Module 3: Feature Engineering

Since this dataset follows a panel-logging structure (multiple devices recorded at fixed 15-minute intervals across multiple homes), time-dependent features such as lag values and rolling averages are computed on the cleaned, continuous dataset before normalization and splitting. This preserves the temporal sequence within each home–device combination and avoids disrupting time-based relationships. The normalization and train–test split steps from Milestone 1 are retained in previous notebook and will be performed again for dataset after feature engineering.

In [1]:
```
import joblib       # to load saved preprocessed dataframe
import pandas as pd     # for dataframe operations
import numpy as np      # for mathematical operations
import os      # to define paths for saving figures
import matplotlib.pyplot as plt     # to plot charts / figures
from sklearn.preprocessing import MinMaxScaler      # to scale numeric input features
from sklearn.linear_model import LinearRegression      # baseline model
from sklearn.metrics import mean_absolute_error, root_mean_squared_error    # to evaluate the performamce of ba
from sklearn.model_selection import TimeSeriesSplit           # to generate splits for CV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score       # for final evaluation
```

In [2]:
```
df = joblib.load('../saved_objects/df_cleaned.joblib')
df
```

Out [2]:

	home_id	timestamp	device_type	room	status	power_watt	user_present	activity	indoor_temp	outdoor_temp	humidity
0	1	2022-01-01 00:00:00	air_conditioner	bedroom	off	0.000000	1	sleeping	11.4	11.9	45.2
1	1	2022-01-01 00:00:00	light	living_room	on	105.880000	1	sleeping	11.4	11.9	45.2
2	1	2022-01-01 00:00:00	tv	living_room	off	0.000000	1	sleeping	11.4	11.9	45.2
3	1	2022-01-01 00:00:00	fridge	kitchen	on	223.460000	1	sleeping	11.4	11.9	45.2
4	1	2022-01-01 00:00:00	washer	laundry_room	off	0.000000	1	sleeping	11.4	11.9	45.2
...	...	...	...	...	...	...	...	...	...	...	...
1751995	10	2022-12-31 23:45:00	air_conditioner	bedroom	off	0.000000	1	sleeping	10.8	11.1	68.0
1751996	10	2022-12-31 23:45:00	light	living_room	off	0.000000	1	sleeping	10.8	11.1	68.0
1751997	10	2022-12-31 23:45:00	tv	living_room	off	0.000000	1	sleeping	10.8	11.1	68.0
1751998	10	2022-12-31 23:45:00	fridge	kitchen	on	261.350000	1	sleeping	10.8	11.1	68.0
1751999	10	2022-12-31 23:45:00	washer	laundry_room	on	1884.819597	1	sleeping	10.8	11.1	68.0

1752000 rows × 15 columns

In [3]:
```
df.columns
```

Out [3]:
```
Index(['home_id', 'timestamp', 'device_type', 'room', 'status', 'power_watt',
       'user_present', 'activity', 'indoor_temp', 'outdoor_temp', 'humidity',
       'light_level', 'day_of_week', 'hour_of_day', 'energy_kWh'],
      dtype='object')
```

Module 3.1: Extract relevant time-based features (hour, day, week, month trends).

since the columns day_of_week, and hour_of day already exist in dataframe for houly, daily and weekly trends, introducing new column 'month_of_year' for monthly trend

In [4]:
```
df['month_of_year'] = df['timestamp'].dt.month
col = df.pop('month_of_year')
df.insert(len(df.columns) - 3, 'month_of_year', col)
df
```

Out [4]:

	home_id	timestamp	device_type	room	status	power_watt	user_present	activity	indoor_temp	outdoor_temp	humidity
0	1	2022-01-01 00:00:00	air_conditioner	bedroom	off	0.000000	1	sleeping	11.4	11.9	45.2
1	1	2022-01-01 00:00:00	light	living_room	on	105.880000	1	sleeping	11.4	11.9	45.2
2	1	2022-01-01 00:00:00	tv	living_room	off	0.000000	1	sleeping	11.4	11.9	45.2
3	1	2022-01-01 00:00:00	fridge	kitchen	on	223.460000	1	sleeping	11.4	11.9	45.2
4	1	2022-01-01 00:00:00	washer	laundry_room	off	0.000000	1	sleeping	11.4	11.9	45.2
...	...	...	...	...	...	...	...	...	...	...	...
1751995	10	2022-12-31 23:45:00	air_conditioner	bedroom	off	0.000000	1	sleeping	10.8	11.1	68.0
1751996	10	2022-12-31 23:45:00	light	living_room	off	0.000000	1	sleeping	10.8	11.1	68.0
1751997	10	2022-12-31 23:45:00	tv	living_room	off	0.000000	1	sleeping	10.8	11.1	68.0
1751998	10	2022-12-31 23:45:00	fridge	kitchen	on	261.350000	1	sleeping	10.8	11.1	68.0
1751999	10	2022-12-31 23:45:00	washer	laundry_room	on	1884.819597	1	sleeping	10.8	11.1	68.0

1752000 rows × 16 columns

Module 3.2: Aggregate device-level consumption statistics.

In [5]:
```
df.groupby(["home_id", "device_type"])["energy_kWh"].describe() # at household level
```

Out [5]:

		count	mean	std	min	25%	50%	75%	max
home_id	**device_type**								
1	**air_conditioner**	35040.0	0.053025	0.104930	0.000000	0.000000	0.000000	0.000000	0.841700
	fridge	35040.0	0.066442	0.023242	0.019378	0.055335	0.062768	0.070668	0.229578
	light	35040.0	0.010374	0.019251	0.000000	0.000000	0.000000	0.025728	0.147431
	tv	35040.0	0.044130	0.051885	0.000000	0.000000	0.000000	0.088311	0.304714
	washer	35040.0	0.016276	0.055588	0.000000	0.000000	0.000000	0.000000	0.557148
2	**air_conditioner**	35040.0	0.052824	0.104390	0.000000	0.000000	0.000000	0.000000	0.837649
	fridge	35040.0	0.066479	0.023453	0.016942	0.055285	0.062687	0.070616	0.228719
	light	35040.0	0.010277	0.019082	0.000000	0.000000	0.000000	0.025548	0.148475
	tv	35040.0	0.044294	0.051850	0.000000	0.000000	0.000000	0.088360	0.302908
	washer	35040.0	0.016805	0.056846	0.000000	0.000000	0.000000	0.000000	0.559197
3	**air_conditioner**	35040.0	0.032710	0.085595	0.000000	0.000000	0.000000	0.000000	0.813298
	fridge	35040.0	0.066426	0.023396	0.017692	0.055170	0.062680	0.070593	0.227691
	light	35040.0	0.010099	0.018888	0.000000	0.000000	0.000000	0.025155	0.146671
	tv	35040.0	0.015541	0.037331	0.000000	0.000000	0.000000	0.000000	0.304015
	washer	35040.0	0.012667	0.048946	0.000000	0.000000	0.000000	0.000000	0.548207
4	**air_conditioner**	35040.0	0.033918	0.087479	0.000000	0.000000	0.000000	0.000000	0.827362
	fridge	35040.0	0.066325	0.023121	0.016615	0.055362	0.062716	0.070623	0.231252
	light	35040.0	0.009895	0.018874	0.000000	0.000000	0.000000	0.000000	0.147335
	tv	35040.0	0.015548	0.037539	0.000000	0.000000	0.000000	0.000000	0.304831
	washer	35040.0	0.011247	0.046903	0.000000	0.000000	0.000000	0.000000	0.546290
5	**air_conditioner**	35040.0	0.033661	0.085979	0.000000	0.000000	0.000000	0.000000	0.753450
	fridge	35040.0	0.066452	0.023476	0.017962	0.055182	0.062710	0.070647	0.230758
	light	35040.0	0.009912	0.018905	0.000000	0.000000	0.000000	0.000000	0.146424
	tv	35040.0	0.015588	0.037199	0.000000	0.000000	0.000000	0.000000	0.302120
	washer	35040.0	0.011778	0.049009	0.000000	0.000000	0.000000	0.000000	0.559293
6	**air_conditioner**	35040.0	0.032466	0.085294	0.000000	0.000000	0.000000	0.000000	0.811404
	fridge	35040.0	0.066270	0.023052	0.018490	0.055245	0.062720	0.070578	0.230474

