# Solar Power Forecasting Analysis (Q1)

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## Introduction

-Based on the case study requirements, we need to use solar power observations from 2022-01-01 to 2025-05-31 to predict the month of June 2025.

We compare five different models:

1. **Persistence Model** - Simple baseline using historical patterns
2. **Ridge Regression** - Linear model with L2 regularization and hyperparameter tuning
3. **XGBoost** - Gradient boosting with comprehensive hyperparameter search
4. **Feedforward Neural Network** - Deep learning without sequence modeling
5. **LSTM** - Recurrent neural network for sequence modeling

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV, TimeSeriesSplit
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import xgboost as xgb
import torch
import torch.nn as nn
from torch.utils.data import TensorDataset, DataLoader
import warnings
warnings.filterwarnings("ignore")

# Set random seeds for reproducibility
np.random.seed(42)
```

```
torch.manual_seed(42)
plt.style.use('default')
```

## Data Loading and Preparation

### EDA Summary Integration

From the EDA analysis, we identified:

- **Strongest predictors:** `surface_solar_radiation_downwards` and `temperature_2m` show high correlation with solar power generation
- 
- **Seasonality:** Clear daily and annual cycles in both solar power and solar radiation
- 
- **Feature selection:** Focus on most correlated meteorological variables plus engineered time features, including interaction terms

The train/validation split will use March 1st as boundary

```
# Load solar power observations (2022-01-01 to 2025-05-31)
solar_q1 = pd.read_csv("../data/germany_solar_observation_q1.csv", parse_dates=['DateTime'])
print(f"Solar data shape: {solar_q1.shape}")
print(f"Solar data range: {solar_q1['DateTime'].min()} to {solar_q1['DateTime'].max()}")

# Load meteorological features (2022-01-01 to 2025-06-30)
atm_q1 = pd.read_csv("../data/germany_atm_features_q1.csv", parse_dates=['DateTime'])
print(f"Atmospheric data shape: {atm_q1.shape}")
print(f"Atmospheric data range: {atm_q1['DateTime'].min()} to {atm_q1['DateTime'].max()}")

# Merge for training/validation (only where both power and features exist)
data_q1 = pd.merge(solar_q1, atm_q1, on="DateTime", how="inner")
data_q1 = data_q1[data_q1['DateTime'] <= '2025-05-31']
print(f"Training data shape: {data_q1.shape}")
print(f"Training data range: {data_q1['DateTime'].min()} to {data_q1['DateTime'].max()}")

# For June 2025 forecast: only meteorological features (no observed power)
forecast_data = atm_q1[(atm_q1['DateTime'] >= '2025-06-01') &
                       (atm_q1['DateTime'] <= '2025-06-30 23:00:00')].copy()
print(f"Forecast data shape: {forecast_data.shape}")
print(f"Forecast data range: {forecast_data['DateTime'].min()} to {forecast_data['DateTime']
```

```
Solar data shape: (29928, 2)
Solar data range: 2022-01-01 00:00:00+00:00 to 2025-05-31 23:00:00+00:00
Atmospheric data shape: (30648, 11)
Atmospheric data range: 2022-01-01 00:00:00+00:00 to 2025-06-30 23:00:00+00:00
Training data shape: (29905, 12)
Training data range: 2022-01-01 00:00:00+00:00 to 2025-05-31 00:00:00+00:00
Forecast data shape: (720, 11)
Forecast data range: 2025-06-01 00:00:00+00:00 to 2025-06-30 23:00:00+00:00
```

### Comprehensive Feature Engineering

```python
def add_comprehensive_features(df):
    """Add comprehensive features including cyclical time features and interactions"""
    df = df.copy()

    # Basic time features
    df['hour'] = df['DateTime'].dt.hour
    df['dayofyear'] = df['DateTime'].dt.dayofyear
    df['month'] = df['DateTime'].dt.month
    df['dayofweek'] = df['DateTime'].dt.dayofweek
    df['is_weekend'] = (df['DateTime'].dt.dayofweek >= 5).astype(int)

    # Cyclical encoding for time features
    df['hour_sin'] = np.sin(2 * np.pi * df['hour'] / 24)
    df['hour_cos'] = np.cos(2 * np.pi * df['hour'] / 24)
    df['dayofyear_sin'] = np.sin(2 * np.pi * df['dayofyear'] / 365)
    df['dayofyear_cos'] = np.cos(2 * np.pi * df['dayofyear'] / 365)
    df['month_sin'] = np.sin(2 * np.pi * df['month'] / 12)
    df['month_cos'] = np.cos(2 * np.pi * df['month'] / 12)

    # Solar-specific features
    df['is_daylight'] = ((df['hour'] >= 6) & (df['hour'] <= 18)).astype(int)
    df['is_peak_solar'] = ((df['hour'] >= 10) & (df['hour'] <= 14)).astype(int)

    # Interaction features
    df['temp_radiation_interaction'] = df['temperature_2m'] * df['surface_solar_radiation_dow
    df['cloud_radiation_interaction'] = df['total_cloud_cover'] * df['surface_solar_radiatio
    df['humidity_temp_interaction'] = df['relative_humidity_2m'] * df['temperature_2m']

    return df
```

```
# Apply comprehensive feature engineering
data_q1 = add_comprehensive_features(data_q1)
forecast_data = add_comprehensive_features(forecast_data)

