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

df = joblib.load('../saved_objects/df_cleaned.joblib')
df
```

Out [1]:

	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 [2]:
```
df.columns
```

Out [2]:
```
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 [3]:
```
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 [3]:

	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	washer	laundry_room	off	0.000000	1	sleeping	11.4	11.9	45.2

	home_id	timestamp	device_type	room	status	power_watt	user_present	activity	indoor_temp	outdoor_temp	humidity
		00:00:00									
...	...	...	...	...	...	...	...	...	...	...	...
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 [4]:

```
df.groupby(["home_id", "device_type"])["energy_kWh"].describe()
```

Out [4]:

home_id	device_type	count	mean	std	min	25%	50%	75%	max
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
	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

home_id	device_type	count	mean	std	min	25%	50%	75%	max
	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

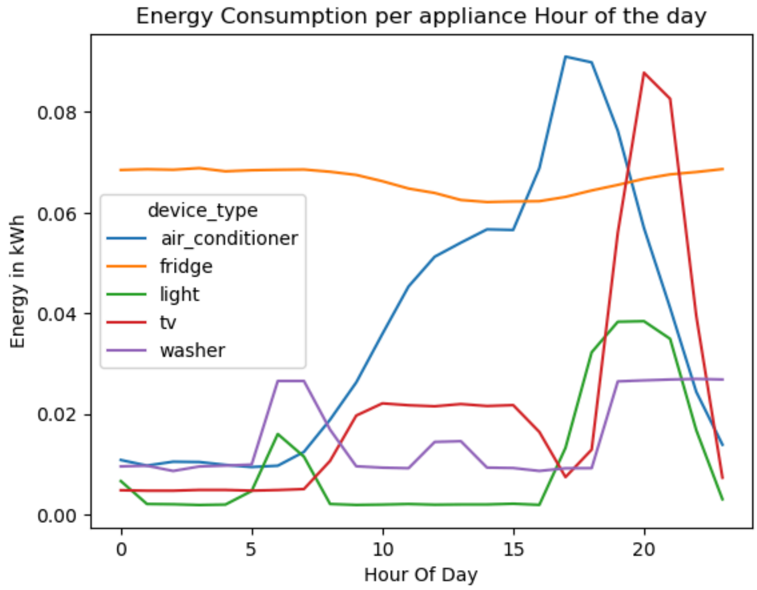
This provides an overview of device-level consumption patterns.

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

In [5]:
```
import os
import matplotlib.pyplot as plt

BASE_dir = os.getcwd()
FIG_PATH = os.path.abspath(BASE_dir + '/../reports/Milestone1/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 [6]:
```
# 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 [7]:
```
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(le
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 [8]:
```
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_rol
```

Out [8]:

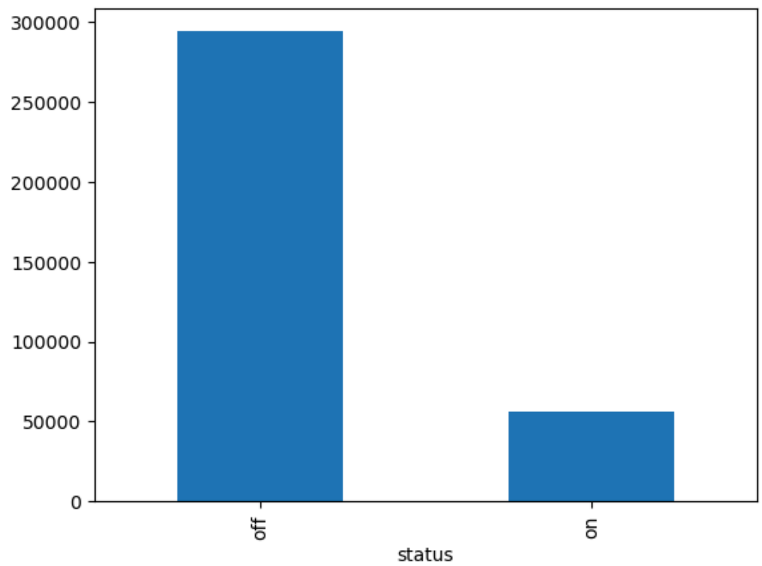
	timestamp	energy_kWh	energy_lag_1H	energy_lag_1D	energy_lag_1W	energy_roll_mean_1hr	energy_roll_mean_6hr	energy_roll_mean_12hr
3	2022-01-01 00:00:00	0.055865	NaN	NaN	NaN	NaN	NaN	NaN
53	2022-01-01 00:15:00	0.053638	NaN	NaN	NaN	NaN	NaN	NaN
103	2022-01-01 00:30:00	0.058825	NaN	NaN	NaN	NaN	NaN	NaN
153	2022-01-01 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
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 [14]:
```
df[df['device_type']=='air_conditioner']['status'].value_counts().plot(kind='bar')
```

Out [14]: <Axes: xlabel='status'>



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.