		count	mean	std	min	25%	50%	75%	max
home_id	device_type								
	light	35040.0	0.010251	0.019103	0.000000	0.000000	0.000000	0.025426	0.145020
	tv	35040.0	0.015429	0.037025	0.000000	0.000000	0.000000	0.000000	0.299925
	washer	35040.0	0.016704	0.056414	0.000000	0.000000	0.000000	0.000000	0.559205
7	air_conditioner	35040.0	0.032253	0.085114	0.000000	0.000000	0.000000	0.000000	0.870574
	fridge	35040.0	0.066246	0.023047	0.016817	0.055202	0.062607	0.070528	0.229838
	light	35040.0	0.010437	0.019126	0.000000	0.000000	0.000000	0.026074	0.147526
	tv	35040.0	0.015383	0.036908	0.000000	0.000000	0.000000	0.000000	0.301539
	washer	35040.0	0.016001	0.055310	0.000000	0.000000	0.000000	0.000000	0.562464
8	air_conditioner	35040.0	0.034845	0.088387	0.000000	0.000000	0.000000	0.000000	0.779704
	fridge	35040.0	0.066220	0.022992	0.018370	0.055235	0.062655	0.070580	0.230277
	light	35040.0	0.009765	0.018749	0.000000	0.000000	0.000000	0.000000	0.147818
	tv	35040.0	0.015731	0.037791	0.000000	0.000000	0.000000	0.000000	0.300214
	washer	35040.0	0.016681	0.056922	0.000000	0.000000	0.000000	0.000000	0.563195
9	air_conditioner	35040.0	0.033113	0.085348	0.000000	0.000000	0.000000	0.000000	0.775050
	fridge	35040.0	0.066317	0.023177	0.018040	0.055266	0.062654	0.070499	0.230130
	light	35040.0	0.010074	0.019014	0.000000	0.000000	0.000000	0.000000	0.147768
	tv	35040.0	0.015646	0.037653	0.000000	0.000000	0.000000	0.000000	0.296094
	washer	35040.0	0.016983	0.057622	0.000000	0.000000	0.000000	0.000000	0.555984
10	air_conditioner	35040.0	0.032243	0.084209	0.000000	0.000000	0.000000	0.000000	0.837820
	fridge	35040.0	0.066306	0.023239	0.018235	0.055203	0.062610	0.070568	0.230179
	light	35040.0	0.009930	0.018906	0.000000	0.000000	0.000000	0.000000	0.146405
	tv	35040.0	0.015288	0.037029	0.000000	0.000000	0.000000	0.000000	0.302330
	washer	35040.0	0.016560	0.056866	0.000000	0.000000	0.000000	0.000000	0.542658

In [6]:
```
df.groupby("device_type")["energy_kWh"].describe()   # device-level
```

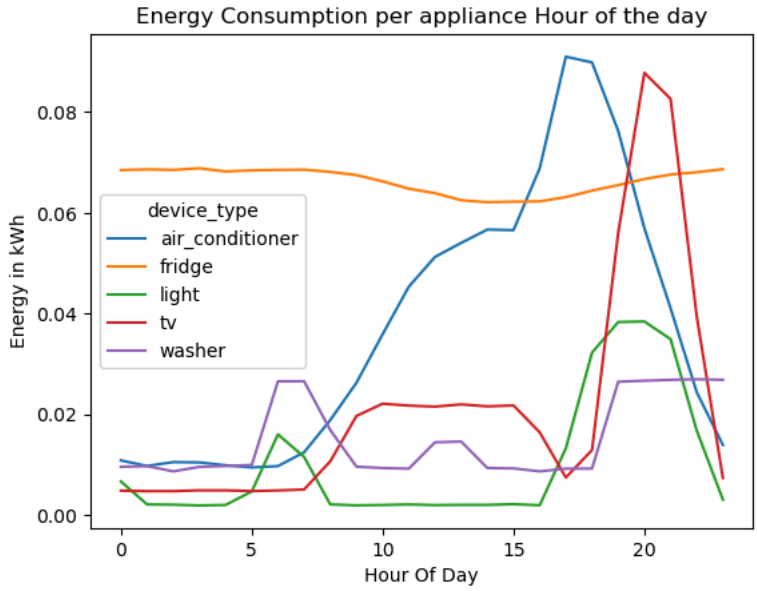
Out [6]:

	count	mean	std	min	25%	50%	75%	max
device_type								
air_conditioner	350400.0	0.037106	0.090341	0.000000	0.000000	0.000000	0.000000	0.870574
fridge	350400.0	0.066348	0.023220	0.016615	0.055245	0.062683	0.070590	0.231252
light	350400.0	0.010101	0.018991	0.000000	0.000000	0.000000	0.025065	0.148475
tv	350400.0	0.021258	0.042231	0.000000	0.000000	0.000000	0.000000	0.304831
washer	350400.0	0.015170	0.054223	0.000000	0.000000	0.000000	0.000000	0.563195

This provides an overview of device-level consumption patterns.

Module 3.3: Create lag features and moving averages for time series learning.

In [7]:
```
BASE_dir = os.getcwd()
FIG_PATH = os.path.abspath(BASE_dir + '/../reports/Milestone2/figures')

df_subset = df.pivot_table(index = 'hour_of_day', columns = 'device_type', values = 'energy_kWh', aggfunc='mea
df_subset.plot(kind='line')
plt.title('Energy Consumption per appliance Hour of the day')
plt.xlabel('Hour Of Day')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Energy_Per_Device_Hourly.png')
plt.show()
```



Since no clear repeating intra-day pattern is observed in the hourly mean energy consumption, the plots were used to guide the selection of appropriate lag intervals rather than derive explicit hourly seasonality. Consequently, lag features at 1 hour, 24 hours, and 1 week were chosen to capture short-term effects, daily context, and longer-term recurring trends observed in the time series (as seen in Milestone 1 plots).

In [8]:
```
# since timestamp interval is 15 min (1hr / 4)

group_cols = ['home_id', 'device_type']

df['energy_lag_1H'] = df.groupby(group_cols)['energy_kWh'].shift(4)
df['energy_lag_1D'] = df.groupby(group_cols)['energy_kWh'].shift(24 * 4)
df['energy_lag_1W'] = df.groupby(group_cols)['energy_kWh'].shift(24 * 7 * 4)
```

Rolling averages with window sizes of 1 hour, 6 hours, 12 hours, and 24 hours were computed to capture intra-day consumption trends at different temporal resolutions. These windows help smooth short-term fluctuations while preserving meaningful daily usage patterns, complementing lag-based features.

Weekly and monthly rolling averages were not included as they tend to over-smooth device-level consumption at a 15-minute resolution and are largely redundant with weekly lag features.

In [9]:
```
df['energy_roll_mean_1hr'] = df.groupby(group_cols)['energy_kWh'].rolling(window=(4)).mean().reset_index(level
df['energy_roll_mean_6hr'] = df.groupby(group_cols)['energy_kWh'].rolling(window=(6 * 4)).mean().reset_index(l
df['energy_roll_mean_12hr'] = df.groupby(group_cols)['energy_kWh'].rolling(window=(12 * 4)).mean().reset_index
df['energy_roll_mean_24hr'] = df.groupby(group_cols)['energy_kWh'].rolling(window=(24 * 4)).mean().reset_index

# reset_index() is applied to match the rolling output back to the original DataFrame structure.
```

In [10]:
```
df[
  (df['home_id'] == 1) &
  (df['device_type'] == 'fridge')
][['timestamp','energy_kWh','energy_lag_1H','energy_lag_1D','energy_lag_1W','energy_roll_mean_1hr','energy_roll
```

Out [10]:

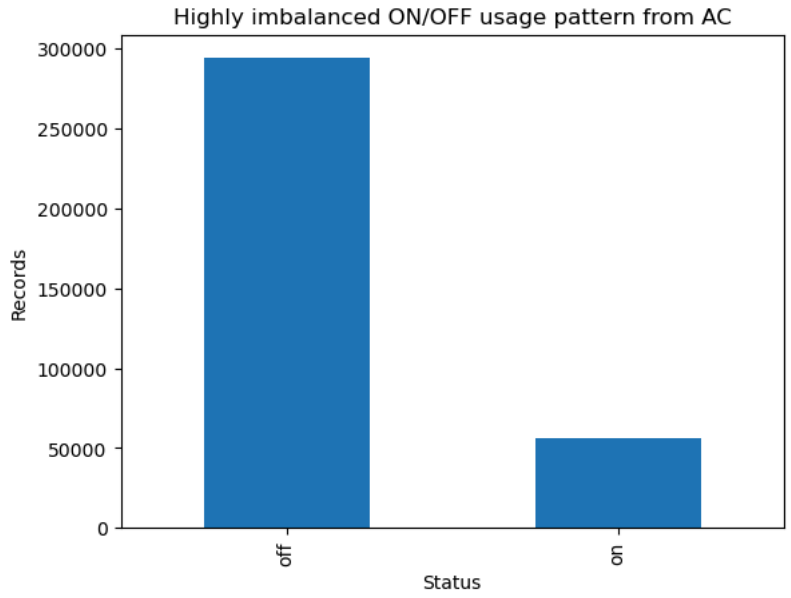
	timestamp	energy_kWh	energy_lag_1H	energy_lag_1D	energy_lag_1W	energy_roll_mean_1hr	energy_roll_mean_6hr	energy_roll_mean_12hr
3	2022-01-01 00:00:00	0.055865	NaN	NaN	NaN	NaN	NaN	NaN
53	2022-01-01 00:15:00	0.053638	NaN	NaN	NaN	NaN	NaN	NaN
103	2022-01-01 00:30:00	0.058825	NaN	NaN	NaN	NaN	NaN	NaN
153	2022-01-01 00:45:00	0.077192	NaN	NaN	NaN	0.061380	NaN	NaN
203	2022-01-01 01:00:00	0.074022	0.055865	NaN	NaN	0.065919	NaN	NaN
...	...	...	...	...	...	...	...	...
4753	2022-01-01 23:45:00	0.071418	0.074645	NaN	NaN	0.066667	0.065010	0.066058
4803	2022-01-02 00:00:00	0.058037	0.065037	0.055865	NaN	0.064917	0.064905	0.065950

	timestamp	energy_kWh	energy_lag_1H	energy_lag_1D	energy_lag_1W	energy_roll_mean_1hr	energy_roll_mean_6hr	energy_roll_mean_12hr
4853	2022-01-02 00:15:00	0.069090	0.071028	0.053638	NaN	0.064433	0.064746	0.065777
4903	2022-01-02 00:30:00	0.052958	0.059185	0.058825	NaN	0.062876	0.063953	0.065416
4953	2022-01-02 00:45:00	0.053700	0.071418	0.077192	NaN	0.058446	0.063131	0.065224

100 rows × 9 columns

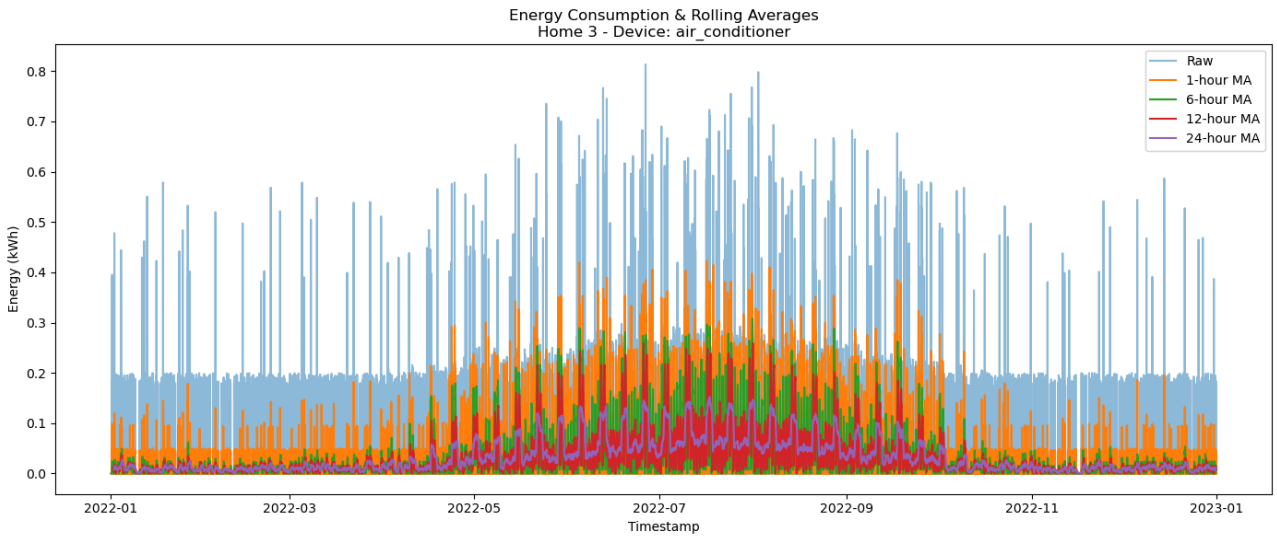
Module 3.4: Prepare final feature set for ML model input.

In [11]:
```
df[df['device_type']=='air_conditioner']['status'].value_counts().plot(kind='bar')
plt.xlabel('Status')
plt.ylabel('Records')
plt.title('Highly imbalanced ON/OFF usage pattern from AC')
plt.savefig(FIG_PATH+'\AC_status_counts.png')
plt.show()
```



The air conditioner was selected for rolling-window analysis due to its highly imbalanced ON/OFF usage pattern. Unlike continuously operating appliances such as fridge, AC consumption is intermittent and season-driven, making it more sensitive to temporal smoothing choices. Analyzing the AC allowed us to identify rolling average windows that capture meaningful short-term activity while preserving long-term usage patterns, which informed the final selection of MA features.

In [12]:
```
def plot_rolling_averages_per_house_device(df, home_id, device_type):
    """
    Plots raw energy consumption and rolling averages for a specific home/device.
    """
    # Filter for specific home and device
    data = df[(df['home_id'] == home_id) & (df['device_type'] == device_type)].copy()

    plt.figure(figsize=(14,6))
    plt.plot(data['timestamp'], data['energy_kWh'], label='Raw', alpha=0.5)
    plt.plot(data['timestamp'], data['energy_roll_mean_1hr'], label='1-hour MA')
    plt.plot(data['timestamp'], data['energy_roll_mean_6hr'], label='6-hour MA')
    plt.plot(data['timestamp'], data['energy_roll_mean_12hr'], label='12-hour MA')
    plt.plot(data['timestamp'], data['energy_roll_mean_24hr'], label='24-hour MA')

    plt.xlabel('Timestamp')
    plt.ylabel('Energy (kWh)')
    plt.title(f'Energy Consumption & Rolling Averages\nHome {home_id} - Device: {device_type}')
    plt.legend()
    plt.tight_layout()
    plt.savefig(f'{FIG_PATH}/Home-{home_id}_Device-{device_type}.png')
    plt.show()

plot_rolling_averages_per_house_device(df, home_id=3, device_type='air_conditioner')
```



In [13]:
```
df.drop('energy_roll_mean_6hr', axis=1, inplace=True)
```

Although multiple rolling averages were initially generated, exploratory analysis showed that the 6-hour moving average was highly correlated with the 12-hour window and did not contribute additional temporal information. It was therefore removed to reduce redundancy and improve model interpretability.

Keeping overlapping rolling windows can introduce multicollinearity in regression models, which affects coefficient stability without improving predictive power.

