Energy Price Prediction - Discovery Document

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1. Project Overview

The **Energy Price Prediction** system is designed to provide accurate electricity price forecasts using a combination of historical market data, meteorological information, and advanced machine learning techniques. By leveraging automated data ingestion, pre-processing, and real-time predictions, the system aims to support energy traders, grid operators, and other stakeholders in making informed decisions.

Key Features:

- **Automated Data Collection**: Integration with multiple data sources to fetch historical and real-time energy pricing and weather data.
- **Machine Learning-Based Predictions**: Implementation of predictive models trained on historical data for accurate price forecasting.
- **Scalability and Deployment**: Designed to handle large volumes of data and deployed in a cloud-based environment for high availability.
- **API-Driven Architecture**: Provides an API to query price predictions, enabling easy integration with external systems.

- **Scheduled Model Retraining**: Periodic updates to the model using the latest available data to improve prediction accuracy.

2. Problem Statement

The energy market is highly volatile, influenced by numerous factors such as supply and demand, geopolitical events, regulatory policies, and weather conditions. The inability to accurately predict energy prices leads to inefficiencies, increased costs, and financial risks for energy producers, grid operators, and traders.

Challenges in Energy Price Prediction

1. **Market Volatility** – Energy prices fluctuate rapidly due to demand spikes, unexpected outages, and policy changes.
2. **Data Complexity** – Prices are affected by multiple variables, including weather patterns, fuel costs, and grid congestion.
3. **Real-Time Decision Making** – Energy traders and operators require fast and reliable predictions to optimize their strategies.
4. **Integration with External Data Sources** – Market and weather data come from different providers, requiring efficient ingestion and harmonization.
5. **Scalability Issues** – Handling large datasets and real-time forecasting demands robust computational infrastructure.

3. Goals and Objectives

The **Energy Price Prediction** system is designed to enhance forecasting capabilities in the energy sector by leveraging historical and real-time data. The primary objectives of this project are as follows:

Primary Goals

1. **Accurate Energy Price Forecasting** – Develop a machine learning model that provides precise short-term and long-term electricity price predictions.
2. **Real-Time Data Processing** – Enable automated ingestion of energy market data and meteorological conditions for up-to-date forecasting.
3. **Scalable and Reliable System** – Design a robust architecture that can handle large datasets and ensure consistent performance under high demand.
4. **Seamless API Integration** – Provide a RESTful API that allows third-party systems to retrieve price predictions effortlessly.
5. **Automated Model Retraining** – Implement scheduled updates to the prediction model using the latest available data to maintain high accuracy.

Secondary Objectives

6. **Market Trend Analysis** – Extract insights from historical pricing data to identify trends and anomalies.
7. **Customizable Forecasting Parameters** – Allow users to configure specific regions, time horizons, and prediction granularity.

8. **User-Friendly Documentation** – Ensure all stakeholders can easily understand and integrate with the system.
9. **Security and Compliance** – Adhere to best practices in data security and regulatory compliance related to energy market data.
10. **Scalability for Future Enhancements** – Design the system to support future extensions, such as renewable energy forecasting and grid optimization.

4. Use Cases

The **Energy Price Prediction** system is designed to serve a diverse set of stakeholders, including energy market participants, policy makers, and infrastructure operators. Below are the key use cases where the system can provide value:

1. Energy Traders & Market Analysts

- **Objective**: Optimize energy trading strategies by leveraging price forecasts.
- **Use Case**: Traders use predictive analytics to determine the best times to buy or sell electricity in short-term and long-term markets.
- **Impact**: Reduces risk and maximizes profitability by minimizing exposure to market volatility.

2. Grid Operators & Energy Providers

- **Objective**: Improve load balancing and resource allocation based on expected price fluctuations.
- **Use Case**: Grid operators adjust power generation schedules to match predicted price trends, ensuring efficient energy distribution.
- **Impact**: Prevents grid overloads and reduces operational costs.

3. Renewable Energy Producers

- **Objective**: Align energy production with market demand and price signals.
- **Use Case**: Wind and solar energy providers use price forecasts to decide when to store energy, sell to the grid, or adjust output levels.
- **Impact**: Enhances the profitability of renewable energy generation and contributes to a more stable grid.

4. Industrial Energy Consumers

- **Objective**: Reduce operational energy costs by scheduling consumption during low-price periods.
- **Use Case**: Large factories and data centers adjust their power consumption based on predicted price trends.
- **Impact**: Lowers electricity expenses and increases energy efficiency.

5. Regulatory Bodies & Policymakers

- **Objective**: Monitor market trends and enforce regulations effectively.

- **Use Case**: Government agencies analyze price trends to design fair policies and prevent market manipulation.
- **Impact**: Promotes transparency and stability in the energy sector.

6. Financial Institutions & Investors

- **Objective**: Assess risks and investment opportunities in the energy sector.
- **Use Case**: Investment firms use predictive insights to evaluate energy market trends and make informed investment decisions.
- **Impact**: Enhances decision-making for long-term asset allocation and risk assessment.

5. Target Users and Stakeholders

The **Energy Price Prediction** system is designed to cater to various stakeholders across the energy sector. Each user type has distinct needs and expectations, which this system aims to address effectively.

1. Energy Traders & Market Analysts

- **Role:** Individuals and institutions engaged in energy market trading.
- **Needs:**
    - Accurate price forecasts for optimizing buy/sell decisions.
    - Real-time data updates for high-frequency trading.
    - Historical trend analysis for strategic planning.

2. Grid Operators & Energy Providers

- **Role:** Organizations responsible for managing electricity generation and distribution.
- **Needs:**
    - Predictive insights to optimize grid load balancing.
    - Forecasts to schedule power generation efficiently.
    - Risk mitigation strategies for market volatility.

3. Renewable Energy Producers

- **Role:** Wind, solar, and other renewable energy companies integrating into the energy grid.
- **Needs:**
    - Price-based energy storage and release strategies.
    - Integration with weather forecast data for production planning.
    - Demand response optimization.

