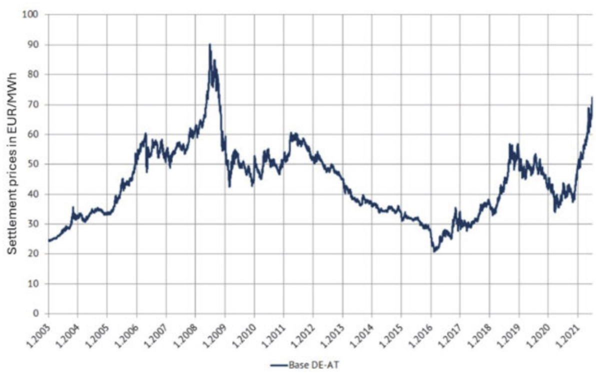
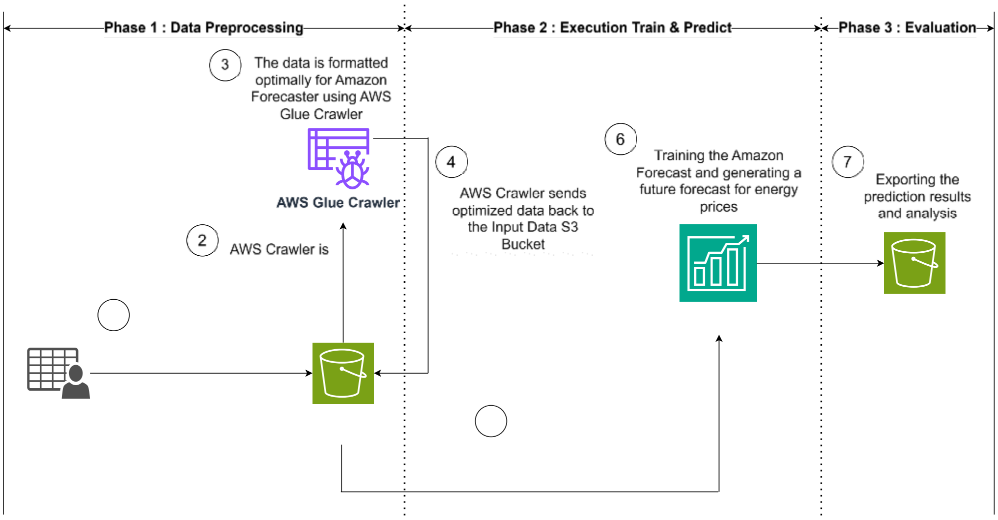


Figure 1: Electricity price development in the German-Austrian energy market from 2003 to 2021 [L1].

Over the years, the price of energy has been dynamic and highly volatile. This makes it essential that electricity traders and producers plan and calculate their purchases and production accurately. Ideally, they should be able to forecast the future so that they can adapt their strategy to changes as early as possible. The price of energy is subject to a certain degree of volatility due to the physical properties of electricity and non-stationary and seasonal demand [1]. As renewable energy, which is largely weather dependent, continues to expand, expected production is also becoming less predictable. The combination of these two factors adds an additional layer of complexity and makes energy price forecasting even more challenging [2].



that takes raw data from the energy market, learns from it, and (based on this) makes predictions (or forecasts) of future energy price developments. Our approach exploits the individual strengths of different cloud services, which in combination lead to the generation of predictive (or forecasting) models for energy prices. A key aspect of our approach is that the selection of the modelling algorithm is done completely autonomously by the AWS

This article explores the feasibility of using cloud services to create a model capable of predicting future energy prices. The objective is to leverage the advanced computational power, AI and Machine Learning (ML) capabilities provided by Amazon Web Services (AWS) to generate precise forecasts based on historical energy price data. To achieve this goal, we propose a prototype designed to operate in the AWS cloud platform, utilising managed services (Amazon Forecast) to predict energy prices. The cloud-based model is expected to be able to understand the behaviour of the electricity market based on the provided data, to recognise patterns and to predict future developments. Our approach extends the scope of the research beyond the evaluation of modelling techniques and (compared to related work) takes advantage of the state-of-the-art technologies provided by the cloud [3]. The overall idea is to let the AI-algorithm itself decide which model is best for modelling, rather than specifying a particular type of model. Figure 2 shows proposed AWS cloud-based prototype for predicting energy prices. The prototype is divided into three distinct phases. Each phase uses different cloud services at different times, and they contribute to each other. First, the raw historical data is imported and then pre-processed using the dedicated AWS Glue Crawler service (Phase 1: Data Preprocessing). This service prepares the data so that the AI can best interpret it and then identify patterns in it. This data is stored in the central Simple Storage Service (S3) bucket and is now ready for analysis. Next, Amazon Forecast Service uses the optimised data to train a predictor to create a model capable of predicting future energy prices (Phase 2: Execution Train & Predict). Amazon Forecast also supports model evaluation using a wide range of scientifically accepted methods and metrics for model validation. Finally, the predicted results are analysed to evaluate the performance of the generated model (Phase 3: Evaluate). To achieve a valid performance evaluation, the chosen approach compares actual energy prices (validation data) with the prices predicted by the model over a fixed period of time before the forecast is run. The purpose of this step is to show how much the Amazon Forecast Service prediction deviates from the actual values and it is used to determine a Proof of Concept (PoC) for the architecture created.

The main contribution of this article is a novel modelling approach to accurately predict future energy prices using cloud-based methods. In addition, we propose a cloud architecture

services, using ML to identify the most appropriate algorithm for the task. The cloud-based model simplifies the process of data handling and model training while enhancing the accuracy of predictions.

The research highlights the potential of cloud technologies in managing data-intensive tasks like energy price forecasting. Future research could explore the inclusion of additional factors, such as weather conditions and geopolitical events, to further improve the model's accuracy. Additionally, investigating other cloud services and ML techniques could provide deeper insights and more robust forecasting capabilities. By demonstrating the effectiveness of AWS cloud services in predicting energy prices, this study opens new avenues for applying cloud-based ML in the energy sector. The results indicate that cloud technology can significantly enhance forecasting accuracy, providing valuable insights for energy producers and traders. This approach not only improves the reliability of energy price forecasts but also offers a scalable and efficient solution for handling large datasets and complex variables, making it a promising tool for the energy industry.

Link: [L1] https://kwz.me/hDy

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