# Define comprehensive feature set
features = [
    'surface_solar_radiation_downwards', 'temperature_2m', 'total_cloud_cover',
    'total_precipitation', 'snowfall', 'snow_depth', 'wind_speed_10m', 'wind_speed_100m',
    'apparent_temperature', 'relative_humidity_2m', 'hour_sin', 'hour_cos', 'dayofyear_sin',
    'dayofyear_cos', 'month_sin', 'month_cos', 'is_weekend', 'is_daylight', 'is_peak_solar',
    'temp_radiation_interaction', 'cloud_radiation_interaction', 'humidity_temp_interaction'
]

target = 'power'
print(f"Selected features ({len(features)}): {features}")
```

```
Selected features (22): ['surface_solar_radiation_downwards', 'temperature_2m', 'total_cloud_
```

### Data Split

```
# The train/validation split using March 1st as boundary
# This provides more validation data and better temporal representation
train_data = data_q1[data_q1['DateTime'] < '2025-03-01'].copy()
val_data = data_q1[data_q1['DateTime'] >= '2025-03-01'].copy()

print(f"Train set: {len(train_data)} samples ({train_data['DateTime'].min()} to {train_data[
print(f"Validation set: {len(val_data)} samples ({val_data['DateTime'].min()} to {val_data['
print(f"Forecast set: {len(forecast_data)} samples")

# Prepare feature matrices
X_train = train_data[features].values
X_val = val_data[features].values
X_forecast = forecast_data[features].values

y_train = train_data[target].values
y_val = val_data[target].values

# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
```

```python
X_val_scaled = scaler.transform(X_val)
X_forecast_scaled = scaler.transform(X_forecast)

print(f"Feature shapes - Train: {X_train_scaled.shape}, Val: {X_val_scaled.shape}, Forecast:
```

```
Train set: 27720 samples (2022-01-01 00:00:00+00:00 to 2025-02-28 23:00:00+00:00)
Validation set: 2185 samples (2025-03-01 00:00:00+00:00 to 2025-05-31 00:00:00+00:00)
Forecast set: 720 samples
Feature shapes - Train: (27720, 22), Val: (2185, 22), Forecast: (720, 22)
```

### Model 1: Persistence Model

```python
class PersistenceModel:
    """
    Persistence model with seasonal patterns and weighted averaging
    """
    def __init__(self, strategy='seasonal_hourly_weighted'):
        self.strategy = strategy
        self.historical_patterns = {}

    def fit(self, data):
        """Fit the persistence model using training data"""
        data = data.copy()
        data['hour'] = data['DateTime'].dt.hour
        data['month'] = data['DateTime'].dt.month

        if self.strategy == 'seasonal_hourly_weighted':
            # Create patterns with exponential weighting (more recent = higher weight)
            patterns = {}
            for month in range(1, 13):
                for hour in range(24):
                    subset = data[(data['month'] == month) & (data['hour'] == hour)]['power']
                    if len(subset) > 0:
                        # Exponential weighting favoring recent observations
                        weights = np.exp(np.linspace(-1, 0, len(subset)))
                        weighted_avg = np.average(subset, weights=weights)
                        patterns[(month, hour)] = weighted_avg
                    else:
                        patterns[(month, hour)] = 0
            self.historical_patterns = patterns
```

```python
    def predict(self, forecast_dates):
        """Generate predictions for forecast dates"""
        predictions = []
        for date in forecast_dates:
            hour = date.hour
            month = date.month
            pred = self.historical_patterns.get((month, hour), 0)
            predictions.append(max(0, pred))  # Ensure non-negative
        return np.array(predictions)

# Fit and evaluate persistence model
print("=== Persistence Model ===")
persistence_model = PersistenceModel()
persistence_model.fit(train_data)
y_val_pred_persistence = persistence_model.predict(val_data['DateTime'])

val_rmse_persistence = np.sqrt(mean_squared_error(y_val, y_val_pred_persistence))
val_mae_persistence = mean_absolute_error(y_val, y_val_pred_persistence)
val_r2_persistence = r2_score(y_val, y_val_pred_persistence)

print(f"Validation RMSE: {val_rmse_persistence:.2f}")
print(f"Validation MAE: {val_mae_persistence:.2f}")
print(f"Validation R2: {val_r2_persistence:.4f}")

# Generate forecast
forecast_persistence = persistence_model.predict(forecast_data['DateTime'])
```

```
=== Persistence Model ===
Validation RMSE: 6846.50
Validation MAE: 3794.41
Validation R2: 0.7800
```

### Model 2: Ridge Regression with Hyperparameter Tuning

```python
print("=== Ridge Regression with Hyperparameter Tuning ===")

# Hyperparameter tuning with time series cross-validation
param_grid = {'alpha': [0.1, 1.0, 10.0, 100.0, 1000.0]}
tscv = TimeSeriesSplit(n_splits=5)
```

```python
ridge_model = GridSearchCV(
    Ridge(random_state=42),
    param_grid,
    cv=tscv,
    scoring='neg_mean_squared_error',
    n_jobs=-1
)

ridge_model.fit(X_train_scaled, y_train)