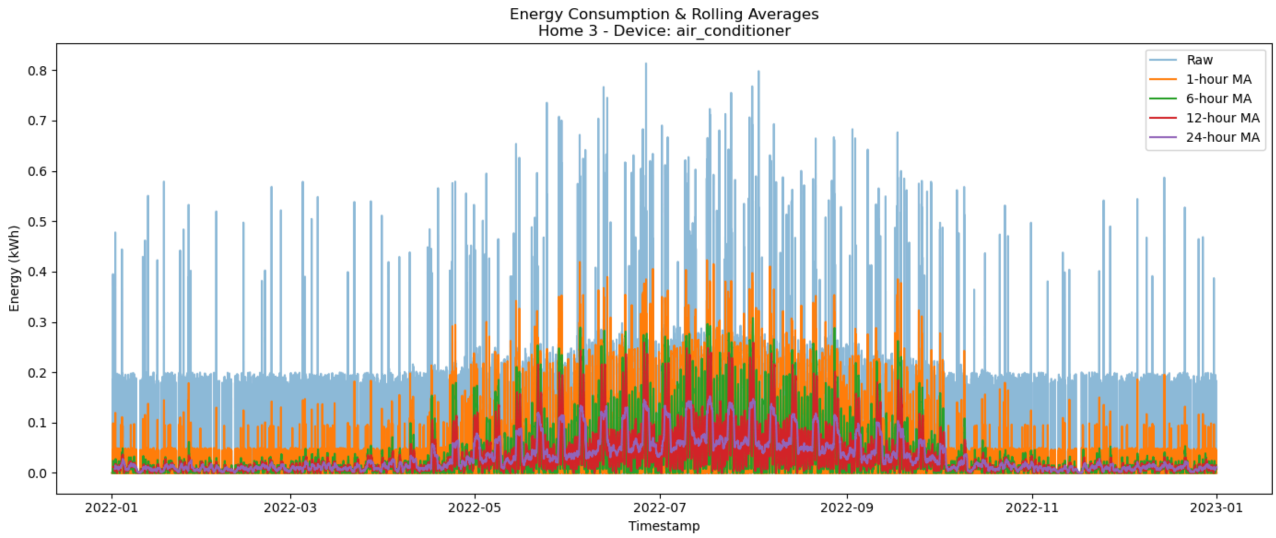
In [15]:

```
def plot_rolling_averages(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.show()

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



In [18]:

```
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 [19]:

```
df.columns
```

Out [19]:

```
Index(['home_id', 'timestamp', 'device_type', 'room', 'status', 'power_watt',
       'user_present', 'activity', 'indoor_temp', 'outdoor_temp', 'humidity',
       'light_level', 'month_of_year', 'is_weekend', '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 [10]:

```
##### 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 [11]:

```
df[['day_of_week', 'is_weekend']]
```

Out [11]:

	day_of_week	is_weekend
0	5	True
1	5	True

	day_of_week	is_weekend
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 [12]:
```
df.columns
```

Out [12]:
```
Index(['home_id', 'timestamp', 'device_type', 'room', 'status', 'power_watt',
       'user_present', 'activity', 'indoor_temp', 'outdoor_temp', 'humidity',
       'light_level', 'month_of_year', 'is_weekend', 'day_of_week',
       'hour_of_day', 'energy_kWh', 'energy_lag_1H', 'energy_lag_1D',
       'energy_lag_1W', 'energy_roll_mean_1hr', 'energy_roll_mean_6hr',
       'energy_roll_mean_12hr', 'energy_roll_mean_24hr'],
      dtype='object')
```

1. Device & Household Context

"`home_id, device_type, room, status, power_watt, 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.

In [ ]: