In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler
import numpy as np
```

In [2]:
```
data = pd.read_csv('HomeC.csv', low_memory=False)
data.head()
```

Out[2]:

	time	use [kW]	gen [kW]	House overall [kW]	Dishwasher [kW]	Furnace 1 [kW]	Furnace 2 [kW]	Home office [kW]	Fridg [kW
0	1451624400	0.932833	0.003483	0.932833	0.000033	0.020700	0.061917	0.442633	0.12415
1	1451624401	0.934333	0.003467	0.934333	0.000000	0.020717	0.063817	0.444067	0.12400
2	1451624402	0.931817	0.003467	0.931817	0.000017	0.020700	0.062317	0.446067	0.12353
3	1451624403	1.022050	0.003483	1.022050	0.000017	0.106900	0.068517	0.446583	0.12313
4	1451624404	1.139400	0.003467	1.139400	0.000133	0.236933	0.063983	0.446533	0.12285

5 rows × 32 columns

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 503911 entries, 0 to 503910
Data columns (total 32 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   time                 503911 non-null  object 
 1   use [kW]             503910 non-null  float64
 2   gen [kW]             503910 non-null  float64
 3   House overall [kW]   503910 non-null  float64
 4   Dishwasher [kW]      503910 non-null  float64
 5   Furnace 1 [kW]       503910 non-null  float64
 6   Furnace 2 [kW]       503910 non-null  float64
 7   Home office [kW]     503910 non-null  float64
 8   Fridge [kW]          503910 non-null  float64
 9   Wine cellar [kW]     503910 non-null  float64
 10  Garage door [kW]     503910 non-null  float64
 11  Kitchen 12 [kW]      503910 non-null  float64
 12  Kitchen 14 [kW]      503910 non-null  float64
 13  Kitchen 38 [kW]      503910 non-null  float64
 14  Barn [kW]            503910 non-null  float64
 15  Well [kW]            503910 non-null  float64
 16  Microwave [kW]       503910 non-null  float64
 17  Living room [kW]     503910 non-null  float64
 18  Solar [kW]           503910 non-null  float64
 19  temperature          503910 non-null  float64
 20  icon                 503910 non-null  object 
 21  humidity             503910 non-null  float64
 22  visibility           503910 non-null  float64
 23  summary              503910 non-null  object 
 24  apparentTemperature  503910 non-null  float64
 25  pressure             503910 non-null  float64
 26  windSpeed            503910 non-null  float64
 27  cloudCover           503910 non-null  object 
 28  windBearing          503910 non-null  float64
 29  precipIntensity      503910 non-null  float64
 30  dewPoint             503910 non-null  float64
 31  precipProbability    503910 non-null  float64
dtypes: float64(28), object(4)
memory usage: 123.0+ MB
```

In [4]:
```
data.tail()
```

Out[4]:

	time	use [kW]	gen [kW]	House overall [kW]	Dishwasher [kW]	Furnace 1 [kW]	Furnace 2 [kW]	Home office [kW]	
503906	1452128306	1.599333	0.003233	1.599333	0.000050	0.104017	0.625033	0.041750	0.
503907	1452128307	1.924267	0.003217	1.924267	0.000033	0.422383	0.637733	0.042033	0.
503908	1452128308	1.978200	0.003217	1.978200	0.000050	0.495667	0.620367	0.042100	0.
503909	1452128309	1.990950	0.003233	1.990950	0.000050	0.494700	0.634133	0.042100	0.
503910	\	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

5 rows × 32 columns

In [5]:
```
data=data[:-1]
data.tail()
```

Out[5]:

	time	use [kW]	gen [kW]	House overall [kW]	Dishwasher [kW]	Furnace 1 [kW]	Furnace 2 [kW]	Home office [kW]	
503905	1452128305	1.601233	0.003183	1.601233	0.000050	0.085267	0.642417	0.041783	0.
503906	1452128306	1.599333	0.003233	1.599333	0.000050	0.104017	0.625033	0.041750	0.
503907	1452128307	1.924267	0.003217	1.924267	0.000033	0.422383	0.637733	0.042033	0.
503908	1452128308	1.978200	0.003217	1.978200	0.000050	0.495667	0.620367	0.042100	0.
503909	1452128309	1.990950	0.003233	1.990950	0.000050	0.494700	0.634133	0.042100	0.

5 rows × 32 columns

In [6]:
```
#given that the time is in UNIX format, let's check
time_index = pd.date_range('2016-01-01 05:00', periods=len(data),  freq='min')
time_index = pd.DatetimeIndex(time_index)
data = data.set_index(time_index)
```

In [7]:
```
data.head()
```

Out[7]:

	time	use [kW]	gen [kW]	House overall [kW]	Dishwasher [kW]	Furnace 1 [kW]	Furnace 2 [kW]	Home office [kW]	
2016-01-01 05:00:00	1451624400	0.932833	0.003483	0.932833	0.000033	0.020700	0.061917	0.442633	(
2016-01-01 05:01:00	1451624401	0.934333	0.003467	0.934333	0.000000	0.020717	0.063817	0.444067	(
2016-01-01 05:02:00	1451624402	0.931817	0.003467	0.931817	0.000017	0.020700	0.062317	0.446067	(
2016-01-01 05:03:00	1451624403	1.022050	0.003483	1.022050	0.000017	0.106900	0.068517	0.446583	(
2016-01-01 05:04:00	1451624404	1.139400	0.003467	1.139400	0.000133	0.236933	0.063983	0.446533	(

5 rows × 32 columns

In [8]:
```
data.columns
```

Out[8]:
```
Index(['time', 'use [kW]', 'gen [kW]', 'House overall [kW]', 'Dishwasher [k
W]',
       'Furnace 1 [kW]', 'Furnace 2 [kW]', 'Home office [kW]', 'Fridge [kW]',
       'Wine cellar [kW]', 'Garage door [kW]', 'Kitchen 12 [kW]',
       'Kitchen 14 [kW]', 'Kitchen 38 [kW]', 'Barn [kW]', 'Well [kW]',
       'Microwave [kW]', 'Living room [kW]', 'Solar [kW]', 'temperature',
       'icon', 'humidity', 'visibility', 'summary', 'apparentTemperature',
       'pressure', 'windSpeed', 'cloudCover', 'windBearing', 'precipIntensit
y',
       'dewPoint', 'precipProbability'],
      dtype='object')
```