# Validation predictions
y_val_pred_lr = ridge_model.predict(X_val_scaled)

val_rmse_lr = np.sqrt(mean_squared_error(y_val, y_val_pred_lr))
val_mae_lr = mean_absolute_error(y_val, y_val_pred_lr)
val_r2_lr = r2_score(y_val, y_val_pred_lr)

print(f"Best alpha: {ridge_model.best_params_['alpha']}")
print(f"Validation RMSE: {val_rmse_lr:.2f}")
print(f"Validation MAE: {val_mae_lr:.2f}")
print(f"Validation R2: {val_r2_lr:.4f}")

# Feature importance analysis
feature_importance_lr = pd.DataFrame({
    'feature': features,
    'coefficient': ridge_model.best_estimator_.coef_
}).sort_values('coefficient', key=abs, ascending=False)

print(f"\nTop 10 most important features:")
print(feature_importance_lr.head(10))

# Generate forecast
forecast_lr = ridge_model.predict(X_forecast_scaled)
```

```
=== Ridge Regression with Hyperparameter Tuning ===
Best alpha: 1.0
Validation RMSE: 4074.83
Validation MAE: 2460.09
Validation R2: 0.9221

Top 10 most important features:
```

```
                              feature  coefficient
0   surface_solar_radiation_downwards  9699.378515
1                      temperature_2m -3018.023171
21          humidity_temp_interaction  1915.841509
8                apparent_temperature  1068.323690
13                      dayofyear_cos   906.292392
9                relative_humidity_2m  -860.582153
7                      wind_speed_100m  -754.387090
6                       wind_speed_10m   593.009324
19         temp_radiation_interaction   581.332126
20        cloud_radiation_interaction  -544.207000
```

### Model 3: XGBoost

```
print("=== XGBoost with Grid Search ===")

# Comprehensive hyperparameter grid
xgb_param_grid = {
    'n_estimators': [200, 300],
    'max_depth': [6, 8],
    'learning_rate': [0.1, 0.15],
    'subsample': [0.8],
    'colsample_bytree': [0.8]
}

xgb_model = GridSearchCV(
    xgb.XGBRegressor(random_state=42, n_jobs=-1),
    xgb_param_grid,
    cv=tscv,
    scoring='neg_mean_squared_error',
    n_jobs=-1
)

xgb_model.fit(X_train_scaled, y_train)

# Validation predictions
y_val_pred_xgb = xgb_model.predict(X_val_scaled)

val_rmse_xgb = np.sqrt(mean_squared_error(y_val, y_val_pred_xgb))
val_mae_xgb = mean_absolute_error(y_val, y_val_pred_xgb)
val_r2_xgb = r2_score(y_val, y_val_pred_xgb)
```

```python
print(f"Best parameters: {xgb_model.best_params_}")
print(f"Validation RMSE: {val_rmse_xgb:.2f}")
print(f"Validation MAE: {val_mae_xgb:.2f}")
print(f"Validation R2: {val_r2_xgb:.4f}")

# Feature importance
feature_importance_xgb = pd.DataFrame({
    'feature': features,
    'importance': xgb_model.best_estimator_.feature_importances_
}).sort_values('importance', ascending=False)

print(f"\nTop 10 most important features:")
print(feature_importance_xgb.head(10))

# Generate forecast
forecast_xgb = xgb_model.predict(X_forecast_scaled)
```

```
=== XGBoost with Grid Search ===
Best parameters: {'colsample_bytree': 0.8, 'learning_rate': 0.1, 'max_depth': 6, 'n_estimato
Validation RMSE: 4079.03
Validation MAE: 2410.77
Validation R2: 0.9219

Top 10 most important features:
                             feature  importance
19        temp_radiation_interaction    0.524532
0   surface_solar_radiation_downwards    0.310214
20       cloud_radiation_interaction    0.038745
10                          hour_sin    0.023511
11                          hour_cos    0.020148
8               apparent_temperature    0.014766
2                  total_cloud_cover    0.009859
5                         snow_depth    0.008512
3                total_precipitation    0.007862
15                         month_cos    0.007454
```

#### Model 4: Feedforward Neural Network

```python
class FFN(nn.Module):
    """Feedforward neural network"""
    def __init__(self, input_dim, hidden_dims=[256, 128, 64], dropout_rate=0.3):
        super().__init__()

        layers = []
        prev_dim = input_dim

        for hidden_dim in hidden_dims:
            layers.extend([
                nn.Linear(prev_dim, hidden_dim),
                nn.BatchNorm1d(hidden_dim),
                nn.ReLU(),
                nn.Dropout(dropout_rate)
            ])
            prev_dim = hidden_dim

        # Output layer
        layers.append(nn.Linear(prev_dim, 1))

        self.network = nn.Sequential(*layers)

    def forward(self, x):
        return self.network(x).squeeze()

def train_pytorch_model(model, train_loader, val_loader, epochs=100, lr=1e-3, patience=15):
    """Training with  early stopping and learning rate scheduling"""
    optimizer = torch.optim.AdamW(model.parameters(), lr=lr, weight_decay=1e-5)
    scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, patience=5, factor=0.5
    criterion = nn.MSELoss()

    best_val_loss = float('inf')
    patience_counter = 0
    train_losses = []
    val_losses = []

    for epoch in range(epochs):
        # Training
        model.train()
        train_loss = 0
        for batch_x, batch_y in train_loader:
            optimizer.zero_grad()
```