In [14]:
```
df.columns
```

Out [14]:
```
Index(['home_id', 'timestamp', 'device_type', 'room', 'status', 'power_watt',
       'user_present', 'activity', 'indoor_temp', 'outdoor_temp', 'humidity',
       'light_level', 'month_of_year', 'day_of_week', 'hour_of_day',
       'energy_kWh', 'energy_lag_1H', 'energy_lag_1D', 'energy_lag_1W',
       'energy_roll_mean_1hr', 'energy_roll_mean_12hr',
       'energy_roll_mean_24hr'],
      dtype='object')
```

In [15]:
```
##### adding columns such as: is_weekend, etc
weekends = (5, 6, 7)
df['is_weekend'] = (df['day_of_week'].isin(weekends))
col = df.pop('is_weekend')
df.insert(len(df.columns) - 10,'is_weekend', col)
```

In [16]:
```
df[['day_of_week', 'is_weekend']]
```

Out [16]:

	day_of_week	is_weekend
0	5	True
1	5	True
2	5	True
3	5	True
4	5	True
...	...	...
1751995	5	True
1751996	5	True
1751997	5	True
1751998	5	True
1751999	5	True

1752000 rows × 2 columns

In [17]:
```
df.columns
```

Out [17]:
```
Index(['home_id', 'timestamp', 'device_type', 'room', 'status', 'power_watt',
       'user_present', 'activity', 'indoor_temp', 'outdoor_temp', 'humidity',
       'light_level', 'is_weekend', 'month_of_year', 'day_of_week',
       'hour_of_day', 'energy_kWh', 'energy_lag_1H', 'energy_lag_1D',
       'energy_lag_1W', 'energy_roll_mean_1hr', 'energy_roll_mean_12hr',
       'energy_roll_mean_24hr'],
      dtype='object')
```

In [18]:
```
df.drop('power_watt', axis = 1, inplace = True)
```

In [19]:
```
df.columns
```

Out [19]:
```
Index(['home_id', 'timestamp', 'device_type', 'room', 'status', 'user_present',
       'activity', 'indoor_temp', 'outdoor_temp', 'humidity', 'light_level',
```

```
       'is_weekend', 'month_of_year', 'day_of_week', 'hour_of_day',
       'energy_kWh', 'energy_lag_1H', 'energy_lag_1D', 'energy_lag_1W',
       'energy_roll_mean_1hr', 'energy_roll_mean_12hr',
       'energy_roll_mean_24hr'],
      dtype='object')
```

1. Device & Household Context

"`home_id, device_type, room, status, user_present, activity`" Captures household and device-specific behavior affecting energy consumption.

1. Environmental Features

"`indoor_temp, outdoor_temp, humidity, light_level`" Represents conditions that influence device usage patterns.

1. Temporal Features

"`month_of_year, day_of_week, is_weekend, hour_of_day`" Encodes seasonal, weekly, weekend, and intra-day trends.

1. Lag Features

"`energy_lag_1H, energy_lag_1D, energy_lag_1W`" Captures short-term, daily, and weekly consumption dependencies.

1. Rolling Averages

"`energy_roll_mean_1hr, energy_roll_mean_12hr, energy_roll_mean_24hr`" Smooths fluctuations and models intra-day and daily trends at multiple scales.

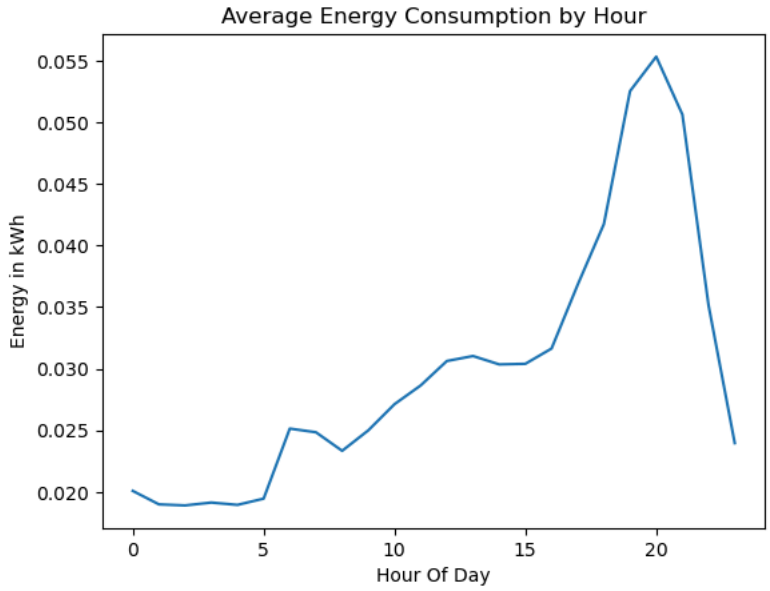
Target: `energy_kWh`

Notes:

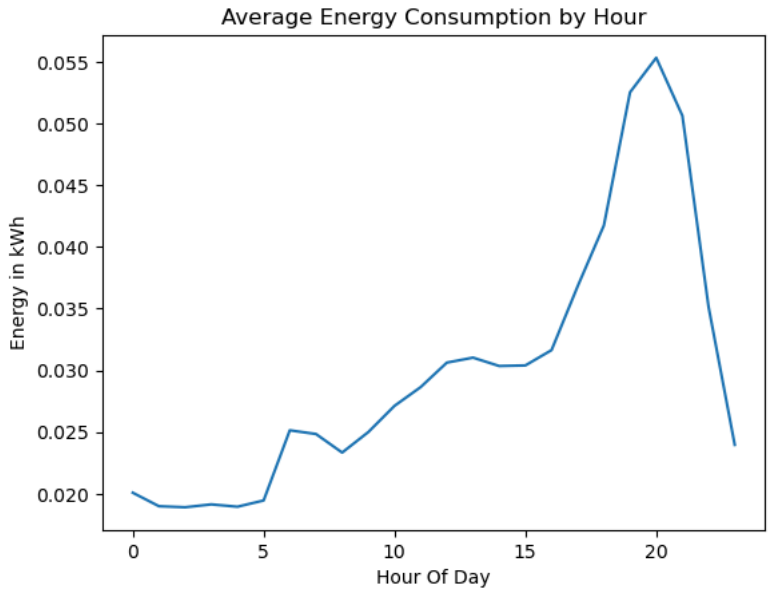
- timestamp is not used as an index due to repeated timestamps across homes/devices.
- All lag and rolling features are computed per device and per home to avoid leakage.

Group energy consumption by time units (hour, day, week, month)

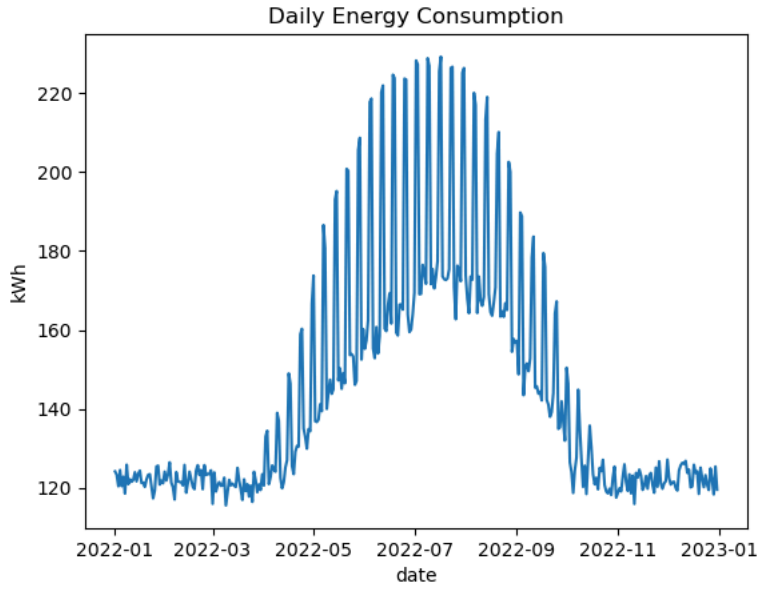
In [20]:
```
df.groupby(df['timestamp'].dt.hour)['energy_kWh'].mean().plot(title='Average Energy Consumption by Hour')
plt.xlabel('Hour Of Day')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Energy_AVG_Hourly(1).png')
plt.show()
```



In [21]:
```
df.groupby(df['hour_of_day'])['energy_kWh'].mean().plot(title='Average Energy Consumption by Hour')
plt.xlabel('Hour Of Day')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Energy_AVG_Hourly(2).png')
plt.show()
```

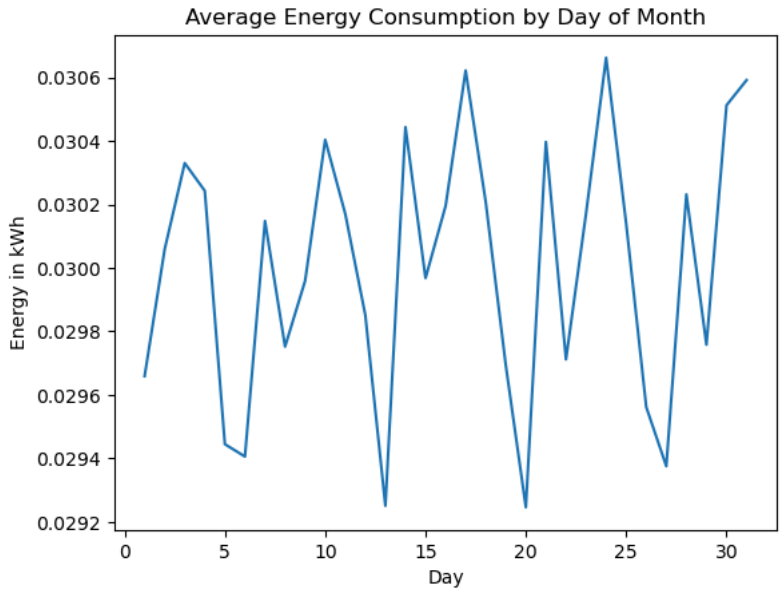


In [22]:
```
df.groupby(df['timestamp'].dt.date)['energy_kWh'].sum().plot(title='Daily Energy Consumption')
plt.xlabel('date')
plt.ylabel('kWh')
plt.savefig(FIG_PATH + '\Daily_Energy_Seasonality.png')
plt.show()
```



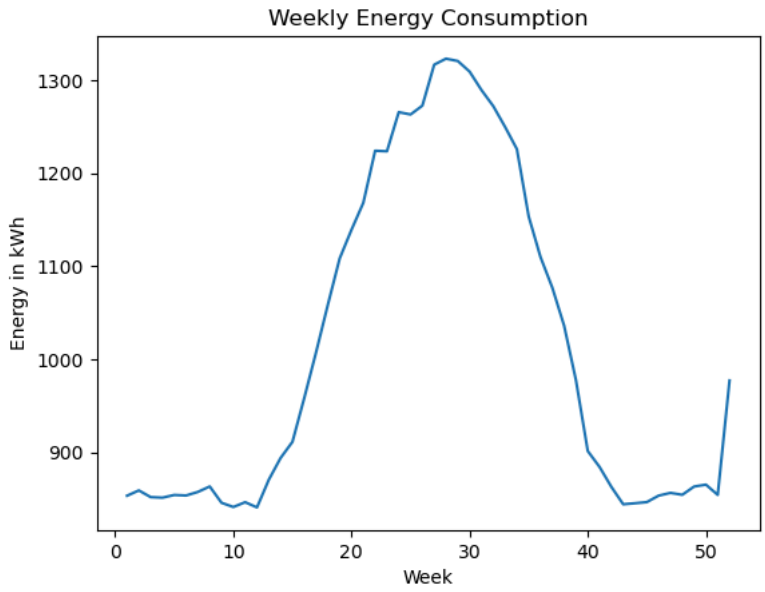
The series exhibits seasonal behavior with a non-stationary trend (multiplicative seasonality) and heteroscedastic variance

In [23]:
```
df.groupby(df['timestamp'].dt.day)['energy_kWh'].mean().plot(title='Average Energy Consumption by Day of Month
plt.xlabel('Day')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Mean_Energy_In_Month.png')
plt.show()
```

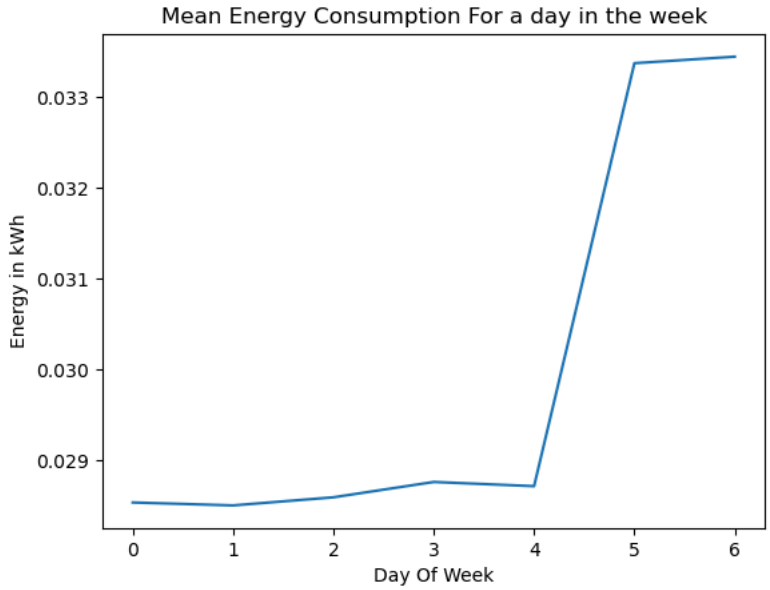


Consumption behavior is consistent across days with minor variations, indicating structured usage patterns rather than noise.

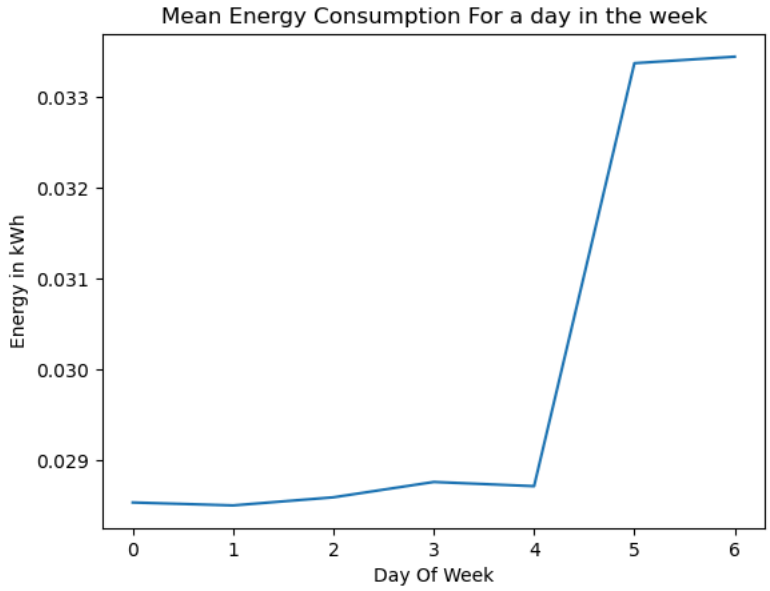
In [24]:
```
df.groupby(df['timestamp'].dt.isocalendar().week)['energy_kWh'].sum().plot(title='Weekly Energy Consumption')
plt.xlabel('Week')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Sum_Weakly_Energy.png')
plt.show()
```



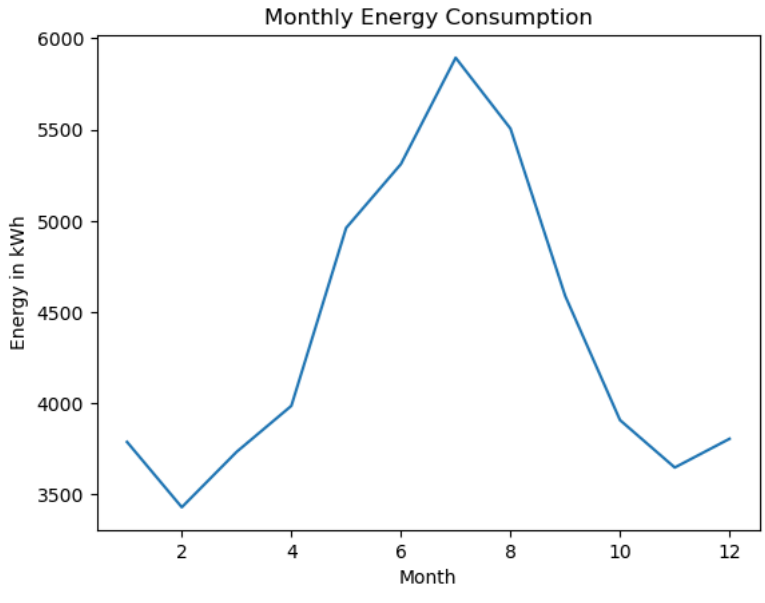
In [25]:
```
df.groupby(df['timestamp'].dt.weekday)['energy_kWh'].mean().plot(title='Mean Energy Consumption For a day in tl
plt.xlabel('Day Of Week')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Mean_Weekdays_Energy(1).png')
plt.show()
```