4. Industrial Energy Consumers

- **Role:** Large manufacturing plants, data centers, and commercial enterprises with high electricity consumption.
- **Needs:**
    - Cost-saving opportunities through consumption scheduling.
    - Real-time insights to manage energy-intensive operations.
    - Demand-side response optimization.

5. Regulatory Bodies & Policymakers

- **Role:** Government agencies and organizations overseeing the energy market.
- **Needs:**
    - Market transparency and fairness monitoring.
    - Regulatory compliance enforcement based on price trends.
    - Policy adjustments informed by predictive analytics.

6. Financial Institutions & Investors

- **Role:** Investment firms and hedge funds analyzing energy market opportunities.
- **Needs:**
    - Risk assessment for energy investments.
    - Market stability forecasting.
    - Price volatility insights for portfolio management.

7. Academic & Research Institutions

- **Role:** Universities, research labs, and think tanks studying energy market dynamics.
- **Needs:**
    - Access to structured datasets for energy economics research.
    - Model performance evaluations for further improvements.
    - Collaboration opportunities in energy forecasting advancements.

6. Data Sources and Integrations

To ensure accurate and reliable energy price predictions, the system integrates multiple **data sources** that provide historical, real-time, and forecasted data. These sources include market price data, meteorological data, and energy grid information.

1. Energy Market Data Sources

The system collects electricity price data from official market operators and energy exchanges.

- **Source:** Energy-Charts API (`https://api.energy-charts.info`)
- **Data Collected:**
    - Hourly, daily, and weekly energy prices
    - Historical market trends
    - Bidding zones pricing

2. Meteorological Data Sources

Weather conditions significantly impact energy demand and renewable energy production.

- **Source:** Open-Meteo API (`https://archive-api.open-meteo.com/v1/archive`)
- **Data Collected:**
    - Temperature, wind speed, solar radiation
    - Historical weather trends from `2015-01-01`
    - Forecasted weather conditions

3. Grid Load and Consumption Data

Grid demand and load balancing affect energy pricing and forecasting accuracy.

- **Source:** Public electricity grid operators and open datasets
- **Data Collected:**
    - Real-time and historical energy consumption
    - Grid congestion and capacity
    - Load balancing strategies

4. Financial & Macroeconomic Indicators

Economic conditions influence energy price fluctuations.

- **Source:** Central banks, economic reports, and financial market APIs
- **Data Collected:**
    - Inflation rates
    - Commodity prices (e.g., natural gas, oil)
    - Currency exchange rates

5. System Integrations

The system integrates with multiple technologies for efficient data ingestion, storage, and processing:

- **MongoDB:** Stores historical energy prices and meteorological data.
- **FastAPI:** Exposes a RESTful API for retrieving predictions.
- **Docker & Kubernetes:** Ensures scalable deployment and microservice management.
- **Scheduled Jobs (APScheduler):** Automates data collection and model retraining.

6. Data Collection & Processing Strategy

- **Batch Data Retrieval:** Periodic extraction of historical data to avoid API rate limits.
- **Streaming Data Integration:** Future roadmap includes direct integration with real-time energy exchanges.
- **Data Validation:** Quality assurance checks to detect anomalies in incoming datasets.

7. Machine Learning Model Selection

The effectiveness of the **Energy Price Prediction** system depends on selecting the right machine learning (ML) models for forecasting electricity prices. The system employs a combination of time-series forecasting, regression models, and ensemble learning to improve accuracy and adaptability.

1. Model Selection Criteria

The chosen model(s) must satisfy the following conditions:

- **Accuracy:** Capable of predicting short-term and long-term energy price fluctuations with minimal error.
- **Scalability:** Able to handle large datasets and adapt to new data without performance degradation.

- **Interpretability:** Provide insights into how different factors (e.g., weather, demand) influence price fluctuations.
- **Real-Time Capability:** Fast inference speed to support real-time decision-making.

2. Selected Models and Approaches

The system utilizes a hybrid approach, combining multiple machine learning techniques:

🔹 **Prophet (Facebook's Time-Series Model)**

- **Purpose:** Baseline forecasting for long-term price trends.
- **Strengths:** Handles seasonality, holidays, and market cycles well.
- **Use Case:** Weekly and monthly price forecasts.

🔹 **XGBoost / LightGBM (Gradient Boosting Trees)**

- **Purpose:** Capturing complex relationships between multiple variables.
- **Strengths:** High performance with structured data, feature importance analysis.
- **Use Case:** Predicting short-term fluctuations based on historical energy prices and external factors (e.g., weather).

🔹 **LSTM (Long Short-Term Memory – Deep Learning Model)**

- **Purpose:** Modeling sequential dependencies in time-series data.
- **Strengths:** Effective for highly volatile markets with non-linear trends.
- **Use Case:** Intraday and hourly price forecasting.

🔹 **Statistical Models (ARIMA / SARIMA)**

- **Purpose:** Benchmarking ML models with traditional statistical approaches.
- **Strengths:** Good interpretability, useful for trend detection.
- **Use Case:** Short-term price movement predictions.

3. Model Training and Optimization

- **Feature Engineering:** Includes energy demand, weather patterns, holidays, and market indicators.
- **Hyperparameter Tuning:** Grid search and Bayesian optimization to improve model accuracy.
- **Cross-Validation:** Ensures robustness using k-fold validation techniques.

4. Model Deployment Strategy

- **Batch Predictions:** Scheduled model retraining based on new data.
- **Real-Time API Integration:** On-demand predictions for energy market stakeholders.
- **Continuous Monitoring:** Retraining triggers based on performance degradation.

8. Data Ingestion Strategy

The **Energy Price Prediction** system relies on a well-structured **data ingestion pipeline** to collect, process, and store energy market and meteorological data efficiently. The strategy ensures high availability, data integrity, and timely updates for accurate predictions.

1. Data Sources

Data is retrieved from multiple external APIs and structured databases, including:

- **Energy Market APIs** (e.g., Energy-Charts API) for electricity prices.
- **Weather Data APIs** (e.g., Open-Meteo) for climate conditions affecting energy production.
- **Historical Energy Consumption Data** from grid operators.
- **Macroeconomic Indicators** (e.g., fuel prices, inflation rates).