In [9]:
```
data.columns = [col.replace(' [kW]', '') for col in data.columns]
data.columns
```

Out[9]:
```
Index(['time', 'use', 'gen', 'House overall', 'Dishwasher', 'Furnace 1',
       'Furnace 2', 'Home office', 'Fridge', 'Wine cellar', 'Garage door',
       'Kitchen 12', 'Kitchen 14', 'Kitchen 38', 'Barn', 'Well', 'Microwave',
       'Living room', 'Solar', 'temperature', 'icon', 'humidity', 'visibilit
y',
       'summary', 'apparentTemperature', 'pressure', 'windSpeed', 'cloudCove
r',
       'windBearing', 'precipIntensity', 'dewPoint', 'precipProbability'],
      dtype='object')
```

In [10]:
```
data['Furnace'] = data[['Furnace 1','Furnace 2']].sum(axis=1)
data['Kitchen'] = data[['Kitchen 12','Kitchen 14','Kitchen 38']].sum(axis=1)
data.drop(['Furnace 1','Furnace 2','Kitchen 12','Kitchen 14','Kitchen 38','icc
data.head(5)
```

Out[10]:

	time	use	gen	House overall	Dishwasher	Home office	Fridge	Win cella
2016-01-01 05:00:00	1451624400	0.932833	0.003483	0.932833	0.000033	0.442633	0.124150	0.00698
2016-01-01 05:01:00	1451624401	0.934333	0.003467	0.934333	0.000000	0.444067	0.124000	0.00698
2016-01-01 05:02:00	1451624402	0.931817	0.003467	0.931817	0.000017	0.446067	0.123533	0.00698
2016-01-01 05:03:00	1451624403	1.022050	0.003483	1.022050	0.000017	0.446583	0.123133	0.00698
2016-01-01 05:04:00	1451624404	1.139400	0.003467	1.139400	0.000133	0.446533	0.122850	0.00685

In [11]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 503910 entries, 2016-01-01 05:00:00 to 2016-12-16 03:29:00
Freq: T
Data columns (total 27 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   time                 503910 non-null  object 
 1   use                  503910 non-null  float64
 2   gen                  503910 non-null  float64
 3   House overall        503910 non-null  float64
 4   Dishwasher           503910 non-null  float64
 5   Home office          503910 non-null  float64
 6   Fridge               503910 non-null  float64
 7   Wine cellar          503910 non-null  float64
 8   Garage door          503910 non-null  float64
 9   Barn                 503910 non-null  float64
 10  Well                 503910 non-null  float64
 11  Microwave            503910 non-null  float64
 12  Living room          503910 non-null  float64
 13  Solar                503910 non-null  float64
 14  temperature          503910 non-null  float64
 15  humidity             503910 non-null  float64
 16  visibility           503910 non-null  float64
 17  apparentTemperature  503910 non-null  float64
 18  pressure             503910 non-null  float64
 19  windSpeed            503910 non-null  float64
 20  cloudCover           503910 non-null  object 
 21  windBearing          503910 non-null  float64
 22  precipIntensity      503910 non-null  float64
 23  dewPoint             503910 non-null  float64
 24  precipProbability    503910 non-null  float64
 25  Furnace              503910 non-null  float64
 26  Kitchen              503910 non-null  float64
dtypes: float64(25), object(2)
memory usage: 107.6+ MB
```

In [12]:
```
data['cloudCover'].unique()
```

Out[12]:
```
array(['cloudCover', '0.75', '0', '1', '0.31', '0.44', '0.13', '0.19',
       '0.25', '0.16', '0.21', '0.15', '0.14', '0.27', '0.28', '0.17',
       '0.05', '0.1', '0.26', '0.29', '0.11', '0.09', '0.12', '0.06',
       '0.02', '0.08', '0.04', '0.35', '0.22', '0.23', '0.54', '0.39',
       '0.03', '0.07', '0.76', '0.62', '0.18', '0.79', '0.48', '0.24',
       '0.57', '0.41', '0.78', '0.2', '0.77', '0.46', '0.55', '0.01',
       '0.51', '0.47', '0.5', '0.4', '0.3', '0.43', '0.33', '0.6', '0.68',
       '0.66', '0.45', '0.34', '0.52', '0.67', '0.49', '0.37', '0.36',
       '0.61', '0.38', '0.42', '0.53', '0.63', '0.32', '0.56', '0.58',
       '0.72', '0.73', '0.71', '0.64', '0.59'], dtype=object)
```

In [13]:
```
data['cloudCover'].replace(['cloudCover'], method='bfill', inplace=True)
data['cloudCover'] = data['cloudCover'].astype('float')
```

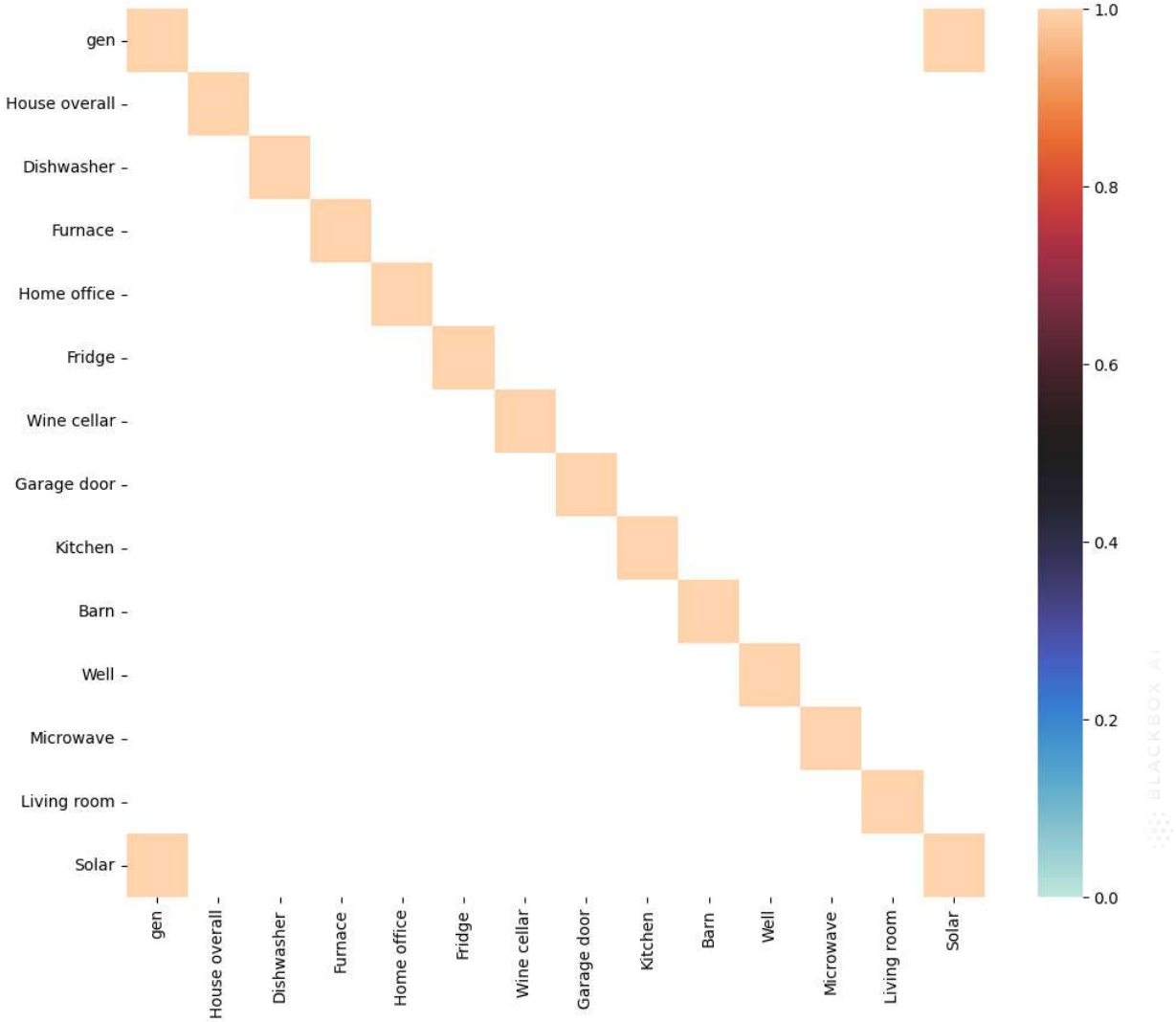
In [14]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 503910 entries, 2016-01-01 05:00:00 to 2016-12-16 03:29:00
Freq: T
Data columns (total 27 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   time                 503910 non-null  object 
 1   use                  503910 non-null  float64
 2   gen                  503910 non-null  float64
 3   House overall        503910 non-null  float64
 4   Dishwasher           503910 non-null  float64
 5   Home office          503910 non-null  float64
 6   Fridge               503910 non-null  float64
 7   Wine cellar          503910 non-null  float64
 8   Garage door          503910 non-null  float64
 9   Barn                 503910 non-null  float64
 10  Well                 503910 non-null  float64
 11  Microwave            503910 non-null  float64
 12  Living room          503910 non-null  float64
 13  Solar                503910 non-null  float64
 14  temperature          503910 non-null  float64
 15  humidity             503910 non-null  float64
 16  visibility           503910 non-null  float64
 17  apparentTemperature  503910 non-null  float64
 18  pressure             503910 non-null  float64
 19  windSpeed            503910 non-null  float64
 20  cloudCover           503910 non-null  float64
 21  windBearing          503910 non-null  float64
 22  precipIntensity      503910 non-null  float64
 23  dewPoint             503910 non-null  float64
 24  precipProbability    503910 non-null  float64
 25  Furnace              503910 non-null  float64
 26  Kitchen              503910 non-null  float64
dtypes: float64(26), object(1)
memory usage: 107.6+ MB
```