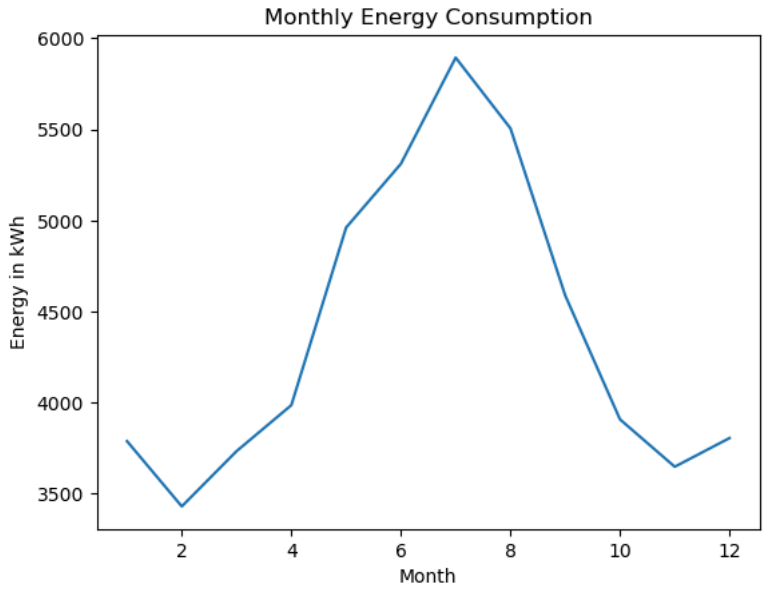
In [26]:
```
df.groupby(df['day_of_week'])['energy_kWh'].mean().plot(title='Mean Energy Consumption For a day in the week')
plt.xlabel('Day Of Week')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Mean_Weekdays_Energy(2).png')
plt.show()
```



In [27]:
```
df.groupby(df['timestamp'].dt.month)['energy_kWh'].sum().plot(title='Monthly Energy Consumption')
plt.xlabel('Month')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Sum_Monthly_Energy(1).png')
plt.show()
```

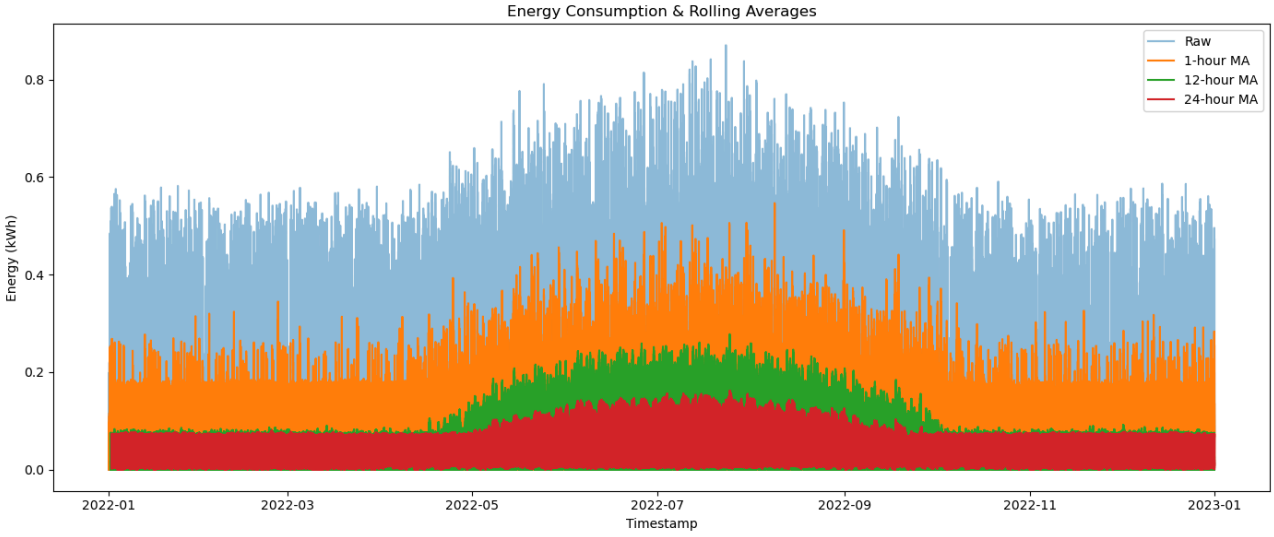


In [28]:
```
df.groupby(df['month_of_year'])['energy_kWh'].sum().plot(title='Monthly Energy Consumption')
plt.xlabel('Month')
plt.ylabel('Energy in kWh')
plt.savefig(FIG_PATH+'\Sum_Monthly_Energy(2).png')
plt.show()
```



These plots highlight clear temporal patterns in energy consumption. The daily time-series reveals strong seasonal behavior across the year, while aggregated views confirm consistent usage cycles.

In [29]:
```
def plot_rolling_averages(df):
    """
    Plots raw energy consumption and rolling averages.
    """
    # Filter the required columns
    data = df[['timestamp', 'energy_kWh', 'energy_roll_mean_1hr', 'energy_roll_mean_12hr', 'energy_roll_mean_24

    plt.figure(figsize=(14,6))
    plt.plot(data['timestamp'], data['energy_kWh'], label='Raw', alpha=0.5)
    plt.plot(data['timestamp'], data['energy_roll_mean_1hr'], label='1-hour MA')
    plt.plot(data['timestamp'], data['energy_roll_mean_12hr'], label='12-hour MA')
    plt.plot(data['timestamp'], data['energy_roll_mean_24hr'], label='24-hour MA')

    plt.xlabel('Timestamp')
    plt.ylabel('Energy (kWh)')
    plt.title('Energy Consumption & Rolling Averages')
    plt.legend(loc="upper right")
    plt.tight_layout()
    plt.savefig(FIG_PATH+'/raw_rolling_avgs_plot.png')
    plt.show()

plot_rolling_averages(df)
```



Scaling / Normalization

In [30]:
```
df.columns
```

Out [30]:
```
Index(['home_id', 'timestamp', 'device_type', 'room', 'status', 'user_present',
       'activity', 'indoor_temp', 'outdoor_temp', 'humidity', 'light_level',
       'is_weekend', 'month_of_year', 'day_of_week', 'hour_of_day',
       'energy_kWh', 'energy_lag_1H', 'energy_lag_1D', 'energy_lag_1W',
       'energy_roll_mean_1hr', 'energy_roll_mean_12hr',
       'energy_roll_mean_24hr'],
      dtype='object')
```

In [31]:
```
df = df.dropna()
```

dropping NaN values (from lag and rolling statistic) as models couldn't learn from them.

Rearraging Dataframe records so that they appear sequential for a home and device

In [32]:
```
df_seq = df.sort_values(['home_id', 'device_type', 'timestamp']).reset_index(drop=True)
df_seq[['home_id', 'device_type', 'timestamp']].head(20)
```

Out [32]:

	home_id	device_type	timestamp
0	1	air_conditioner	2022-01-08 00:00:00
1	1	air_conditioner	2022-01-08 00:15:00
2	1	air_conditioner	2022-01-08 00:30:00
3	1	air_conditioner	2022-01-08 00:45:00
4	1	air_conditioner	2022-01-08 01:00:00
5	1	air_conditioner	2022-01-08 01:15:00
6	1	air_conditioner	2022-01-08 01:30:00
7	1	air_conditioner	2022-01-08 01:45:00
8	1	air_conditioner	2022-01-08 02:00:00
9	1	air_conditioner	2022-01-08 02:15:00
10	1	air_conditioner	2022-01-08 02:30:00
11	1	air_conditioner	2022-01-08 02:45:00
12	1	air_conditioner	2022-01-08 03:00:00
13	1	air_conditioner	2022-01-08 03:15:00
14	1	air_conditioner	2022-01-08 03:30:00
15	1	air_conditioner	2022-01-08 03:45:00
16	1	air_conditioner	2022-01-08 04:00:00
17	1	air_conditioner	2022-01-08 04:15:00
18	1	air_conditioner	2022-01-08 04:30:00
19	1	air_conditioner	2022-01-08 04:45:00

In [33]:
```
non_num_cat = ['device_type', 'room', 'activity']
```

OneHotEncoder is used for categorical features because they do not possess any inherent order, and encoding them as independent binary variables prevents the model from learning false numerical relationships.

In [34]:
```
binary_cat = ['status', 'is_weekend']  # turn to 0s and 1s
```

Binary categorical features are converted to 0 and 1 since they naturally represent two possible states.

In [35]:
```
num_cols = ['indoor_temp', 'outdoor_temp', 'humidity', 'light_level']
```

The above columns are continuous numerical features and are scaled before modeling. (not include `power_watt` as it is directly correlated to energy and cause leakage).

In [36]:
```
target_col = ['energy_kWh']
```

Note: `energy_kWh` is not scaled

The target variable is left unchanged because:

- Models can directly learn from its natural scale
- Scaling the target is only necessary for neural networks or extreme ranges
- Keeping it raw makes evaluation metrics (MAE, RMSE) easier to interpret

In [37]:
```
other_cols = ['home_id', 'device_type', 'user_present', 'timestamp', 'day_of_week', 'hour_of_day', 'month_of_y
       'energy_lag_1W', 'energy_roll_mean_1hr', 'energy_roll_mean_12hr',
       'energy_roll_mean_24hr']
```

Above columns carry contextual or already-numeric info that doesn't need transformation, so they remain as-is.

Extracting Independent and dependent feature separately

In [38]:
```
# separating numeric columns to scale after splitting
X_num = df_seq[num_cols].copy()

# Columns that do not need to undergo transformation
X_rem = df_seq[other_cols].copy()

X_bin = df_seq[binary_cat].copy()
# turn to 0s and 1s
X_bin['status'] =  X_bin['status'].map({'off': 0, 'on': 1})
X_bin['is_weekend'] =  X_bin['is_weekend'].astype(int)

# Concatenating all features after transformation to form independent features
X = pd.concat([X_rem, X_bin, X_num], axis=1)

# Extracting the target variable for regression.
y = df_seq[target_col].copy()
```

Encode Categorical Labelled Data

In [39]:
```
encoder = joblib.load('../saved_objects/ohe.joblib')    # loading saved encoder from milestone 1

# Encoding labeled data
X_cat_array = encoder.transform(df_seq[non_num_cat])
encoded_cols = encoder.get_feature_names_out(non_num_cat)
X_cat = pd.DataFrame(X_cat_array, columns=encoded_cols, index=df_seq.index)

X = pd.concat([X, X_cat], axis=1)
```

In [40]:
```
X.columns
```

Out [40]:
```
Index(['home_id', 'device_type', 'user_present', 'timestamp', 'day_of_week',
       'hour_of_day', 'month_of_year', 'energy_lag_1H', 'energy_lag_1D',
       'energy_lag_1W', 'energy_roll_mean_1hr', 'energy_roll_mean_12hr',
       'energy_roll_mean_24hr', 'status', 'is_weekend', 'indoor_temp',
       'outdoor_temp', 'humidity', 'light_level',
       'device_type_air_conditioner', 'device_type_fridge',
       'device_type_light', 'device_type_tv', 'device_type_washer',
       'room_bedroom', 'room_kitchen', 'room_laundry_room', 'room_living_room',
       'activity_away', 'activity_cooking', 'activity_idle',
       'activity_sleeping', 'activity_watching_tv'],
      dtype='object')
```

In [41]:
```
final_col_order = ['home_id','device_type', 'timestamp', 'user_present', 'status', 'is_weekend', 'hour_of_day'

X = X.reindex(columns=final_col_order)
```

Columns are explicitly re-ordered after transformation to maintain a consistent feature layout

In [42]:
```
X.columns
```

Out [42]:
```
Index(['home_id', 'device_type', 'timestamp', 'user_present', 'status',
       'is_weekend', 'hour_of_day', 'day_of_week', 'month_of_year',
       'indoor_temp', 'outdoor_temp', 'humidity', 'light_level',
       'device_type_air_conditioner', 'device_type_fridge',
       'device_type_light', 'device_type_tv', 'device_type_washer',
       'room_bedroom', 'room_kitchen', 'room_laundry_room', 'room_living_room',
       'activity_away', 'activity_cooking', 'activity_idle',
       'activity_sleeping', 'activity_watching_tv', 'energy_lag_1H',
       'energy_lag_1D', 'energy_lag_1W', 'energy_roll_mean_1hr',
       'energy_roll_mean_12hr', 'energy_roll_mean_24hr'],
      dtype='object')
```

In [43]:
```
X[['home_id', 'device_type', 'timestamp']].head(20)      # groups formed ussing metadata home_id and device_ty
```

Out [43]:

	home_id	device_type	timestamp
0	1	air_conditioner	2022-01-08 00:00:00
1	1	air_conditioner	2022-01-08 00:15:00
2	1	air_conditioner	2022-01-08 00:30:00
3	1	air_conditioner	2022-01-08 00:45:00

	home_id	device_type	timestamp
4	1	air_conditioner	2022-01-08 01:00:00
5	1	air_conditioner	2022-01-08 01:15:00
6	1	air_conditioner	2022-01-08 01:30:00
7	1	air_conditioner	2022-01-08 01:45:00
8	1	air_conditioner	2022-01-08 02:00:00
9	1	air_conditioner	2022-01-08 02:15:00
10	1	air_conditioner	2022-01-08 02:30:00
11	1	air_conditioner	2022-01-08 02:45:00
12	1	air_conditioner	2022-01-08 03:00:00
13	1	air_conditioner	2022-01-08 03:15:00
14	1	air_conditioner	2022-01-08 03:30:00
15	1	air_conditioner	2022-01-08 03:45:00
16	1	air_conditioner	2022-01-08 04:00:00
17	1	air_conditioner	2022-01-08 04:15:00
18	1	air_conditioner	2022-01-08 04:30:00
19	1	air_conditioner	2022-01-08 04:45:00

Split the dataset

In [44]:
```
df_split = pd.concat([X, y], axis = 1)

train_rec = []
test_rec = []

# splitting the train and test records in such a way that they have sequential and grouped data
for _, group in df_split.groupby(['home_id', 'device_type']):
    n = len(group)
    split = int(n * 0.7)

    train_rec.append(group.iloc[: split])
    test_rec.append(group.iloc[split:])

train_df = pd.concat(train_rec)
test_df = pd.concat(test_rec)

# Splitting the dataset so the model learns on 70% of data and is tested on the remaining 30%.
print("Train shape:", train_df.shape)
print("Test shape:", test_df.shape)
```

```
Train shape: (1202850, 34)
Test shape: (515550, 34)
```

splliting the dataset before scaling, to fit scaler on train set's values and accordingly transform the unseen/test values.

Scaling wrt Train dataset range

In [45]:
```
scaler = MinMaxScaler()

# scaling numerical value columns:
train_df[num_cols] = pd.DataFrame(scaler.fit_transform(train_df[num_cols]), columns=num_cols, index=train_df.i
```

save the scaler for new inputs from web

In [46]:
```
joblib.dump(scaler, '../saved_objects/scaler.joblib')
```

Out [46]:
```
['../saved_objects/scaler.joblib']
```

scale numerical feature of test set wrt train's scaler

In [47]:
```
test_df[num_cols] = pd.DataFrame(scaler.transform(test_df[num_cols]), columns=num_cols, index=test_df.index)
```

In [48]:
```
joblib.dump(train_df, '../saved_objects/train_df.joblib')     # saving train dataframe for lstm
joblib.dump(test_df, '../saved_objects/temp_df.joblib')       #saving the rest 30% to be split into validation
```

Out [48]:
```
['../saved_objects/temp_df.joblib']
```

Module 4: Baseline Model Development

Module 4.1: Implement Linear Regression as baseline forecasting model

In [49]:
```
baseline_mod = LinearRegression()
```

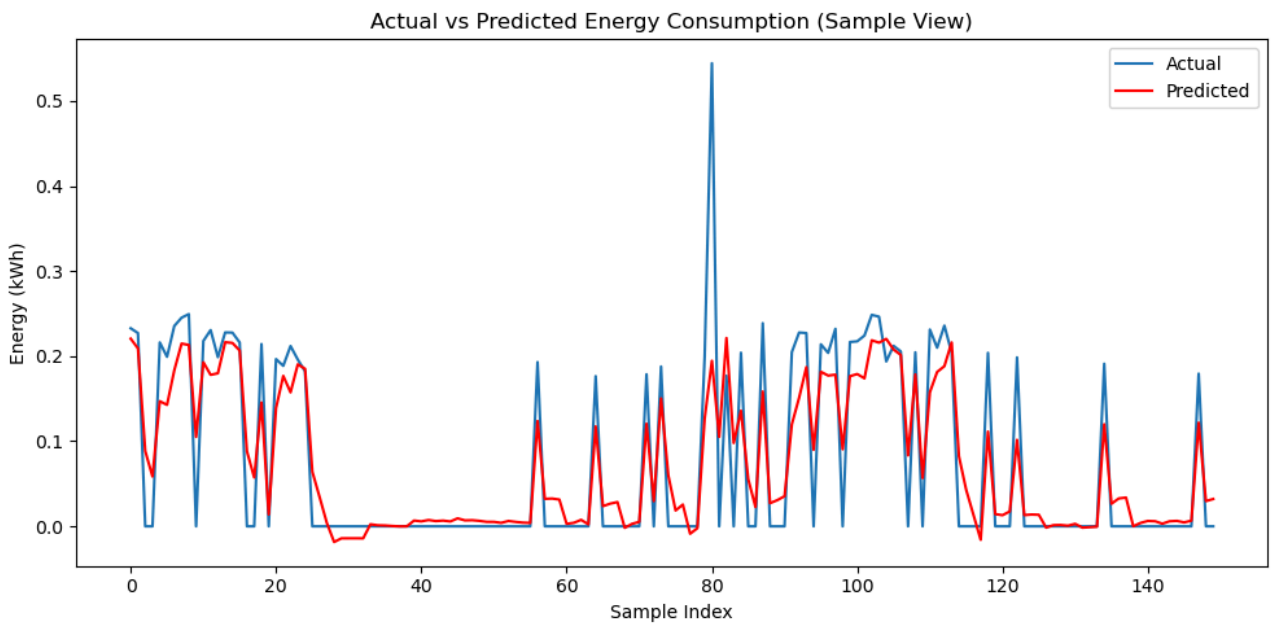
Module 4.2: Train and evaluate baseline using MAE, RMSE metrics

In [50]:
```
drop_cols = ['home_id', 'device_type', 'timestamp', 'energy_kWh']    # linear regression can only utilize nume

X_lr_train = train_df.drop(columns = drop_cols)
X_lr_test = test_df.drop(columns = drop_cols)

y_lr_train = train_df['energy_kWh']
y_lr_test = test_df['energy_kWh']

CHANGES = False

if CHANGES:
    baseline_mod.fit(X_lr_train, y_lr_train)
    joblib.dump(baseline_mod, "../saved_objects/LR_baseline.joblib")
else:
    baseline_mod = joblib.load("../saved_objects/LR_baseline.joblib")

y_pred_train = baseline_mod.predict(X_lr_train)
y_pred_test = baseline_mod.predict(X_lr_test)

mae_train = mean_absolute_error(y_lr_train, y_pred_train)
rmse_train = root_mean_squared_error(y_lr_train, y_pred_train)

mae_test = mean_absolute_error(y_lr_test, y_pred_test)
rmse_test = root_mean_squared_error(y_lr_test, y_pred_test)

print("Train MAE:", mae_train)
print("Train RMSE:", rmse_train)
print()
print("Test MAE:", mae_test)
print("Test RMSE:", rmse_test)
```

```
Train MAE: 0.016271256252779188
Train RMSE: 0.028673813401775477

Test MAE: 0.016088512253311087
Test RMSE: 0.025856943300317858
```

Module 4.3: Plot actual vs predicted energy usage.

In [51]:
```
sample_size = 150  # avoid clutter
plt.figure(figsize=(10, 5))
plt.plot(y_lr_test.values[:sample_size], label="Actual")
plt.plot(y_pred_test[:sample_size], label="Predicted", color='red')
plt.xlabel("Sample Index")
plt.ylabel("Energy (kWh)")
plt.title("Actual vs Predicted Energy Consumption (Sample View)")
plt.legend()
plt.tight_layout()
plt.show()
```



Linear regression captures average consumption trends but struggles with rare high-energy events due to its linear assumptions

In [52]:
```
mae = mean_absolute_error(y_lr_test, y_pred_test)
rmse = np.sqrt(mean_squared_error(y_lr_test, y_pred_test))
r2 = r2_score(y_lr_test, y_pred_test)

print(f"Test MAE  : {mae:.5f}")
print(f"Test RMSE : {rmse:.5f}")
print(f"Test R²   : {r2:.4f}")
```

```
Test MAE  : 0.01609
Test RMSE : 0.02586
Test R²   : 0.7084
```

Baseline Model Metrics (Linear Regression)

MAE, RMSE, and R² are reported to quantify prediction accuracy and goodness of fit. These establish a reference point for comparing more complex models.

Module 4.4: Use baseline model for model comparison.

The linear regression model serves as a baseline reference to evaluate future LSTM model.
Its performance metrics and prediction behavior establish a minimum benchmark against which LSTM will be compared.

`Train MAE ≈ Test MAE ≈ 0.016`

But

`Train RMSE: 0.02867 > Test RMSE: 0.02585`

Test error < Train error

Cross Validation

In [53]:
```
_df = pd.concat([train_df, test_df], axis = 0)
_df = _df.sort_values(["home_id", "device_type", "timestamp"])

X = _df.drop(columns = drop_cols)
y = _df['energy_kWh']
```

In [54]:
```
tscv = TimeSeriesSplit(n_splits=5)

mae_scores=[]
rmse_scores=[]

for train_idx, val_idx in tscv.split(X):
    X_tr, X_val = X.iloc[train_idx], X.iloc[val_idx]
    y_tr, y_val = y.iloc[train_idx], y.iloc[val_idx]

    X_tr = X_tr[[c for c in X_tr.columns if c  not in drop_cols]]
    X_val = X_val[[c for c in X_val.columns if c not in drop_cols]]

    val_model = LinearRegression()
```

```
    val_model.fit(X_tr, y_tr)

    preds = val_model.predict(X_val)

    mae_scores.append(mean_absolute_error(y_val, preds))
    rmse_scores.append(root_mean_squared_error(y_val, preds))

print("CV MAE:", np.mean(mae_scores))
print("CV RMSE:", np.mean(rmse_scores))
```

```
CV MAE: 0.01564493042434372
CV RMSE: 0.027149118449888814
```

In [55]:
```
mae_scores
```

Out [55]:
```
[0.016718619851732824,
 0.015440713385055286,
 0.015943147285023204,
 0.01506369397928797,
 0.015058477620619326]
```

In [56]:
```
rmse_scores
```

Out [56]:
```
[0.0292547160020338,
 0.025108799694969854,
 0.027654056097313556,
 0.028094578125960303,
 0.025633442329166572]
```

The Linear Regression baseline shows stable and consistent performance across train, test, and time-series cross-validation splits. The low variance across CV folds and close alignment between CV and test metrics indicate strong generalization and minimal temporal leakage.

CV mean stats:

`mae = 0.015 rmse = 0.027`

mae score for different splits lies in range `0.015 - 0.016`

rmse score for different splits lie in range `0.025 - 0.029`