2. Data Collection Methods

The ingestion process follows a **hybrid approach**, combining batch processing and real-time streaming:

A. Batch Data Retrieval

- **Historical Data Ingestion:**
    - Fetches bulk data from **2015-01-01** onward.
    - Avoids API rate limits using controlled requests (`DAYS_PER_REQUEST=7`).
    - Stored in **MongoDB** for long-term analysis.
- **Scheduled Updates:**
    - Uses **APScheduler** to periodically request new data.
    - Interval controlled via `.env` variables (`EXTRACTION_INTERVAL=43200` seconds).
    - Runs during off-peak hours (`CRON_HOUR=3`).

B. Real-Time Data Streaming (Future Enhancement)

- Direct integration with market exchanges for continuous price updates.
- Web scraping for alternative data sources (`web_scrapper.py`).
- Low-latency ingestion using **Apache Kafka** (planned).

3. Data Validation & Preprocessing

Before storage, the system applies a series of data integrity checks:

- **Missing Value Handling:** Fills gaps using statistical imputation techniques.
- **Anomaly Detection:** Identifies and removes outliers in price fluctuations.
- **Feature Engineering:** Creates additional attributes like **price volatility**, **moving averages**, and **weather correlations**.

4. Data Storage & Management

- **MongoDB:** Stores raw and processed energy pricing and weather data.
- **Indexed Collections:** Optimized for fast queries and retrieval.
- **Partitioned Datasets:** Segmented by country (`COUNTRY=RO`) and bidding zone (`BIDDING_ZONE=RO`).

5. API Integration & Automation

- **ETL Process (`data_ingestion.py`)**: Extracts, transforms, and loads data into the database.
- **Automated Retries:** If API calls fail (`MAX_RETRIES=3`), the system retries with exponential backoff.
- **Logging & Monitoring:** Every ingestion task is logged for debugging (`logs/` directory).

9. Historical Data Processing

To ensure accurate long-term energy price forecasting, the **Energy Price Prediction** system relies on a structured **historical data processing pipeline**. This process involves collecting, cleaning, transforming, and storing historical energy price and meteorological data for model training and validation.

1. Data Sources for Historical Processing

The system retrieves historical records from various sources:

- **Energy Market Prices:**
    - Collected from **Energy-Charts API** (`API_BASE_URL=https://api.energy-charts.info`).
    - Covers historical price data from **2015-01-01** onward.
- **Meteorological Data:**
    - Obtained from **Open-Meteo API** (`METEO_API_URL=https://archive-api.open-meteo.com/v1/archive`).
    - Includes weather conditions such as temperature, wind speed, solar radiation.
- **Macroeconomic Factors (Planned Enhancement):**
    - Fuel prices, inflation rates, and other financial indicators.

2. Batch Processing Strategy

Given the large volume of historical data, the system employs a **batch processing approach** to efficiently extract, clean, and store historical records.

- **Scheduled Historical Data Retrieval:**
    - Data is fetched in chunks (`DAYS_PER_REQUEST=7`) to avoid API rate limits.
    - Process executes during low-traffic hours (`CRON_HOUR=3`).
    - If an API request fails, it retries up to (`MAX_RETRIES=3`).
- **Data Cleaning & Preprocessing (`historical_data_ingestion.py`)**
    - **Handling Missing Data:**
        - Uses interpolation methods to fill gaps in price and weather records.
    - **Outlier Detection:**
        - Removes extreme fluctuations that may distort model predictions.
    - **Feature Engineering:**

- Adds computed attributes such as **moving averages**, **volatility indexes**, and **weather impact factors**.

3. Storage & Data Organization

Once cleaned, historical data is structured and stored efficiently for rapid retrieval:

- **Database: MongoDB**
- **Collections:**
  - `energy_prices`: Stores price data categorized by **country (`COUNTRY=RO`)** and **bidding zone (`BIDDING_ZONE=RO`)**.
  - `weather_data`: Stores weather conditions corresponding to energy price timestamps.
- **Indexed Queries for Fast Retrieval:**
  - Optimized to allow **time-series analysis**.
  - Supports efficient access for training ML models.

4. Data Utilization in Model Training

- **Training Datasets:**
  - Historical energy prices and weather data are used to train **Prophet, XGBoost, and LSTM models**.
- **Performance Evaluation:**
  - Older data is used for backtesting and validation.
  - Model retraining occurs periodically to incorporate new data (`TRAINING_INTERVAL=86400`).

10. Real-Time Data Processing

The **Energy Price Prediction** system requires a **real-time data processing pipeline** to continuously ingest and analyze the latest energy market and meteorological data. This enables the system to provide up-to-date price forecasts and adapt to sudden market fluctuations.

1. Data Sources for Real-Time Processing

The system collects **real-time** and **near real-time** data from multiple external sources:

- **Energy Market Prices** (via Energy-Charts API)
  - Updates every **hour** for short-term price forecasting.
  - Tracks electricity price variations across different **bidding zones**.
- **Weather Data** (via Open-Meteo API)
  - Retrieves current weather conditions impacting energy production (e.g., wind speed, solar radiation).
- **Grid Load & Demand Data** (Future Enhancement)
  - Direct API integration with electricity grid operators to monitor real-time consumption patterns.
- **Market News & Events** (Planned Enhancement)

- Web scraping from news sources to detect external factors influencing energy prices.

2. Streaming Data Processing Workflow

Real-time data is continuously collected, processed, and stored using an **event-driven pipeline**:

A. Data Collection

- **Automated API Calls (`data_ingestion.py`)**
  - Queries external APIs at a fixed interval (`EXTRACTION_INTERVAL=43200` seconds).
  - Uses retry mechanisms (`MAX_RETRIES=3`) to ensure robustness.
- **Web Scraping (`web_scrapper.py`)**
  - Extracts alternative energy market insights.
  - Runs in parallel with API data ingestion.

B. Data Transformation & Quality Checks

- **Data Preprocessing (`quality_tester.py`)**
  - Validates incoming data for inconsistencies.
  - Cleans, normalizes, and merges new data into existing datasets.
- **Feature Engineering in Real-Time**
  - Computes **short-term price volatility**, **weather correlations**, and **demand fluctuations** dynamically.