In [15]:
```
energy_data = data.filter(items=[ 'gen', 'House overall', 'Dishwasher', 'Furna
                                  'Wine cellar', 'Garage door', 'Kitchen',
                                  'Microwave', 'Living room', 'Solar'])

sensor_data = data.filter(items=['temperature',
                                   'humidity', 'visibility', 'apparentTempe
                                   'windSpeed', 'windBearing', 'dewPoint'])
```

In [16]:
```
fig = plt.subplots(figsize=(12, 10))
corr = energy_data.corr()
sns.heatmap(corr[corr>0.9], vmax=1, vmin=0, center=0.5)
plt.show()
```



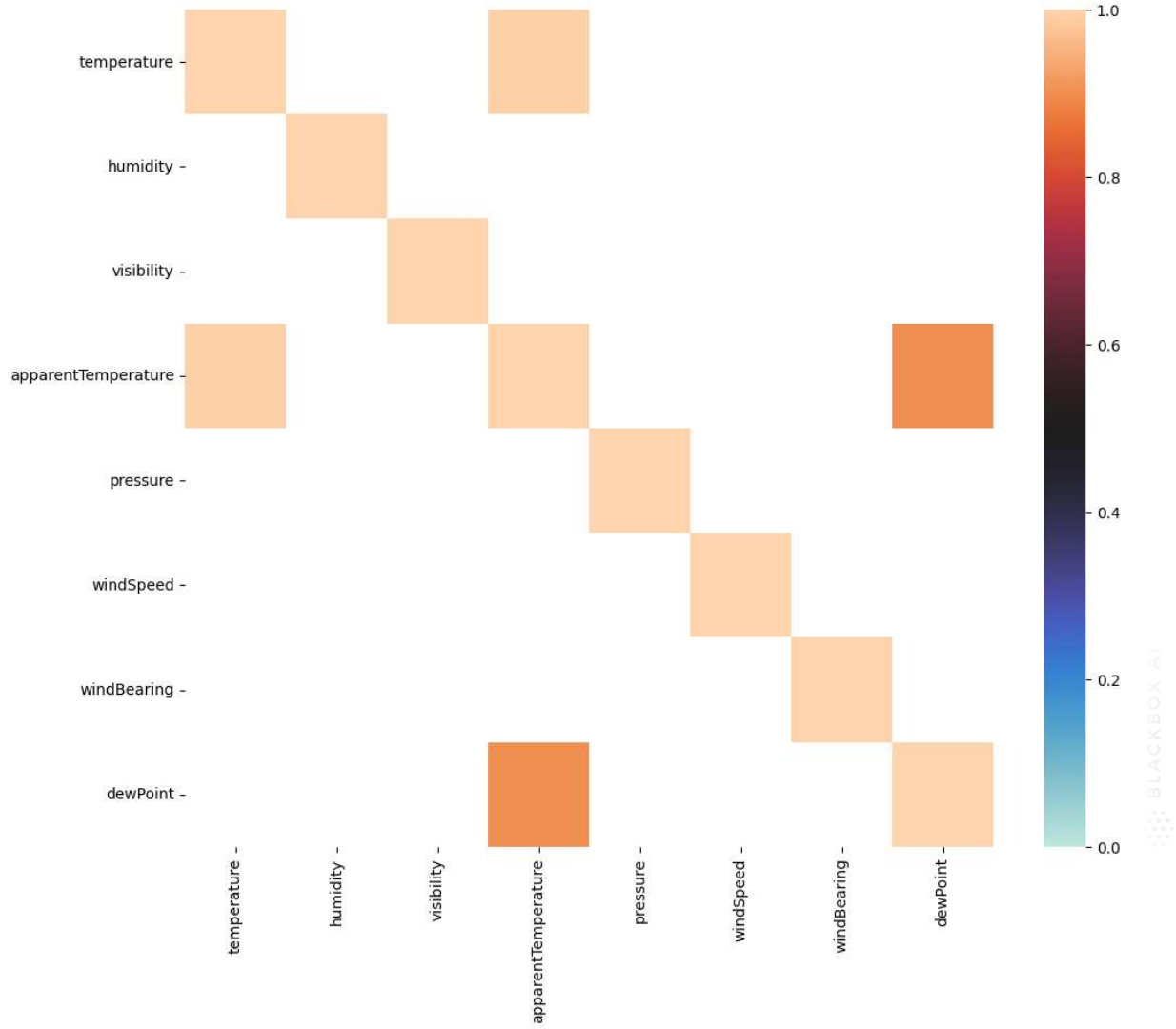
In [17]:
```
energy_data.drop(['Solar'], axis=1, inplace=True)
```

In [18]:
```
energy_data.head()
```

Out[18]:

	gen	House overall	Dishwasher	Furnace	Home office	Fridge	Wine cellar	Garage door	Ki
2016-01-01 05:00:00	0.003483	0.932833	0.000033	0.082617	0.442633	0.124150	0.006983	0.013083	0.0(
2016-01-01 05:01:00	0.003467	0.934333	0.000000	0.084533	0.444067	0.124000	0.006983	0.013117	0.0(
2016-01-01 05:02:00	0.003467	0.931817	0.000017	0.083017	0.446067	0.123533	0.006983	0.013083	0.0(
2016-01-01 05:03:00	0.003483	1.022050	0.000017	0.175417	0.446583	0.123133	0.006983	0.013000	0.0(
2016-01-01 05:04:00	0.003467	1.139400	0.000133	0.300917	0.446533	0.122850	0.006850	0.012783	0.0(

In [19]:
```
fig = plt.subplots(figsize=(12, 10))
corr = sensor_data.corr()
sns.heatmap(corr[corr>0.9], vmax=1, vmin=0, center=0.5)
plt.show()
```



In [20]:
```
sensor_data.drop(['apparentTemperature'], axis=1, inplace=True)
```

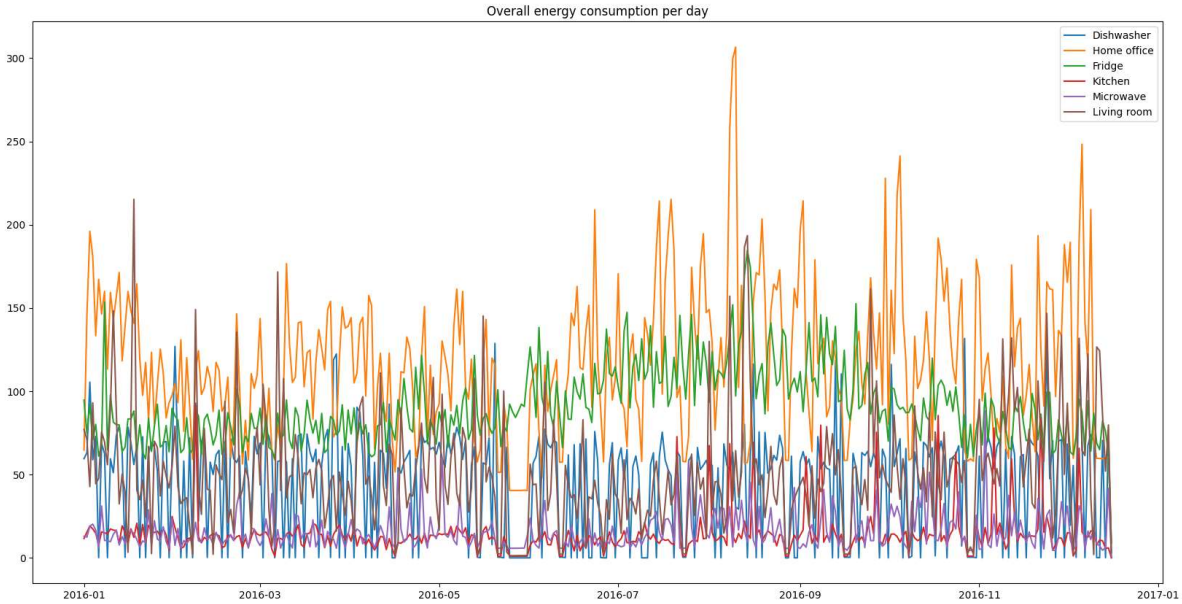
In [21]:
```
sensor_data.head()
```

Out[21]:

	temperature	humidity	visibility	pressure	windSpeed	windBearing	dewPoint
2016-01-01 05:00:00	36.14	0.62	10.0	1016.91	9.18	282.0	24.4
2016-01-01 05:01:00	36.14	0.62	10.0	1016.91	9.18	282.0	24.4
2016-01-01 05:02:00	36.14	0.62	10.0	1016.91	9.18	282.0	24.4
2016-01-01 05:03:00	36.14	0.62	10.0	1016.91	9.18	282.0	24.4
2016-01-01 05:04:00	36.14	0.62	10.0	1016.91	9.18	282.0	24.4

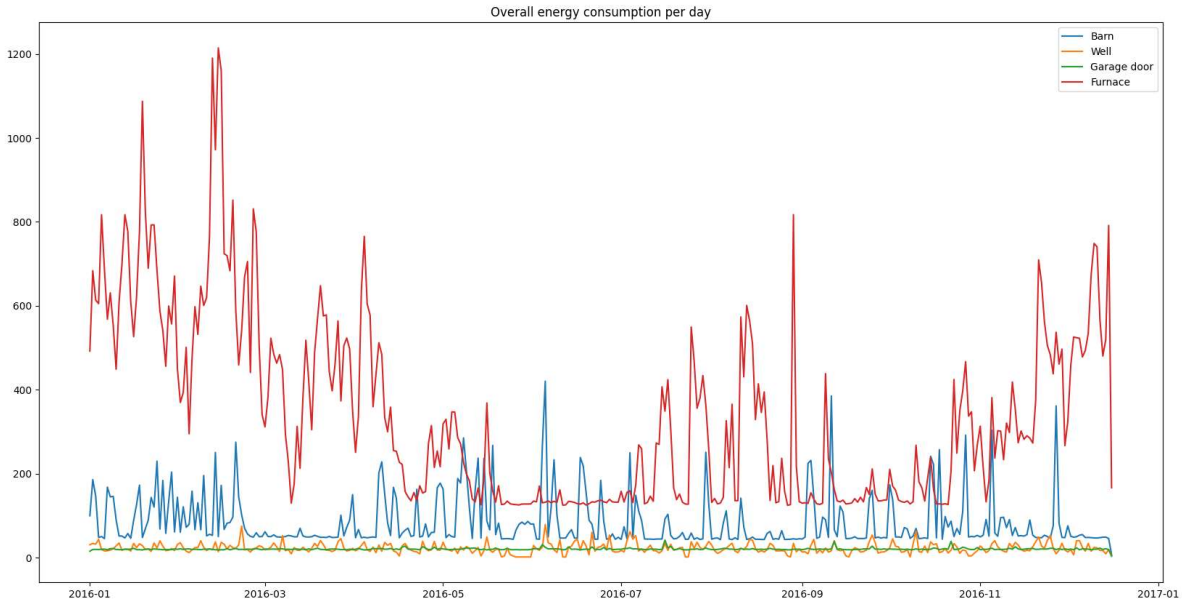
In [22]:
```
energy_per_day = energy_data.resample('D').sum()
plt.figure(figsize=(20,10))
plt.title("Overall energy consumption per day")
sns.lineplot(data = energy_per_day.filter(items=[ 'Dishwasher', 'Home office',
#'Dishwasher', 'Furnace', 'Home office', 'Fridge','Wine cellar', 'Garage door'
```

Out[22]: <Axes: title={'center': 'Overall energy consumption per day'}>



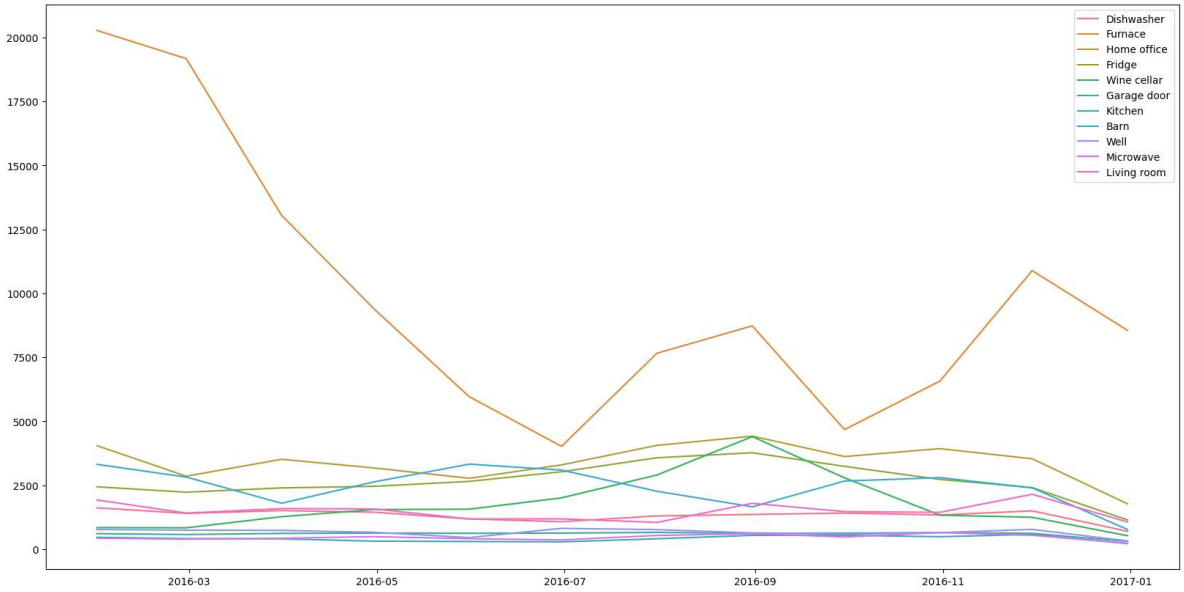
In [23]:
```
energy_per_day = energy_data.resample('D').sum()
plt.figure(figsize=(20,10))
plt.title("Overall energy consumption per day")
sns.lineplot(data = energy_per_day.filter(items=[ 'Barn', 'Well', 'Garage door
#'Dishwasher', 'Furnace', 'Home office', 'Fridge','Wine cellar', 'Garage door'
```

Out[23]: <Axes: title={'center': 'Overall energy consumption per day'}>



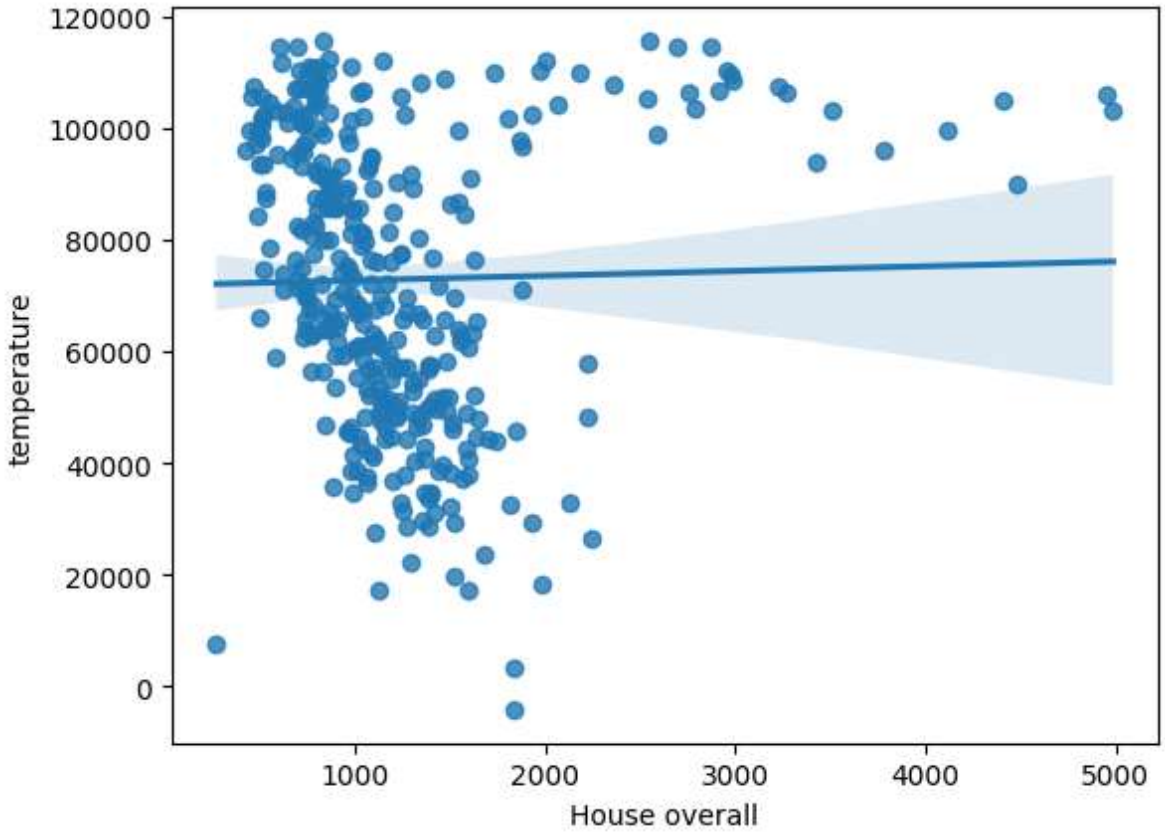
In [24]:
```
energy_per_month = energy_data.resample('M').sum() # for energy we use sum to
plt.figure(figsize=(20,10))
sns.lineplot(data= energy_per_month.filter(items=[  'Dishwasher', 'Furnace', '
                                        'Wine cellar', 'Garage door', 'Kitchen',
                                        'Microwave', 'Living room']) , dashes=Fal
```

Out[24]: <Axes: >



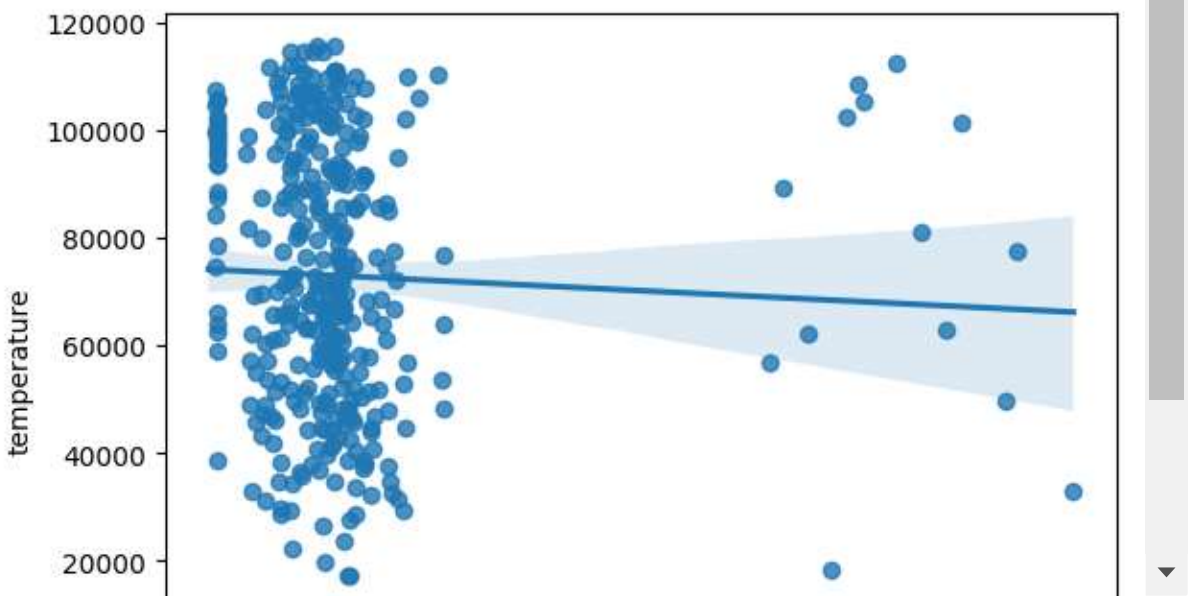
In [25]:
```
energy_per_day = energy_data.resample('D').sum()
sensor_per_day = sensor_data.resample('D').sum()
sns.regplot(x=energy_per_day['House overall'], y= sensor_per_day['temperature'
```