```
            pred = model(batch_x)
            loss = criterion(pred, batch_y)
            loss.backward()
            torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm=1.0)
            optimizer.step()
            train_loss += loss.item()

        train_loss /= len(train_loader)
        train_losses.append(train_loss)

        # Validation
        model.eval()
        val_loss = 0
        with torch.no_grad():
            for batch_x, batch_y in val_loader:
                pred = model(batch_x)
                loss = criterion(pred, batch_y)
                val_loss += loss.item()

        val_loss /= len(val_loader)
        val_losses.append(val_loss)

        scheduler.step(val_loss)

        # Early stopping
        if val_loss < best_val_loss:
            best_val_loss = val_loss
            patience_counter = 0
            # Save best model state
            best_model_state = model.state_dict().copy()
        else:
            patience_counter += 1
            if patience_counter >= patience:
                print(f"Early stopping at epoch {epoch}")
                # Load best model state
                model.load_state_dict(best_model_state)
                break

        if epoch % 20 == 0:
            current_lr = optimizer.param_groups[0]['lr']
            print(f"Epoch {epoch}: Train Loss = {train_loss:.4f}, Val Loss = {val_loss:.4f},
```

```
    return model, train_losses, val_losses

def get_predictions(model, data_loader):
    """Get predictions from trained model"""
    model.eval()
    predictions = []
    with torch.no_grad():
        for batch_x, _ in data_loader:
            pred = model(batch_x)
            predictions.extend(pred.cpu().numpy())
    return np.array(predictions)

print("=== Feedforward Neural Network ===")

# Prepare PyTorch datasets and loaders
train_ds_ffn = TensorDataset(
    torch.tensor(X_train_scaled, dtype=torch.float32),
    torch.tensor(y_train, dtype=torch.float32)
)
val_ds_ffn = TensorDataset(
    torch.tensor(X_val_scaled, dtype=torch.float32),
    torch.tensor(y_val, dtype=torch.float32)
)
forecast_ds_ffn = TensorDataset(
    torch.tensor(X_forecast_scaled, dtype=torch.float32),
    torch.zeros(len(X_forecast_scaled), dtype=torch.float32)
)

train_loader_ffn = DataLoader(train_ds_ffn, batch_size=128, shuffle=True)
val_loader_ffn = DataLoader(val_ds_ffn, batch_size=128)
forecast_loader_ffn = DataLoader(forecast_ds_ffn, batch_size=128)

# Initialize and train model
ffn_model = FFN(input_dim=len(features), hidden_dims=[256, 128, 64])
ffn_model, train_losses_ffn, val_losses_ffn = train_pytorch_model(
    ffn_model, train_loader_ffn, val_loader_ffn, epochs=100, lr=1e-3
)

# Get validation predictions
y_val_pred_ffn = get_predictions(ffn_model, val_loader_ffn)

# Metrics
```

```
val_rmse_ffn = np.sqrt(mean_squared_error(y_val, y_val_pred_ffn))
val_mae_ffn = mean_absolute_error(y_val, y_val_pred_ffn)
val_r2_ffn = r2_score(y_val, y_val_pred_ffn)

print(f"Validation RMSE: {val_rmse_ffn:.2f}")
print(f"Validation MAE: {val_mae_ffn:.2f}")
print(f"Validation R2: {val_r2_ffn:.4f}")

# Generate forecast
forecast_ffn = get_predictions(ffn_model, forecast_loader_ffn)
```

```
=== Feedforward Neural Network ===
Epoch 0: Train Loss = 143896508.0922, Val Loss = 332073007.7778, LR = 0.001000
Epoch 20: Train Loss = 106960176.2028, Val Loss = 259182275.1111, LR = 0.001000
Epoch 40: Train Loss = 40535532.8203, Val Loss = 126138233.3333, LR = 0.001000
Epoch 60: Train Loss = 7511131.6048, Val Loss = 33624885.2639, LR = 0.001000
Epoch 80: Train Loss = 4739726.2131, Val Loss = 18301381.4028, LR = 0.001000
Early stopping at epoch 94
Validation RMSE: 4148.52
Validation MAE: 2413.53
Validation R2: 0.9192
```

### Model 5: LSTM

```
class LSTM(nn.Module):
    """Enhanced LSTM with better architecture and regularization"""
    def __init__(self, input_dim, hidden_dim=128, num_layers=2, dropout_rate=0.3):
        super().__init__()

        self.lstm = nn.LSTM(
            input_dim,
            hidden_dim,
            num_layers,
            batch_first=True,
            dropout=dropout_rate,
            bidirectional=False
        )

        # Enhanced output layers
        self.fc_layers = nn.Sequential(
```

```
            nn.Linear(hidden_dim, hidden_dim // 2),
            nn.BatchNorm1d(hidden_dim // 2),
            nn.ReLU(),
            nn.Dropout(dropout_rate),
            nn.Linear(hidden_dim // 2, 1)
        )

    def forward(self, x):
        lstm_out, _ = self.lstm(x)
        # Use the last time step output
        last_output = lstm_out[:, -1, :]
        return self.fc_layers(last_output).squeeze()

def create_sequences_corrected(X, y, seq_length):
    """Create sequences for LSTM training with proper handling"""
    X_seq, y_seq = [], []
    for i in range(seq_length, len(X)):
        X_seq.append(X[i-seq_length:i])
        y_seq.append(y[i])
    return np.array(X_seq), np.array(y_seq)

def create_forecast_sequences(X_val, X_forecast, seq_length):
    """Create sequences for forecasting using validation data as initial context"""
    X_forecast_seq = []