C. Storage & Query Optimization

- **MongoDB Storage**
  - Real-time data is appended to existing collections (`energy_prices`, `weather_data`).
  - Indexed queries allow rapid retrieval for model inference.
- **Data Partitioning**
  - Records are categorized by **country (`COUNTRY=RO`)** and **bidding zone (`BIDDING_ZONE=RO`)**.

3. Real-Time Model Inference

Once processed, data is fed into the **machine learning models** for instant predictions:

- **FastAPI Prediction Endpoint (`main.py`)**
  - Accepts real-time energy market and weather inputs.
  - Returns price predictions based on the latest available data.
- **Low-Latency Model Inference**
  - Optimized to return predictions **within milliseconds** for API users.
- **On-Demand Model Retraining**
  - If data distribution shifts significantly, automatic model retraining is triggered (`TRAINING_INTERVAL=86400`).

4. Future Enhancements

- **Apache Kafka Integration** for real-time event streaming.
- **GraphQL Support** for more flexible data retrieval.
- **AI-based Anomaly Detection** to flag unusual market behavior.

11. Model Training and Evaluation

The **Energy Price Prediction** system relies on **continuous model training and evaluation** to ensure accurate, adaptive, and reliable price forecasting. This process involves selecting appropriate datasets, defining evaluation metrics, and implementing retraining strategies to keep the models updated.

1. Training Data Selection

The system trains models using a combination of:

- **Historical Energy Prices** (via Energy-Charts API)
- **Weather Conditions** (via Open-Meteo API)
- **Grid Load & Consumption Data** (Planned Integration)
- **Macroeconomic Indicators** (Future Enhancement)

A. Data Preprocessing Steps:

- **Feature Engineering:**
  - Computes **price volatility**, **moving averages**, and **seasonality trends**.
  - Correlates **weather conditions** with energy production and price fluctuations.
- **Handling Missing Values:**
  - Uses interpolation techniques to fill gaps.
- **Outlier Detection:**
  - Filters anomalies in pricing and consumption trends.

2. Model Training Process

The training pipeline is fully automated and follows these steps:

1. **Data Collection & Preprocessing (`train_model_batch.py`)**
   - Retrieves the latest cleaned and structured data from MongoDB.
2. **Model Selection & Training**
   - Evaluates multiple models (Prophet, XGBoost, LSTM) and selects the best-performing one.
3. **Hyperparameter Tuning**
   - Uses **Grid Search** and **Bayesian Optimization** to optimize model performance.
4. **Cross-Validation**
   - Applies **k-fold validation** to ensure robustness.
5. **Model Storage & Versioning**
   - Trained models are serialized and stored (`MODEL_PATH="models/energy_price_model.pkl"`).

3. Model Evaluation Metrics

Each trained model is evaluated based on multiple performance indicators:

- **Mean Absolute Error (MAE):** Measures average prediction error.
- **Root Mean Squared Error (RMSE):** Penalizes large deviations in forecasts.
- **Mean Absolute Percentage Error (MAPE):** Evaluates percentage-based accuracy.
- **R-Squared (R^2):** Measures how well predictions match actual prices.

The best-performing model is selected for deployment based on these metrics.

4. Continuous Model Retraining

- **Scheduled Retraining (`scheduler.py`)**
  - Periodically re-trains the model using the latest data (`TRAINING_INTERVAL=86400`).
- **Dynamic Retraining Triggers**
  - If model performance degrades beyond a threshold, automatic retraining is initiated.

5. Deployment & Model Serving

- **FastAPI Model Inference (`main.py`)**
  - The trained model is exposed via API for real-time price predictions.
- **Batch Prediction Jobs**
  - Scheduled scripts generate forecasts for long-term planning.

6. Future Enhancements

- **Federated Learning:** Distributed training across multiple data sources.
- **Reinforcement Learning:** Adaptive decision-making based on market behavior.
- **Explainable AI (XAI):** Improves transparency in model decisions.

12. Prediction API Design

The **Energy Price Prediction** system provides an API-based interface for retrieving forecasts, enabling seamless integration with third-party applications, dashboards, and automated trading systems. The API is designed for **high availability, low latency, and scalability** to support real-time and batch predictions.

1. API Architecture

The system is built using **FastAPI**, a high-performance Python framework for asynchronous API services.

Core Features:

- **RESTful API Design:** Standardized HTTP endpoints for easy integration.
- **JSON Response Format:** Ensures compatibility with diverse client applications.
- **CORS Support:** Allows access from web-based frontends and mobile applications.
- **Asynchronous Processing:** Uses `async` functions to handle multiple requests efficiently.

2. API Endpoints

The API exposes several key endpoints for retrieving energy price predictions:

A. Real-Time Predictions

- **Endpoint:** `GET /predict`
- **Description:** Returns price predictions based on the latest real-time data.
- **Parameters:**
  - `country`: The energy market region (e.g., `"RO"` for Romania).
  - `bidding_zone`: The specific market bidding zone.
  - `forecast_horizon`: Time window for predictions (e.g., `"24h"`, `"7d"`).
- **Response:**

```
{
  "timestamp": "2025-02-26T12:00:00Z",
  "country": "RO",
  "bidding_zone": "RO",
  "forecast_horizon": "24h",
  "predictions": [
    {"hour": "12:00", "price": 50.23},
    {"hour": "13:00", "price": 49.87},
    ...
  ]
}
```

B. Historical Predictions for Backtesting

- **Endpoint:** `GET /historical-predictions`
- **Description:** Retrieves past forecasts to compare against actual prices.

C. Model Performance Metrics

- **Endpoint:** `GET /model-metrics`
- **Description:** Provides evaluation scores such as MAE, RMSE, and MAPE.

D. Trigger Model Retraining (Admin Only)

- **Endpoint:** `POST /retrain`
- **Description:** Manually triggers model retraining with updated data.

3. Authentication & Security

- **API Key Authentication:** Each client must provide a valid API key for access.
- **Role-Based Access Control (RBAC):** Admins can retrain models, while regular users can only fetch predictions.
- **Rate Limiting:** Prevents excessive API requests to ensure system stability.

4. Scalability & Performance Optimization

- **Load Balancing:** API runs in a containerized environment (`Docker` + `Kubernetes`).
- **Asynchronous Execution:** Reduces request latency via `async/await`.
- **Caching Strategies:** Stores frequently requested predictions to reduce computation load.

5. Future Enhancements

- **GraphQL API:** Flexible querying for customized data retrieval.
- **WebSocket Integration:** Enables live updates on price fluctuations.
- **Edge Deployment:** Expands real-time predictions to IoT and smart grid devices.

13. Scheduler and Automation

The **Energy Price Prediction** system incorporates a **scheduler and automation framework** to handle periodic data ingestion, model retraining, and forecasting updates without manual intervention. The scheduler ensures that all components of the system operate seamlessly in the background, maintaining data freshness and model accuracy.

1. Scheduling Framework

The system uses **APScheduler** (Advanced Python Scheduler) to automate tasks at predefined intervals. The scheduler runs in a separate **Docker container** to ensure isolation and scalability.

Core Automation Features:

- **Data Extraction:** Automatically fetches updated energy price and meteorological data.
- **Model Retraining:** Re-trains the ML models based on new data to improve accuracy.
- **Scheduled Forecast Generation:** Computes price predictions at regular intervals.
- **Health Checks & Logging:** Monitors system performance and logs task execution.

2. Key Scheduled Tasks

A. Data Ingestion Jobs (`data_ingestion.py`)

- **Runs Every:** `EXTRACTION_INTERVAL=43200` seconds (12 hours)
- **Description:**
    - Fetches historical and real-time data from external APIs.
    - Updates **MongoDB** with the latest market and weather data.
    - Ensures missing data is handled gracefully.

B. Model Retraining (`train_model_batch.py`)

- **Runs Every:** `TRAINING_INTERVAL=86400` seconds (24 hours)
- **Description:**
    - Retrieves the latest data and re-trains the ML models.
    - Performs hyperparameter tuning to maintain accuracy.
    - Stores the new model in `models/energy_price_model.pkl`.
    - Triggers alerts if performance metrics degrade.

C. Forecast Generation (`scheduler.py`)

- **Runs Every:** 1 hour
- **Description:**
    - Uses the latest trained model to generate price predictions.
    - Stores forecasts in the database for API access.
    - Implements caching to reduce redundant computations.

3. Environment Variables for Automation

The `.env` file provides configurable parameters to adjust scheduling behavior:

```
# Data ingestion frequency (seconds)
EXTRACTION_INTERVAL=43200

# Model retraining frequency (seconds)
TRAINING_INTERVAL=86400

# Daily scheduled run time (UTC)
CRON_HOUR=3
```

4. Logging & Monitoring

- **Task Execution Logs:** Stored in `/logs/` for debugging and audit purposes.
- **Failure Handling:** If a task fails, the system retries up to `MAX_RETRIES=3` times.
- **Health Checks:** API endpoints (`/health`) verify that scheduled jobs run correctly.

5. Future Enhancements

- **Dynamic Retraining Triggers:** Instead of fixed intervals, the model retrains when accuracy drops below a threshold.
- **Distributed Task Execution:** Integration with **Celery** for parallel task processing.
- **Adaptive Scheduling:** Uses AI to optimize execution timing based on market trends.

14. System Architecture and Deployment

The **Energy Price Prediction** system is designed with a **modular, scalable, and cloud-ready architecture**, ensuring efficient data processing, robust model training, and seamless API integration. The deployment strategy leverages containerization, microservices, and cloud-based orchestration.

1. System Architecture Overview

The system follows a **microservices-based architecture**, where each component operates independently and communicates through well-defined APIs.

Key Architectural Components:

1. **Data Ingestion Service**
    - Fetches real-time and historical data from external APIs.
    - Cleans and stores the data in **MongoDB**.
2. **Machine Learning Model Service**
    - Trains and evaluates energy price prediction models.
    - Handles scheduled retraining using APScheduler.
3. **FastAPI Prediction API**
    - Exposes a REST API for querying price forecasts.
    - Provides real-time and batch prediction endpoints.
4. **Scheduler and Automation**

- Automates data ingestion, model training, and forecast updates.
- Runs as a background process in a dedicated container.

5. **Database (MongoDB)**
    - Stores **energy price data**, **weather records**, and **predictions**.
    - Optimized for **fast retrieval and indexing**.

System Workflow:

1. The **Scheduler** triggers data ingestion at predefined intervals.
2. The **Data Ingestion Service** collects, cleans, and stores the data.
3. The **Model Training Service** retrieves updated data and re-trains models.
4. The **Prediction API** serves price forecasts to external users.

2. Deployment Strategy

The system is deployed using **Docker** and **Kubernetes** for scalability and reliability.

A. Containerization (Docker)

Each system component runs as a separate **Docker container**:

- **FastAPI Service** (`main.py`) → Handles API requests.
- **Scheduler Service** (`scheduler.py`) → Manages automation tasks.
- **MongoDB Container** → Stores all collected and processed data.

B. Orchestration (Kubernetes - Future Enhancement)

- Enables **auto-scaling** and **fault tolerance**.
- Deploys services across multiple cloud instances.
- Uses **Helm Charts** for simplified management.

C. Cloud Hosting (AWS/GCP/Azure - Future Enhancement)

- **Database Scaling:** Uses **MongoDB Atlas** for managed cloud storage.
- **Model Hosting:** Deploys models using **AWS SageMaker** or **Vertex AI**.
- **API Load Balancing:** Uses **AWS ALB** or **NGINX** to distribute requests efficiently.

3. Deployment Process

To deploy the system, follow these steps:

A. Local Deployment (Docker-Compose)

```
docker-compose up --build -d
```

- Starts all services in isolated containers.
- Ensures easy development and debugging.

B. Production Deployment (Docker + Kubernetes - Future Roadmap)

```
kubectl apply -f deployment.yaml
```

- Deploys the system on a cloud-based Kubernetes cluster.

4. Monitoring and Maintenance

- **Logging:** All system events are recorded in the `/logs/` directory.
- **Health Checks:** API endpoint `/health` monitors service availability.
- **Performance Metrics:** System usage statistics are tracked via **Prometheus/Grafana**.