Out[25]:
```
<Axes: xlabel='House overall', ylabel='temperature'>
```



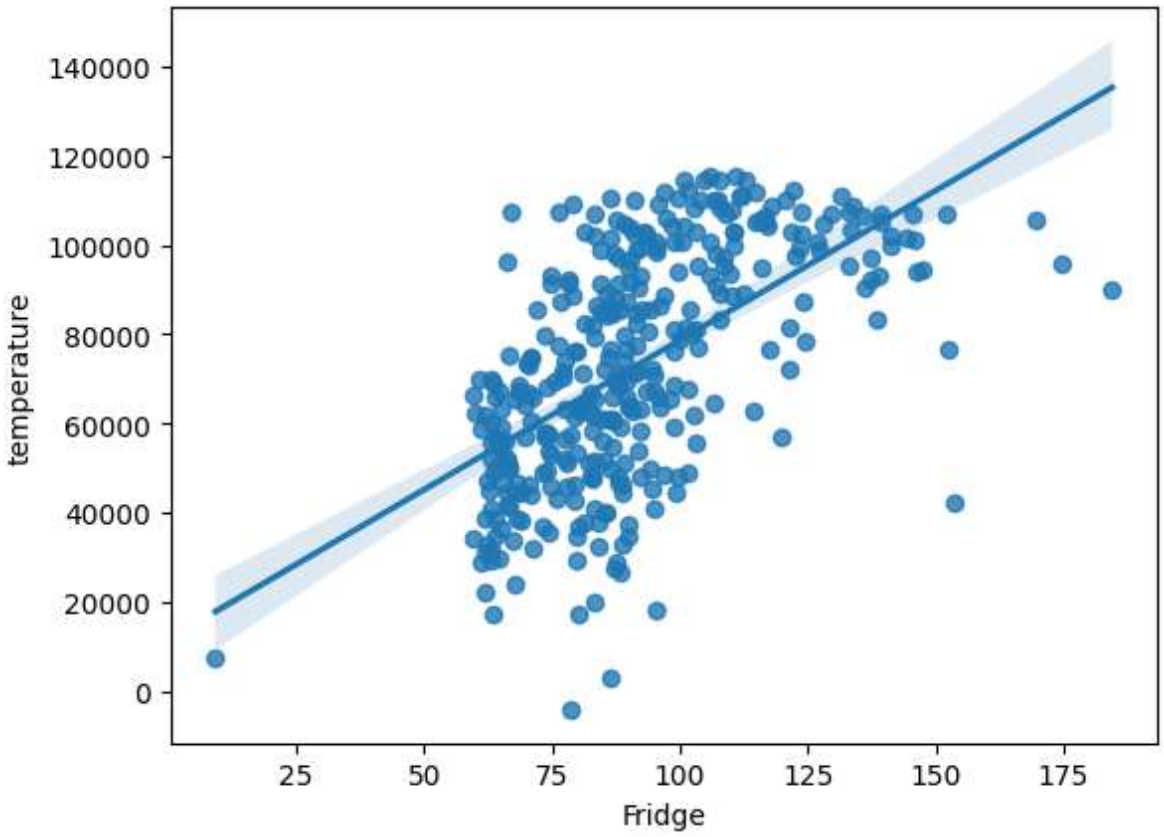
In [26]:
```
sns.regplot(x=energy_per_day['Kitchen'], y= sensor_per_day['temperature'])
```

Out[26]:
```
<Axes: xlabel='Kitchen', ylabel='temperature'>
```



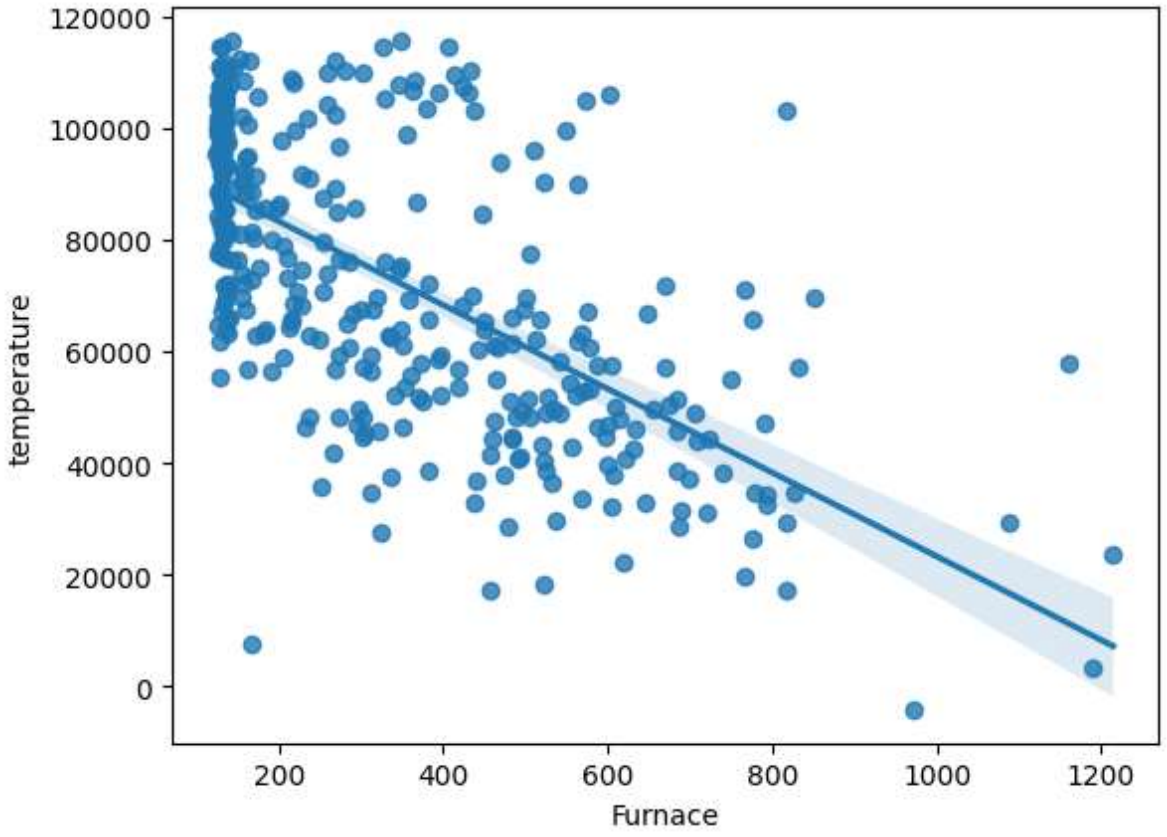
In [27]:
```
sns.regplot(x=energy_per_day['Fridge'], y= sensor_per_day['temperature'])
```

Out[27]:
```
<Axes: xlabel='Fridge', ylabel='temperature'>
```



In [28]:
```
sns.regplot(x=energy_per_day['Furnace'], y= sensor_per_day['temperature'])
```

Out[28]: <Axes: xlabel='Furnace', ylabel='temperature'>



In [29]:
```
combined_data = pd.concat([energy_data, sensor_data], axis=1)
```

In [30]:
```
combined_data.dropna(inplace=True)
```

In [31]:
```
X = combined_data.drop('House overall', axis=1)  # Features
y = combined_data['House overall']  # Target variable

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randc
```

In [32]:
```
# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [33]:
```
# Linear Regression Model
model_lr = LinearRegression()
model_lr.fit(X_train_scaled, y_train)
```

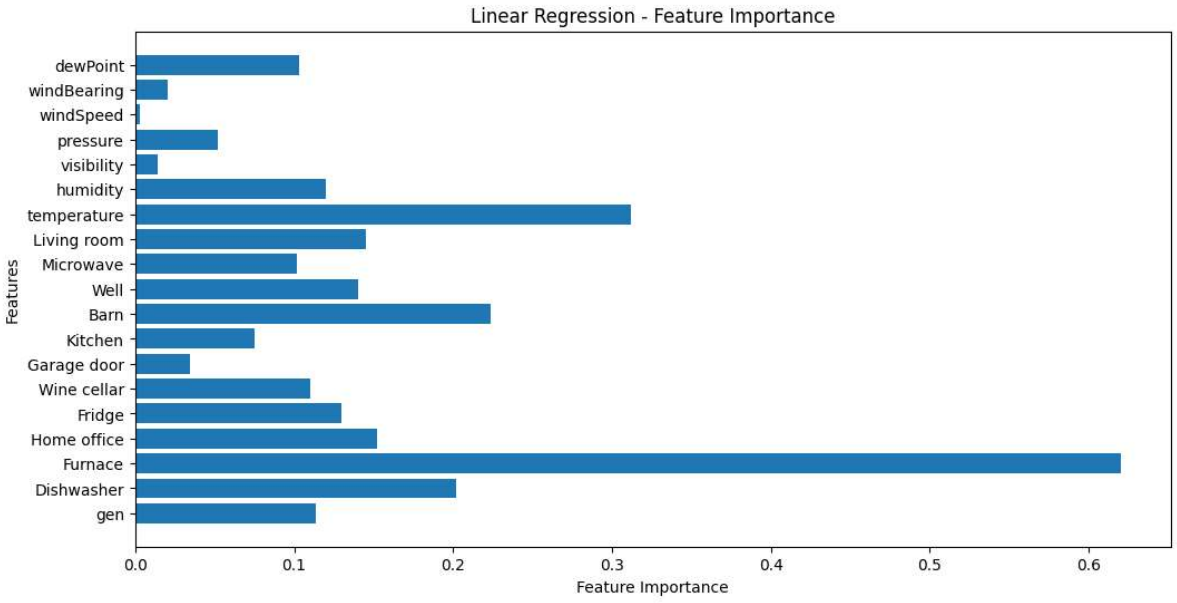
Out[33]:
```
LinearRegression()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [34]:
```
y_pred_lr = model_lr.predict(X_test_scaled)
```

In [35]:
```
mse_lr = mean_squared_error(y_test, y_pred_lr)
```

In [36]:
```
feature_importance_lr = np.abs(model_lr.coef_)
feature_names = X.columns

# Visualize feature importance
plt.figure(figsize=(12, 6))
plt.barh(feature_names, feature_importance_lr)
plt.xlabel('Feature Importance')
plt.ylabel('Features')
plt.title('Linear Regression - Feature Importance')
plt.show()
```



In [37]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import r2_score
```

In [ ]:
```
# Random Forest Regressor
model_rf = RandomForestRegressor(n_estimators=100, random_state=42)
model_rf.fit(X_train_scaled, y_train)
y_pred_rf = model_rf.predict(X_test_scaled)
r2_rf = r2_score(y_test, y_pred_rf)
print(f"Random Forest R-squared: {r2_rf}")
```

```
Random Forest R-squared: 0.9721649392555222
```

In [ ]:
```
# Support Vector Regressor
model_svr = SVR()
model_svr.fit(X_train_scaled, y_train)
y_pred_svr = model_svr.predict(X_test_scaled)
r2_svr = r2_score(y_test, y_pred_svr)
print(f"SVR R-squared: {r2_svr}")
```

In [38]:
```
# K-Nearest Neighbors Regressor
model_knn = KNeighborsRegressor()
model_knn.fit(X_train_scaled, y_train)
y_pred_knn = model_knn.predict(X_test_scaled)
r2_knn = r2_score(y_test, y_pred_knn)
print(f"K-Nearest Neighbors R-squared: {r2_knn}")
```

```
K-Nearest Neighbors R-squared: 0.9157151225896871
```

In [40]:
```
# Multi-layer Perceptron (Feedforward Neural Network)
from keras.models import Sequential
from keras.layers import Dense

model_fnn = Sequential()
model_fnn.add(Dense(128, input_dim=X_train_scaled.shape[1], activation='relu'))
model_fnn.add(Dense(64, activation='relu'))
model_fnn.add(Dense(1))  # Output layer with linear activation

model_fnn.compile(optimizer='adam', loss='mean_squared_error')
model_fnn.fit(X_train_scaled, y_train, epochs=20, batch_size=32, verbose=1)

y_pred_fnn = model_fnn.predict(X_test_scaled)
r2_fnn = r2_score(y_test, y_pred_fnn)
print(f"FNN R-squared: {r2_fnn}")
```

```
Epoch 1/20
12598/12598 [==============================] - 43s 3ms/step - loss: 0.1629
Epoch 2/20
12598/12598 [==============================] - 28s 2ms/step - loss: 0.1133
Epoch 3/20
12598/12598 [==============================] - 29s 2ms/step - loss: 0.0980
Epoch 4/20
12598/12598 [==============================] - 28s 2ms/step - loss: 0.0904
Epoch 5/20
12598/12598 [==============================] - 29s 2ms/step - loss: 0.0860
Epoch 6/20
12598/12598 [==============================] - 30s 2ms/step - loss: 0.0813
Epoch 7/20
12598/12598 [==============================] - 29s 2ms/step - loss: 0.0792
Epoch 8/20
12598/12598 [==============================] - 30s 2ms/step - loss: 0.0768
Epoch 9/20
12598/12598 [==============================] - 28s 2ms/step - loss: 0.0745
Epoch 10/20
12598/12598 [==============================] - 31s 2ms/step - loss: 0.0731
Epoch 11/20
12598/12598 [==============================] - 32s 3ms/step - loss: 0.0713
Epoch 12/20
12598/12598 [==============================] - 28s 2ms/step - loss: 0.0699
Epoch 13/20
12598/12598 [==============================] - 30s 2ms/step - loss: 0.0691
Epoch 14/20
12598/12598 [==============================] - 31s 2ms/step - loss: 0.0677
Epoch 15/20
12598/12598 [==============================] - 28s 2ms/step - loss: 0.0668
Epoch 16/20
12598/12598 [==============================] - 30s 2ms/step - loss: 0.0659
Epoch 17/20
12598/12598 [==============================] - 31s 2ms/step - loss: 0.0655
Epoch 18/20
12598/12598 [==============================] - 36s 3ms/step - loss: 0.0644
Epoch 19/20
12598/12598 [==============================] - 31s 2ms/step - loss: 0.0639
Epoch 20/20
12598/12598 [==============================] - 31s 2ms/step - loss: 0.0631
3150/3150 [==============================] - 5s 1ms/step
FNN R-squared: 0.94086830717272
```