    # Use the last seq_length samples from validation as initial context
    context = X_val[-seq_length:]

    for i in range(len(X_forecast)):
        if i == 0:
            # First prediction uses validation context
            X_forecast_seq.append(context)
        else:
            # Subsequent predictions use rolling window
            if i < seq_length:
                # Mix validation context with forecast data
                context_needed = seq_length - i
                new_context = np.vstack([context[-context_needed:], X_forecast[:i]])
            else:
                # Use only forecast data
                new_context = X_forecast[i-seq_length:i]
            X_forecast_seq.append(new_context)
```

```python
    return np.array(X_forecast_seq)

print("=== LSTM Model ===")

# Create sequences for LSTM (24-hour lookback window)
seq_length = 24
X_train_seq, y_train_seq = create_sequences_corrected(X_train_scaled, y_train, seq_length)
X_val_seq, y_val_seq = create_sequences_corrected(X_val_scaled, y_val, seq_length)
X_forecast_seq = create_forecast_sequences(X_val_scaled, X_forecast_scaled, seq_length)

print(f"LSTM training sequences: {X_train_seq.shape}")
print(f"LSTM validation sequences: {X_val_seq.shape}")
print(f"LSTM forecast sequences: {X_forecast_seq.shape}")

# Prepare PyTorch datasets
train_ds_lstm = TensorDataset(
    torch.tensor(X_train_seq, dtype=torch.float32),
    torch.tensor(y_train_seq, dtype=torch.float32)
)
val_ds_lstm = TensorDataset(
    torch.tensor(X_val_seq, dtype=torch.float32),
    torch.tensor(y_val_seq, dtype=torch.float32)
)
forecast_ds_lstm = TensorDataset(
    torch.tensor(X_forecast_seq, dtype=torch.float32),
    torch.zeros(len(X_forecast_seq), dtype=torch.float32)
)

train_loader_lstm = DataLoader(train_ds_lstm, batch_size=64, shuffle=True)
val_loader_lstm = DataLoader(val_ds_lstm, batch_size=64)
forecast_loader_lstm = DataLoader(forecast_ds_lstm, batch_size=64)

# Initialize and train model
lstm_model = LSTM(input_dim=len(features), hidden_dim=128, num_layers=2)
lstm_model, train_losses_lstm, val_losses_lstm = train_pytorch_model(
    lstm_model, train_loader_lstm, val_loader_lstm, epochs=100, lr=1e-3
)

# Get validation predictions
y_val_pred_lstm = get_predictions(lstm_model, val_loader_lstm)

# Metrics (note: LSTM validation has fewer samples due to sequence creation)
```

```python
val_rmse_lstm = np.sqrt(mean_squared_error(y_val_seq, y_val_pred_lstm))
val_mae_lstm = mean_absolute_error(y_val_seq, y_val_pred_lstm)
val_r2_lstm = r2_score(y_val_seq, y_val_pred_lstm)

print(f"Validation RMSE: {val_rmse_lstm:.2f}")
print(f"Validation MAE: {val_mae_lstm:.2f}")
print(f"Validation R2: {val_r2_lstm:.4f}")

# Generate forecast
forecast_lstm = get_predictions(lstm_model, forecast_loader_lstm)
```

```
=== LSTM Model ===
LSTM training sequences: (27696, 24, 22)
LSTM validation sequences: (2161, 24, 22)
LSTM forecast sequences: (720, 24, 22)
Epoch 0: Train Loss = 143719954.6790, Val Loss = 350893633.6471, LR = 0.001000
Epoch 20: Train Loss = 60073284.3926, Val Loss = 172966243.7647, LR = 0.001000
Epoch 40: Train Loss = 5218628.7022, Val Loss = 13436518.7941, LR = 0.001000
Epoch 60: Train Loss = 4423402.0856, Val Loss = 14035063.8768, LR = 0.000250
Early stopping at epoch 70
Validation RMSE: 4486.92
Validation MAE: 2648.39
Validation R2: 0.9061
```

### Model Comparison and Results

```python
print("=== Model Comparison ===")

# Create comprehensive results dataframe
results_df = pd.DataFrame({
    'Model': ['Persistence', 'Ridge Regression', 'XGBoost', 'Enhanced FFN', 'Enhanced LSTM']
    'Validation RMSE': [val_rmse_persistence, val_rmse_lr, val_rmse_xgb, val_rmse_ffn, val_r
    'Validation MAE': [val_mae_persistence, val_mae_lr, val_mae_xgb, val_mae_ffn, val_mae_ls
    'Validation R2': [val_r2_persistence, val_r2_lr, val_r2_xgb, val_r2_ffn, val_r2_lstm]
})

print("\nModel Performance Comparison:")
print(results_df.round(4))

# Calculate improvement over persistence baseline
```

```
results_df['RMSE Improvement (%)'] = (val_rmse_persistence - results_df['Validation RMSE']) /
results_df['MAE Improvement (%)'] = (val_mae_persistence - results_df['Validation MAE']) / va

print("\nImprovement over Persistence Baseline:")
improvement_df = results_df[['Model', 'RMSE Improvement (%)', 'MAE Improvement (%)']].copy()
print(improvement_df.round(2))