5. Future Enhancements

- **CI/CD Integration:** Automates deployments with **GitHub Actions**.
- **Hybrid Cloud Support:** Allows on-premise and cloud integration.
- **Serverless API Hosting:** Moves prediction endpoints to **AWS Lambda** for cost efficiency.

15. Technology Stack

The **Energy Price Prediction** system is built using a **modern, scalable, and performance-oriented technology stack**, ensuring efficiency in data processing, model training, and API deployment. The selected technologies support **high availability, automation, and extensibility** for future enhancements.

1. Programming Languages

- **Python** → Primary language for data ingestion, machine learning, and API development.
- **Bash (Shell Scripting)** → Used for deployment automation and system administration tasks.

2. Machine Learning & Data Science

- **Prophet** → Time-series forecasting model for energy prices.
- **XGBoost / LightGBM** → Gradient boosting models for short-term price prediction.
- **LSTM (Long Short-Term Memory)** → Deep learning model for sequential energy price forecasting.
- **Scikit-Learn** → General ML utilities (preprocessing, feature engineering).
- **Statsmodels / ARIMA** → Statistical modeling for baseline comparisons.

3. Data Ingestion & Storage

- **MongoDB** → NoSQL database for storing energy price, weather, and model results.
- **Requests / BeautifulSoup / Selenium** → APIs and web scraping tools for external data sources.

4. API Development & Backend Services

- **FastAPI** → High-performance Python framework for serving RESTful APIs.
- **Pydantic** → Ensures data validation and serialization for API requests.
- **Uvicorn** → ASGI server for running FastAPI applications efficiently.

5. Task Scheduling & Automation

- **APScheduler** → Manages periodic jobs for data ingestion and model retraining.
- **Celery (Future Enhancement)** → Distributed task queue for parallel job execution.

6. Containerization & Orchestration

- **Docker** → Containers for all system components (API, scheduler, database).
- **Docker Compose** → Simplifies local development and multi-container management.
- **Kubernetes (Future Enhancement)** → Auto-scaling and high-availability orchestration.

7. Deployment & Cloud Services

- **AWS EC2 / Google Cloud Compute (Planned)** → Cloud-based server hosting.
- **MongoDB Atlas (Planned)** → Fully managed cloud NoSQL database.
- **AWS SageMaker / Vertex AI (Planned)** → Cloud-based model training and deployment.

8. Monitoring & Logging

- **Prometheus & Grafana (Future Enhancement)** → System performance tracking.
- **ELK Stack (Elasticsearch, Logstash, Kibana)** → Centralized log management.

9. Security & Authentication

- **OAuth2 / JWT Tokens (Planned)** → API authentication and access control.
- **SSL/TLS Encryption** → Secure data transmission over API endpoints.
- **Role-Based Access Control (RBAC)** → Limits administrative actions (e.g., retraining models).

10. CI/CD & DevOps

- **GitHub Actions (Future Enhancement)** → Automates builds, tests, and deployments.
- **Terraform / Helm (Planned)** → Infrastructure as Code (IaC) for managing cloud resources.

16. Security Considerations

The **Energy Price Prediction** system follows **best practices in cybersecurity** to ensure data integrity, secure API access, and prevent unauthorized access to sensitive information. The system is designed with multiple security layers to **protect data, enforce authentication, and mitigate cyber threats.**

1. API Security

- **OAuth2 / JWT Authentication (Planned)**
  - API endpoints require valid authentication tokens to access protected resources.
  - User roles (admin, analyst, read-only) restrict API actions.
- **Rate Limiting & Throttling**
  - Prevents API abuse and DDoS attacks by limiting request frequency per user.
- **CORS Policy Enforcement**
  - Restricts API access to approved domains and prevents cross-site request forgery (CSRF).
- **Input Validation with Pydantic**
  - Ensures strict type checking and sanitization to prevent SQL/NoSQL injection.

2. Data Security & Privacy

- **SSL/TLS Encryption**
  - Secures API communication using HTTPS to prevent man-in-the-middle attacks.
- **MongoDB Security Best Practices**
  - **Access Control:** Only authorized applications and users can query data.
  - **Data Partitioning:** User-specific or region-based data segmentation.
  - **Audit Logging:** Monitors database access patterns for anomaly detection.
- **Environment Variables for Secrets Management**
  - Database credentials and API keys are stored securely in `.env` files, **never hardcoded.**

3. Infrastructure & Deployment Security

- **Docker Container Isolation**
  - Each service runs in an isolated container to minimize cross-service vulnerabilities.
- **Role-Based Access Control (RBAC) for Deployment**
  - Only authorized personnel can modify infrastructure and deploy models.
- **Firewall Rules & IP Whitelisting (Planned)**
  - Restricts API access to approved IP addresses or VPN connections.
- **Automatic Security Patching**
  - Regular updates of OS, dependencies, and containers to fix known vulnerabilities.

4. Logging, Monitoring & Threat Detection

- **Centralized Logging with ELK Stack (Planned)**
  - Stores API and system logs in Elasticsearch for real-time monitoring.
- **Intrusion Detection System (IDS) (Future Enhancement)**
  - Detects and alerts on suspicious system activities.
- **Prometheus & Grafana for Security Metrics**
  - Monitors unusual request patterns or performance anomalies that indicate security risks.

5. Compliance & Regulatory Considerations

- **GDPR Compliance**
  - Ensures proper handling of personal and market-sensitive data.
- **Data Retention Policies**
  - Historical data is stored with access restrictions and retention limits.

6. Future Enhancements

- **AI-driven Anomaly Detection**
  - Uses ML to detect unusual spikes in API requests or database queries.
- **Penetration Testing**
  - Conducts ethical hacking tests to identify potential vulnerabilities.

17. Scalability and Performance

The **Energy Price Prediction** system is designed to be **highly scalable and performant**, ensuring it can handle large datasets, real-time API requests, and complex machine learning computations without performance degradation. The architecture is optimized for **horizontal scaling, efficient data processing, and fast model inference**.

