When predicting total energy demand across different time frames (hourly, daily, weekly, monthly, and yearly), the choice of model can significantly impact the accuracy of the predictions. Here's a breakdown of how the different models rate for these time frames:

**1. Linear Regression Model**

* **Hourly:** Linear regression might struggle with capturing the complex non-linear relationships in hourly data, especially when multiple variables like windspeed, temperature, and humidity interact. Not the best choice for high-frequency data.
* **Daily:** It can provide a baseline model for daily predictions, but it might not capture the nuances of daily variations effectively.
* **Weekly:** Linear regression can work reasonably well for weekly aggregates, where the effect of short-term variability is reduced.
* **Monthly:** This model can be effective for monthly predictions if the relationships are mostly linear and the seasonality is not too complex.
* **Yearly:** It can be a good fit for yearly predictions, especially if trends are mostly linear over time.

**Rating:**

* **Hourly:** ★☆☆☆☆
* **Daily:** ★★☆☆☆
* **Weekly:** ★★★☆☆
* **Monthly:** ★★★★☆
* **Yearly:** ★★★★☆

**2. Convolutional Neural Network (CNN)**

* **Hourly:** CNNs are generally more suitable for spatial data, but they can capture complex patterns in time-series data when used with 1D convolutions. Effective for high-frequency data like hourly predictions, especially if capturing local patterns (e.g., within a day) is crucial.
* **Daily:** Can perform well for daily predictions by capturing daily patterns and interactions between variables.
* **Weekly:** CNNs can handle weekly aggregates, but they may be less effective than other models specifically designed for time series.
* **Monthly:** Effective for capturing seasonal patterns over monthly intervals.
* **Yearly:** CNNs may overfit if not carefully tuned, especially for yearly predictions where the data points are fewer.

**Rating:**

* **Hourly:** ★★★★☆
* **Daily:** ★★★★☆
* **Weekly:** ★★★☆☆
* **Monthly:** ★★★★☆
* **Yearly:** ★★★☆☆

**3. Random Forest Model**

* **Hourly:** Random Forest can handle complex interactions between variables, making it a solid choice for hourly predictions, though it may struggle with temporal dependencies.
* **Daily:** Performs well for daily predictions, capturing non-linear interactions and providing robust predictions.
* **Weekly:** Effective for weekly predictions, though computational cost can be higher.
* **Monthly:** Good for monthly predictions, with the ability to capture seasonality through non-linear relationships.
* **Yearly:** Random Forests can handle yearly predictions well, particularly when there are clear trends and non-linear effects.

**Rating:**

* **Hourly:** ★★★★☆
* **Daily:** ★★★★☆
* **Weekly:** ★★★★☆
* **Monthly:** ★★★★☆
* **Yearly:** ★★★★☆

**4. Prophet Model**

* **Hourly:** Prophet is not ideal for high-frequency data like hourly predictions. It’s better suited for daily or higher-level aggregations.
* **Daily:** Excellent for daily predictions, particularly with strong seasonal patterns and holiday effects.
* **Weekly:** Works well for weekly predictions, especially if the data exhibits strong seasonality and trends.
* **Monthly:** Very effective for monthly predictions, with built-in seasonality and trend modeling.
* **Yearly:** Also performs well for yearly predictions, capturing long-term trends and seasonality effectively.

**Rating:**

* **Hourly:** ★★☆☆☆
* **Daily:** ★★★★★
* **Weekly:** ★★★★★
* **Monthly:** ★★★★★
* **Yearly:** ★★★★★

**5. XGBoost**

* **Hourly:** XGBoost is highly effective for high-frequency predictions like hourly data, capturing non-linear interactions and temporal patterns.
* **Daily:** Performs exceptionally well for daily predictions, handling complex relationships between variables.
* **Weekly:** Very effective for weekly predictions, providing robust and accurate forecasts.
* **Monthly:** Excellent for monthly predictions, capturing seasonality and trends.
* **Yearly:** XGBoost can handle yearly predictions effectively, though careful tuning is required to avoid overfitting.

**Rating:**

* **Hourly:** ★★★★★
* **Daily:** ★★★★★
* **Weekly:** ★★★★★
* **Monthly:** ★★★★★
* **Yearly:** ★★★★★

**Summary:**

* **Best Overall Model:** **XGBoost** – Provides strong performance across all time frames, from hourly to yearly predictions.
* **Best for Long-Term Predictions:** **Prophet** – Excels at capturing trends and seasonality for daily, weekly, monthly, and yearly predictions.
* **Best for High-Frequency Data:** **XGBoost** and **CNN** – Both are well-suited for hourly and daily predictions, with XGBoost having a slight edge in overall flexibility and performance.