# Identify best model
best_model_idx = results_df['Validation RMSE'].idxmin()
best_model_name = results_df.loc[best_model_idx, 'Model']
best_rmse = results_df.loc[best_model_idx, 'Validation RMSE']

print(f"\nBest Model: {best_model_name}")
print(f"Best RMSE: {best_rmse:.2f}")
print(f"Improvement over Persistence: {results_df.loc[best_model_idx, 'RMSE Improvement (%)']

# Select best forecast
forecasts = {
    'Persistence': forecast_persistence,
    'Ridge Regression': forecast_lr,
    'XGBoost': forecast_xgb,
    'Enhanced FFN': forecast_ffn,
    'Enhanced LSTM': forecast_lstm
}

best_forecast = forecasts[best_model_name]
```

```
=== Model Comparison ===

Model Performance Comparison:
              Model  Validation RMSE  Validation MAE  Validation R2
0       Persistence        6846.5047       3794.4113         0.7800
1  Ridge Regression        4074.8302       2460.0932         0.9221
2           XGBoost        4079.0261       2410.7749         0.9219
3      Enhanced FFN        4148.5198       2413.5346         0.9192
4     Enhanced LSTM        4486.9157       2648.3932         0.9061

Improvement over Persistence Baseline:
              Model  RMSE Improvement (%)  MAE Improvement (%)
0       Persistence                  0.00                 0.00
1  Ridge Regression                 40.48                35.17
2           XGBoost                 40.42                36.47
```

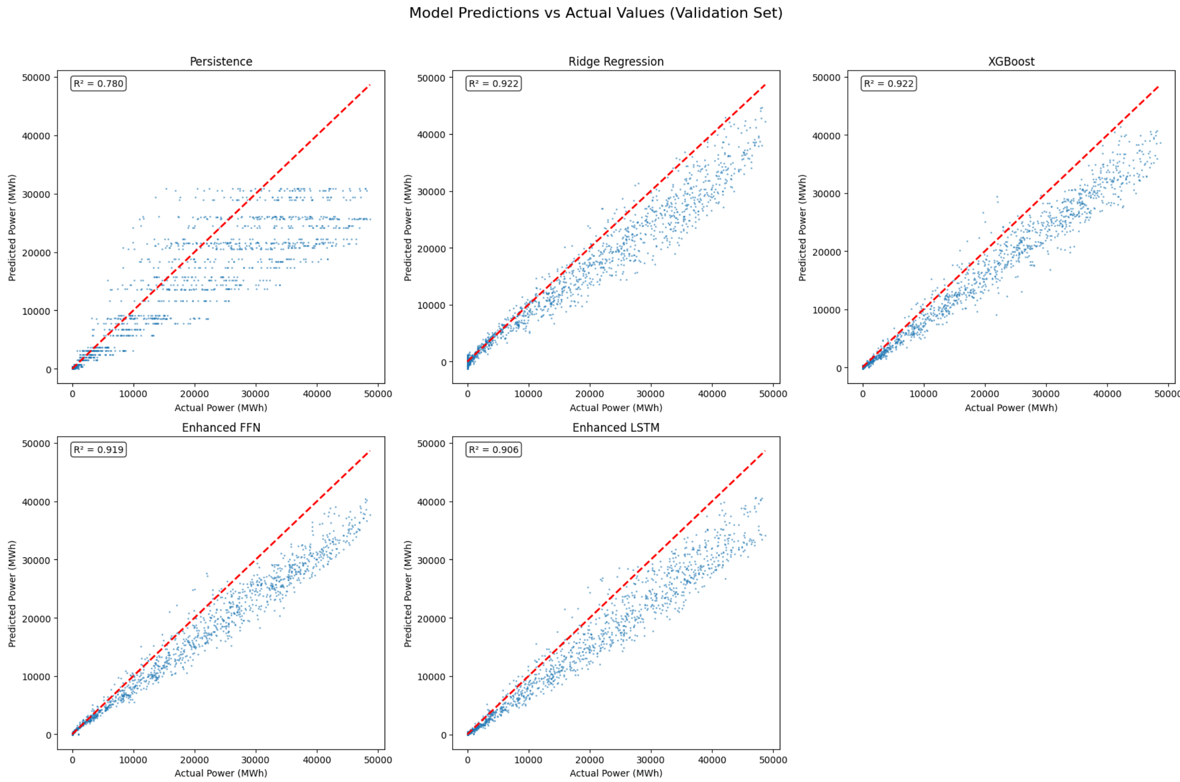
```
3      Enhanced FFN                    39.41                   36.39
4     Enhanced LSTM                    34.46                   30.20