1. Scalability Strategies

A. Horizontal and Vertical Scaling

- **Microservices Architecture:** The system is designed with independent services (API, data ingestion, model training) that can scale independently.
- **Kubernetes-Based Auto-Scaling (Planned):** Enables automatic provisioning of additional API and ML model servers based on demand.
- **Database Scaling:**
  - **Sharding:** Distributes data across multiple MongoDB instances.
  - **Read Replicas:** Improves query performance by handling read-heavy workloads.

B. Load Balancing

- **NGINX / AWS Application Load Balancer (Planned):** Distributes API requests evenly across multiple instances.
- **FastAPI Async Support:** Uses asynchronous request handling to maximize throughput.

C. Distributed Processing (Future Enhancements)

- **Apache Kafka (Planned):** Enables event-driven data streaming and parallel processing.
- **Celery Task Queue:** Supports distributed execution of ML training jobs and background tasks.

2. Performance Optimization Techniques

A. Optimized Machine Learning Inference

- **ONNX Model Optimization (Planned):** Converts ML models to an optimized format for fast inference.
- **Batch Processing for Predictions:** Reduces overhead by processing multiple prediction requests together.
- **Caching Predictions:** Stores frequently requested predictions in **Redis** to minimize API response times.

B. Efficient Data Handling

- **Indexed MongoDB Queries:** Uses **compound indexing** for fast retrieval of historical data.
- **Partitioned Storage:** Organizes energy price and weather data by **bidding zone** and **time range** to enhance query efficiency.

C. API Performance Enhancements

- **Asynchronous API Processing:** Uses FastAPI's async/await capabilities to handle concurrent requests.
- **Response Compression:** Implements **gzip** compression to reduce response size.

- **Rate Limiting:** Prevents API overloading by restricting excessive requests from a single client.

3. Benchmarking and Performance Monitoring

A. Benchmarking Metrics

- **API Response Time:** Ensures API responses are processed within **100ms** on average.
- **Model Inference Speed:** Aims for **<50ms** latency for real-time price forecasts.
- **Data Ingestion Throughput:** Supports processing **millions of records daily** without bottlenecks.

B. Monitoring Tools

- **Prometheus & Grafana (Planned):** Real-time dashboards for tracking system performance.
- **Logging with ELK Stack:** Centralized log collection and anomaly detection.

4. Future Enhancements for Scalability

- **Edge Computing Deployment:** Moves prediction models to **IoT devices** for decentralized forecasting.
- **Multi-Cloud Deployments:** Supports hybrid cloud setups across **AWS, GCP, and Azure** for global scalability.
- **Federated Learning:** Enables distributed ML training without centralized data storage, improving privacy and scalability.

18. Monitoring and Logging

To ensure **reliability, performance, and security**, the **Energy Price Prediction** system incorporates a comprehensive **monitoring and logging** framework. This setup enables real-time tracking of system health, proactive issue detection, and efficient debugging.

1. Monitoring Framework

The system uses **Prometheus and Grafana (Planned)** for real-time performance monitoring, enabling in-depth visualization of key metrics.

A. Key System Metrics Tracked

- **API Performance Metrics:**
    - Request throughput (requests per second)
    - Response time (latency)
    - Error rate (4xx and 5xx status codes)
- **Database Metrics:**
    - Query execution time
    - Storage usage and indexing efficiency
    - Replication lag for distributed setups
- **Model Performance Metrics:**
    - Model inference speed (prediction latency)
    - Prediction accuracy metrics (MAE, RMSE, MAPE)

        - Model retraining frequency and drift detection
    - **Infrastructure Health:**
        - CPU, memory, and disk usage for containers
        - Network bandwidth utilization
        - Scheduler task execution status

B. Monitoring Tools

- **Prometheus (Planned):** Collects system-wide metrics and alerts on anomalies.
- **Grafana Dashboards:** Provides real-time visualization of API, database, and ML performance.
- **Health Check API (`/health`):** FastAPI exposes a health check endpoint to verify system status.

2. Logging Strategy

A **centralized logging** approach ensures **efficient debugging, auditing, and security compliance**.

A. Logging Categories

- **API Logs:**
    - Records all incoming requests and responses.
    - Logs API authentication attempts and failed access requests.
- **Data Pipeline Logs:**
    - Tracks data ingestion and preprocessing operations.
    - Logs errors in fetching external data (e.g., API failures).
- **Machine Learning Logs:**
    - Records model training results, including hyperparameters and evaluation scores.
    - Logs prediction requests and their confidence scores.
- **Scheduler Logs:**
    - Monitors scheduled tasks (data ingestion, retraining) and their execution status.
    - Flags any job failures for manual intervention.

B. Logging Tools

- **ELK Stack (Elasticsearch, Logstash, Kibana) (Planned):**
    - **Elasticsearch** for storing structured logs.
    - **Logstash** for collecting and filtering logs from various services.
    - **Kibana** for visualization and log search capabilities.
- **File-Based Logging:**
    - Logs stored locally in `/logs/` directory for easy access.
    - Rotates logs to prevent excessive disk usage.

3. Alerting and Issue Detection

Proactive alerts help detect and mitigate potential system failures before they impact users.

A. Automated Alerts (Planned)

- **Prometheus Alert Manager:**
    - Sends alerts when API response time exceeds **500ms**.

        - Notifies on repeated API failures (5xx errors).
        - Detects anomalies in energy price predictions.
    - **Email & Slack Alerts (Planned):**
        - Notifies engineers about failed scheduled jobs or database downtime.
        - Sends real-time alerts on security-related incidents.

4. Future Enhancements for Monitoring & Logging

- **AI-Powered Anomaly Detection:** Identifies unusual system behaviors using machine learning.
- **Distributed Tracing with OpenTelemetry:** Provides detailed insights into API request processing times.
- **Integration with Security Information and Event Management (SIEM) Systems:** Enhances cybersecurity monitoring.

19. Testing and Validation Strategy

The **Energy Price Prediction** system follows a rigorous **testing and validation strategy** to ensure accuracy, reliability, and robustness across all components, including **data ingestion, machine learning models, API endpoints, and automation scripts**. The strategy consists of multiple testing phases, ensuring the system meets performance and quality requirements before deployment.

1. Types of Testing Applied

A. Unit Testing

- **Scope:**
    - Tests individual functions and modules in data processing, API logic, and model training.
- **Tools:**
    - **Pytest** for testing core Python logic.
    - **unittest** for API and ML model function tests.
- **Example Test Cases:**
    - Validate that missing data handling fills gaps correctly.
    - Ensure API endpoints return expected status codes and responses.

B. Integration Testing

- **Scope:**
    - Verifies interactions between different system components (e.g., API, database, ML model).
- **Tools:**
    - **Postman / Pytest-requests** for API testing.
    - **Docker Test Containers** to validate interactions with MongoDB.
- **Example Test Cases:**
    - Ensure the API correctly fetches predictions from the ML model.
    - Validate that data ingestion scripts store records in MongoDB correctly.

C. Functional Testing

- **Scope:**
  - Ensures the system behaves as expected from an end-user perspective.
- **Tools:**
  - **Selenium / Playwright (Planned)** for web interface validation.
- **Example Test Cases:**
  - Ensure that historical data queries return expected price trends.
  - Validate that prediction results are correctly formatted for API consumers.

D. Performance Testing

- **Scope:**
  - Measures system speed, resource usage, and scalability.
- **Tools:**
  - **Locust / JMeter** for API load testing.
  - **Prometheus & Grafana** for monitoring performance under stress.
- **Example Test Cases:**
  - Ensure the API handles **1000+ concurrent requests** with low latency.
  - Verify that model inference completes within **50ms** per prediction.

E. Model Validation & Accuracy Testing

- **Scope:**
  - Ensures that machine learning predictions meet accuracy benchmarks.
- **Tools:**
  - **Scikit-Learn & Statsmodels** for statistical analysis.
- **Validation Metrics:**
  - **Mean Absolute Error (MAE)**
  - **Root Mean Squared Error (RMSE)**
  - **Mean Absolute Percentage Error (MAPE)**
- **Example Test Cases:**
  - Ensure the ML model maintains **MAE < 5% deviation** from actual market prices.
  - Validate model retraining improves accuracy over time.

F. Security & Penetration Testing

- **Scope:**
  - Identifies vulnerabilities in API endpoints and infrastructure.
- **Tools:**
  - **OWASP ZAP / Burp Suite** for API security testing.
- **Example Test Cases:**
  - Validate that authentication prevents unauthorized data access.
  - Ensure input sanitization prevents SQL/NoSQL injection attacks.

2. Automated Testing Strategy

- **Continuous Integration (CI) Pipeline (Planned)**
  - Runs **unit tests, integration tests, and model validation** on every code commit.
  - Uses **GitHub Actions / Jenkins** for automation.

- **End-to-End API Testing (Planned)**
    - **Newman (Postman CLI)** automates API regression testing.
- **Scheduled Model Evaluation (Planned)**
    - **Retrains models periodically and logs performance trends.**

3. Future Enhancements in Testing

- **Synthetic Data Generation:** Tests edge cases with AI-generated energy market data.
- **Federated Testing for Distributed Models:** Evaluates predictions across multiple data sources.
- **Explainability Testing (XAI):** Ensures models provide **interpretable** predictions.

20. Future Enhancements (General View) and Roadmap

The **Energy Price Prediction** system is designed with scalability and continuous improvement in mind. The following roadmap outlines **planned enhancements** to improve accuracy, security, scalability, and usability. These upgrades aim to **enhance model performance, expand integrations, and optimize system efficiency**.

1. Short-Term Enhancements (3-6 Months)

A. API & Infrastructure Improvements

- **GraphQL API Support:** Enables flexible queries for retrieving custom forecasting data.
- **WebSocket Integration:** Provides real-time price updates for clients subscribed to specific markets.
- **Rate-Limiting & API Key Management:** Enhances security and prevents unauthorized API abuse.

B. Machine Learning Model Upgrades

- **Hyperparameter Auto-Tuning:** Implements automated tuning (Bayesian optimization) to enhance model accuracy.
- **Model Drift Detection:** Triggers re-training when the model's performance drops below a defined threshold.
- **ONNX Model Conversion:** Optimizes inference speed by converting ML models into a lightweight format.

C. Data Processing & Storage Enhancements

- **Partitioned Database Storage:** Improves data retrieval speed for historical energy price analysis.
- **Streaming Data Integration (Kafka):** Implements real-time ingestion of energy prices and weather updates.

2. Mid-Term Enhancements (6-12 Months)

A. Advanced AI & Forecasting Features

- **Federated Learning Implementation:** Enhances privacy and model robustness by training across multiple data sources.
- **Reinforcement Learning for Dynamic Trading Optimization:** Allows adaptive decision-making based on market fluctuations.
- **Anomaly Detection for Price Spikes:** Uses AI to flag unusual price fluctuations in the market.

B. Deployment & Scalability Enhancements

- **Kubernetes Deployment:** Enables auto-scaling of API and model inference services.
- **Multi-Cloud Support:** Allows hybrid deployments on AWS, GCP, and Azure.
- **Serverless Model Hosting (AWS Lambda / Vertex AI):** Reduces costs by running models on demand.

C. Expanded Market & Weather Data Sources

- **Integration with Grid Operators:** Fetches real-time consumption and energy demand data.
- **Incorporation of Economic Indicators:** Factors in inflation, fuel prices, and geopolitical risks in forecasts.

3. Long-Term Enhancements (12+ Months)

A. Industry Adoption & Business Applications

- **Custom Forecasting Models per Client:** Enables enterprise users to train models on private datasets.
- **Energy Trading Bot (AI-driven Automation):** Implements autonomous trading decisions based on forecasted energy prices.
- **IoT Edge Deployment for Smart Grids:** Deploys lightweight ML models to edge devices for localized forecasting.

B. Security & Compliance Upgrades

- **ISO 27001 Compliance for Energy Data Security:** Enhances system credibility for enterprise adoption.
- **Explainable AI (XAI) for Transparency:** Provides users with **interpretable** predictions to justify model decisions.
- **AI-Powered Risk Analysis:** Evaluates long-term risks in energy price fluctuations for investment firms.