Best Model: Ridge Regression
Best RMSE: 4074.83
Improvement over Persistence: 40.5%
```

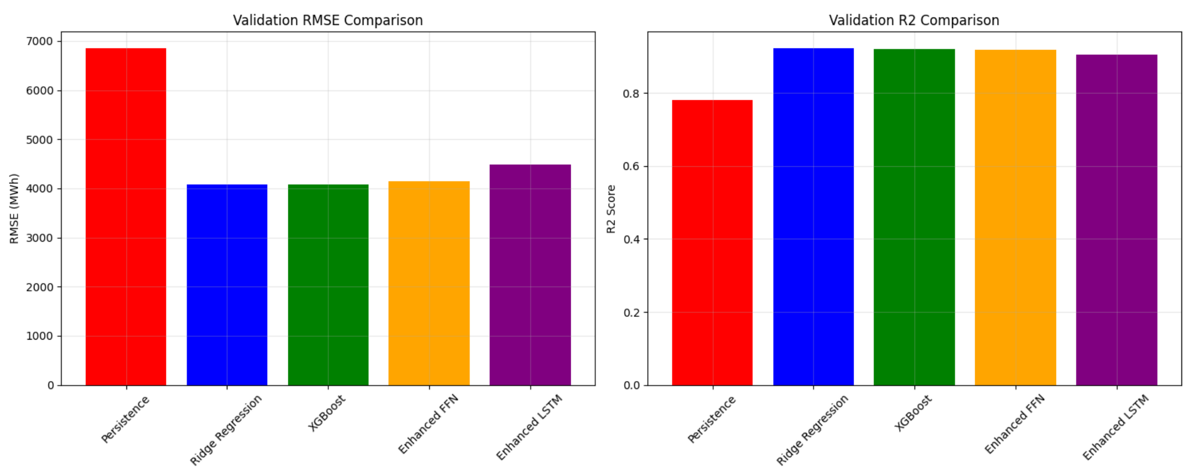
### Visualization

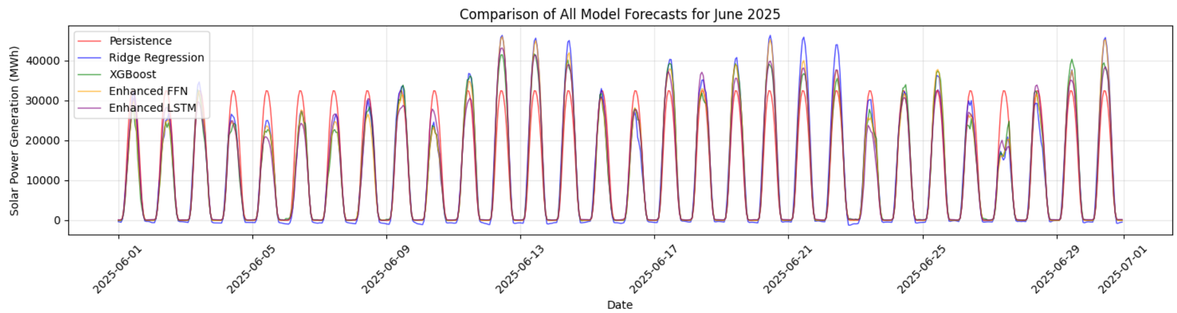
```python
# Create forecast dataframes needed for visualization
forecast_df = pd.DataFrame({
    'DateTime': forecast_data['DateTime'].values,
    'power': best_forecast
})
# Ensure no negative predictions
forecast_df['power'] = np.maximum(forecast_df['power'], 0)

persistence_forecast_df = pd.DataFrame({
    'DateTime': forecast_data['DateTime'].values,
    'power': forecast_persistence
})
import matplotlib.dates as mdates

# Plot validation predictions vs actual values
fig, axes = plt.subplots(2, 3, figsize=(18, 12))
fig.suptitle('Model Predictions vs Actual Values (Validation Set)', fontsize=16)

models_data = [
    ('Persistence', y_val_pred_persistence, y_val),
    ('Ridge Regression', y_val_pred_lr, y_val),
    ('XGBoost', y_val_pred_xgb, y_val),
    ('Enhanced FFN', y_val_pred_ffn, y_val),
    ('Enhanced LSTM', y_val_pred_lstm, y_val_seq)  # LSTM has fewer validation samples
]

for idx, (name, pred, actual) in enumerate(models_data):
    row = idx // 3
    col = idx % 3
    ax = axes[row, col]
    ax.scatter(actual, pred, alpha=0.5, s=1)
    ax.plot([actual.min(), actual.max()], [actual.min(), actual.max()], 'r--', lw=2)
```

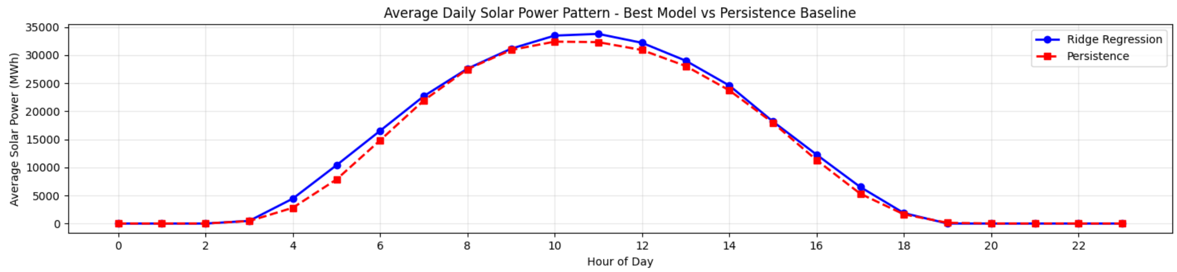
```
    ax.set_xlabel('Actual Power (MWh)')
    ax.set_ylabel('Predicted Power (MWh)')
    ax.set_title(f'{name}')
    r2 = r2_score(actual, pred)
    ax.text(0.05, 0.95, f'R² = {r2:.3f}', transform=ax.transAxes,
            bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# Remove empty subplot (bottom right)
axes[1, 2].remove()
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()

# Model performance comparison bar charts
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))

# RMSE comparison
colors = ['red', 'blue', 'green', 'orange', 'purple']
ax1.bar(results_df['Model'], results_df['Validation RMSE'], color=colors)
ax1.set_title('Validation RMSE Comparison')
ax1.set_ylabel('RMSE (MWh)')
ax1.tick_params(axis='x', rotation=45)
ax1.grid(True, alpha=0.3)

# R2 comparison
ax2.bar(results_df['Model'], results_df['Validation R2'], color=colors)
ax2.set_title('Validation R2 Comparison')
ax2.set_ylabel('R2 Score')
ax2.tick_params(axis='x', rotation=45)
ax2.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Forecast visualization
plt.figure(figsize=(15, 12))

# 1. Plot all model forecasts for June 2025
plt.subplot(3, 1, 1)
for i, (model_name, forecast) in enumerate(forecasts.items()):
    plt.plot(forecast_data['DateTime'], forecast, label=model_name, alpha=0.7, linewidth=1,
plt.xlabel('Date')
plt.ylabel('Solar Power Generation (MWh)')
```

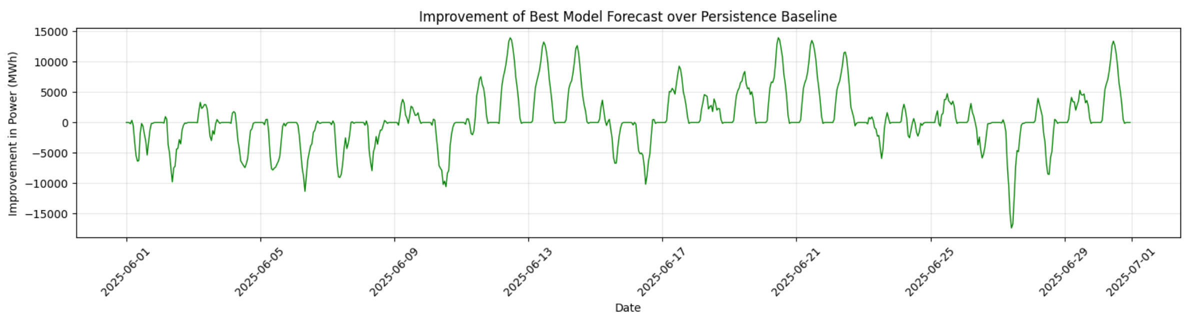
```python
plt.title('Comparison of All Model Forecasts for June 2025')
plt.legend()
plt.xticks(rotation=45)
plt.grid(True, alpha=0.3)

# 2. Average daily solar power pattern - best model vs persistence
plt.subplot(3, 1, 2)
forecast_df['hour'] = forecast_df['DateTime'].dt.hour
persistence_forecast_df['hour'] = persistence_forecast_df['DateTime'].dt.hour
hourly_avg_best = forecast_df.groupby('hour')['power'].mean()
hourly_avg_persistence = persistence_forecast_df.groupby('hour')['power'].mean()
plt.plot(hourly_avg_best.index, hourly_avg_best.values,
         marker='o', linewidth=2, label=f'{best_model_name}', color='blue')
plt.plot(hourly_avg_persistence.index, hourly_avg_persistence.values,
         marker='s', linewidth=2, label='Persistence', color='red', linestyle='--')
plt.xlabel('Hour of Day')
plt.ylabel('Average Solar Power (MWh)')
plt.title('Average Daily Solar Power Pattern - Best Model vs Persistence Baseline')
plt.legend()
plt.grid(True, alpha=0.3)
plt.xticks(range(0, 24, 2))

# 3. Improvement over persistence baseline (forecast difference)
plt.subplot(3, 1, 3)
improvement = forecast_df['power'] - persistence_forecast_df['power']
plt.plot(forecast_df['DateTime'], improvement, color='green', linewidth=1)
plt.xlabel('Date')
plt.ylabel('Improvement in Power (MWh)')
plt.title('Improvement of Best Model Forecast over Persistence Baseline')
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()

plt.show()
```


Model Predictions vs Actual Values (Validation Set)
Persistence
R² = 0.780
Ridge Regression
R² = 0.922
XGBoost
R² = 0.922
Enhanced FFN
R² = 0.919
Enhanced LSTM
R² = 0.906
Predicted Power (MWh)
Actual Power (MWh)
0
10000
20000
30000
40000
50000


Validation RMSE Comparison
RMSE (MWh)
0
1000
2000
3000
4000
5000
6000
7000
Validation R2 Comparison
R2 Score
0.0
0.2
0.4
0.6
0.8
Persistence
Ridge Regression
XGBoost
Enhanced FFN
Enhanced LSTM


Comparison of All Model Forecasts for June 2025
Persistence
Ridge Regression
XGBoost
Enhanced FFN
Enhanced LSTM
Solar Power Generation (MWh)
Date


Average Daily Solar Power Pattern - Best Model vs Persistence Baseline
Ridge Regression
Persistence
Average Solar Power (MWh)
Hour of Day


Improvement of Best Model Forecast over Persistence Baseline
Improvement in Power (MWh)
Date