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## **Project: Forecasting France's Day-ahead Electricity Price Using LASSO-Based Regression Models**

# 1- Motivation

- ✓ Accurate day-ahead electricity price forecasting is crucial for grid efficiency and reliability, benefiting stakeholders
- ✓ Challenges from the dynamic and complex energy landscape (integration of energy sources and cross-border electricity trading) and recent geopolitical events.
- ✓ Inspired by the paper of (Babii and Striaukas, 2023), focus on the high-dimensional projections advancement for time series forecasting
- ✓ 3 Shrinkage methods (Ridge Regression, LASSO, and Elastic Net) are employed
- ✓ Two benchmark models are utilized: Naive model, Expert model



## 2. Data – Regressors selection

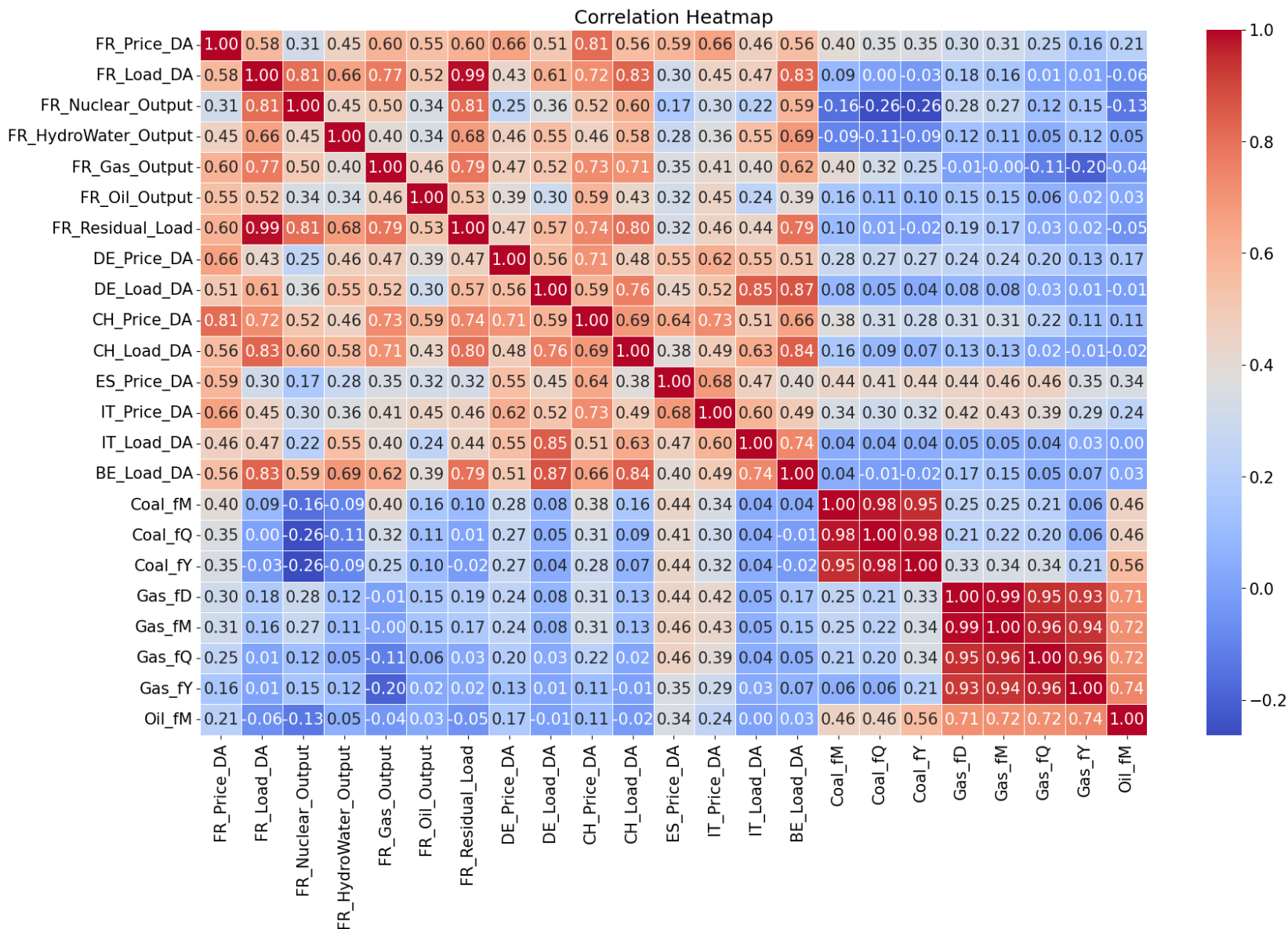


Figure 1: Correlation heatmap

Two main features:

- Feature of France: Price, Load, Output, Residual Load

- Interconnection features: Price, Load of other countries + Oil, Gas and Coal prices

- Total of 33 variables: including 24 variables and its lagged value

- Data taken from ENTSOE

## 2. Data – Regressors selection

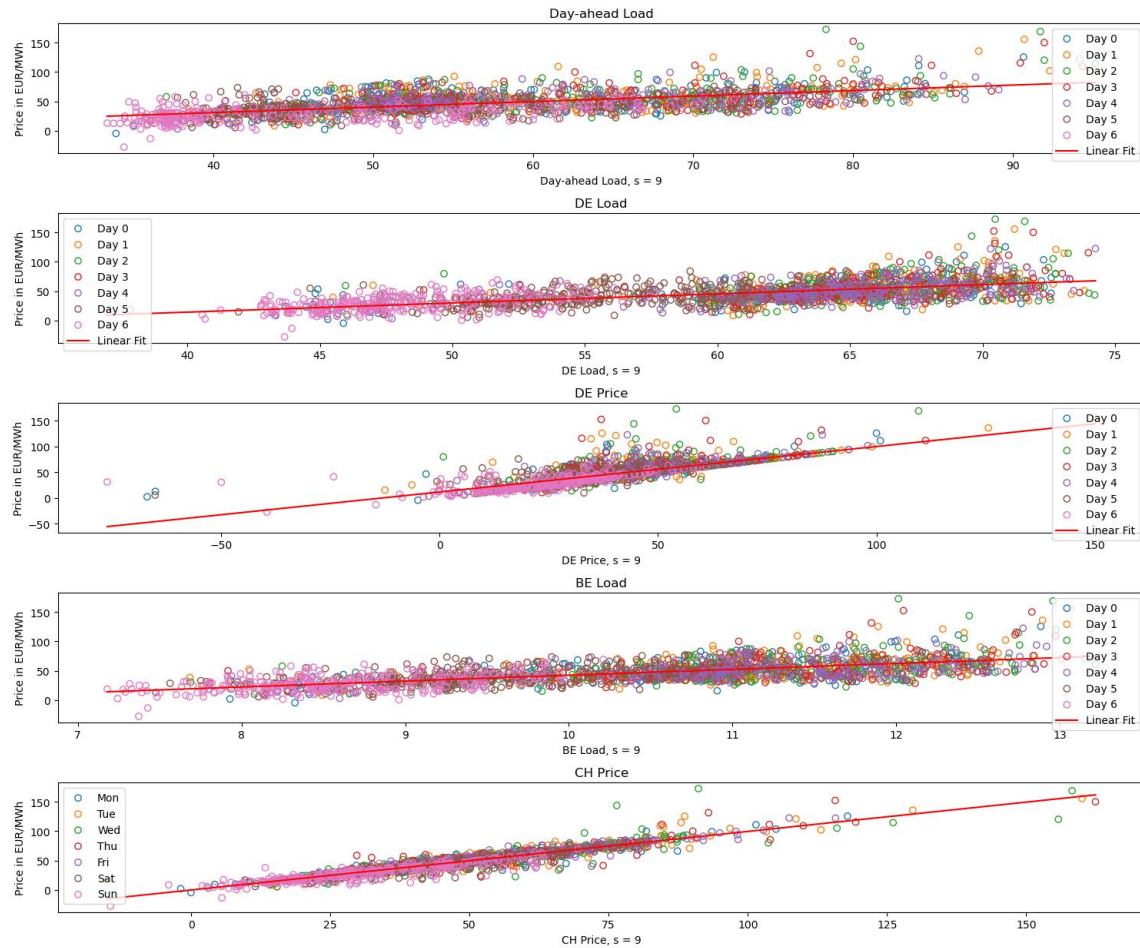


Figure 2: Relationship between some variables and DA price of France

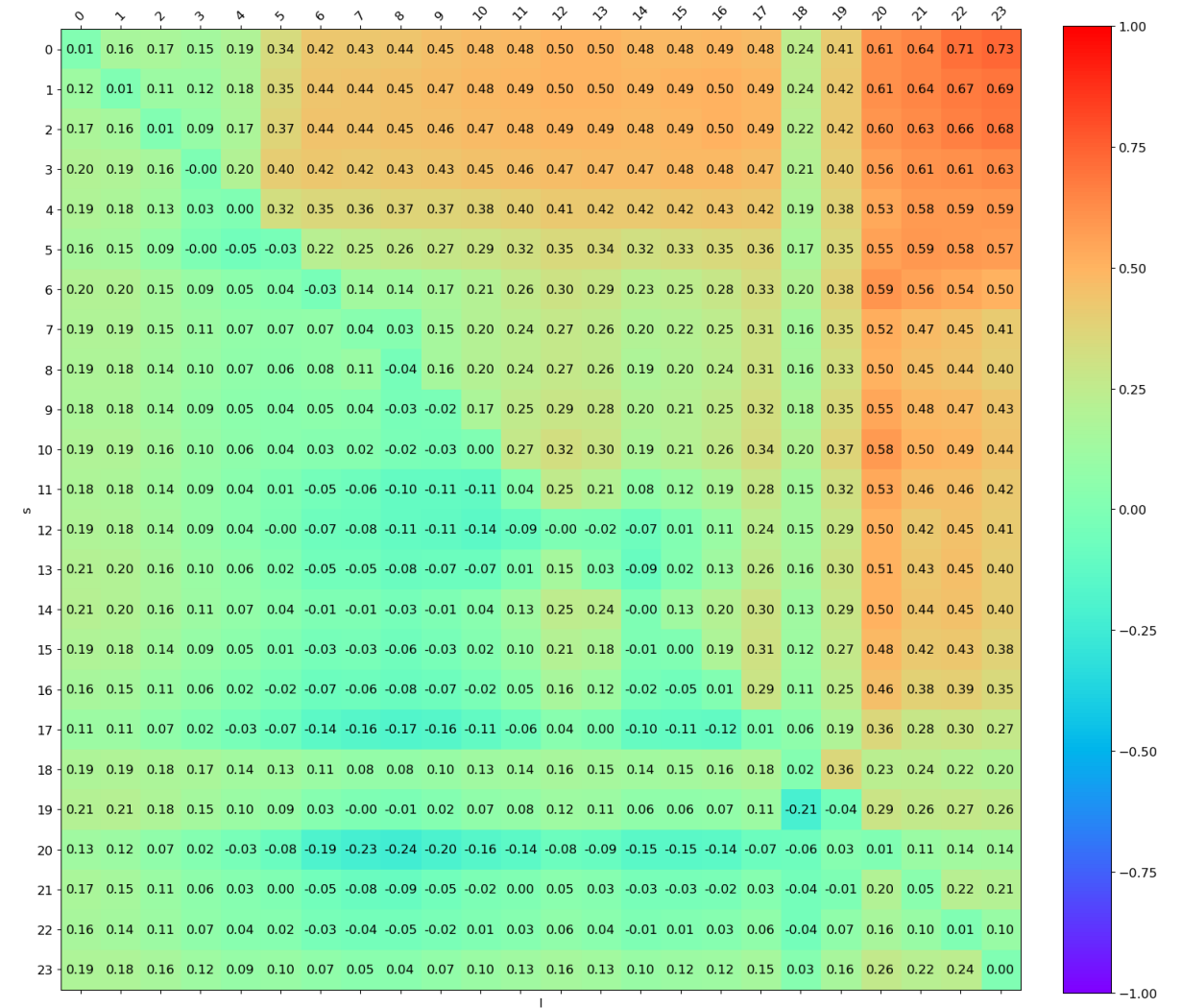


Figure 3: Correlation heatmap for all hours

## 2. Data - Target variable

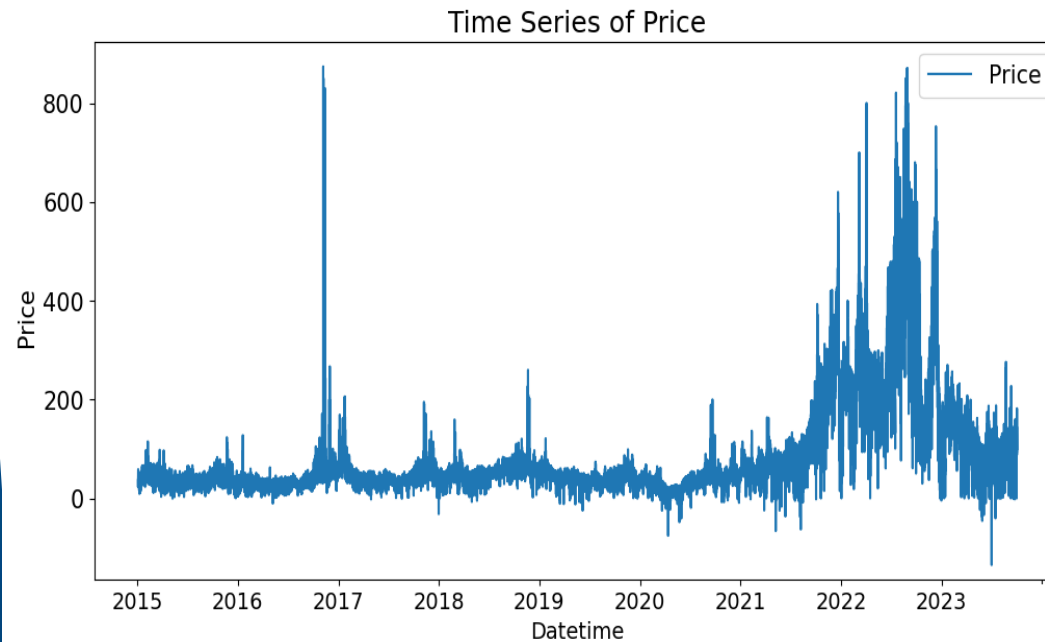


Figure 4a: France's Day-ahead price over time  
(after outlier cleaning on 2022-04-04)

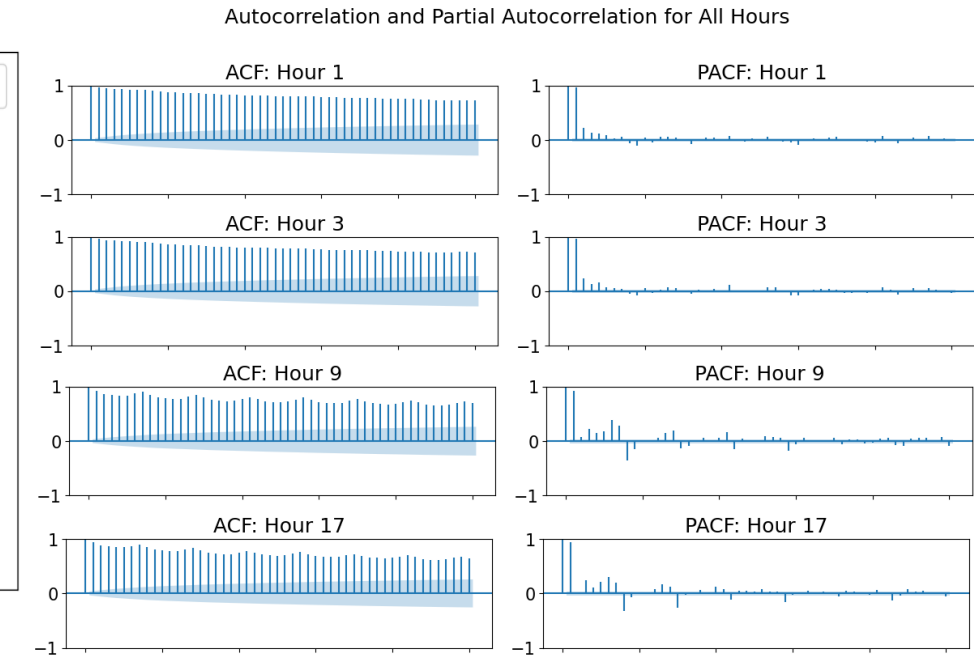
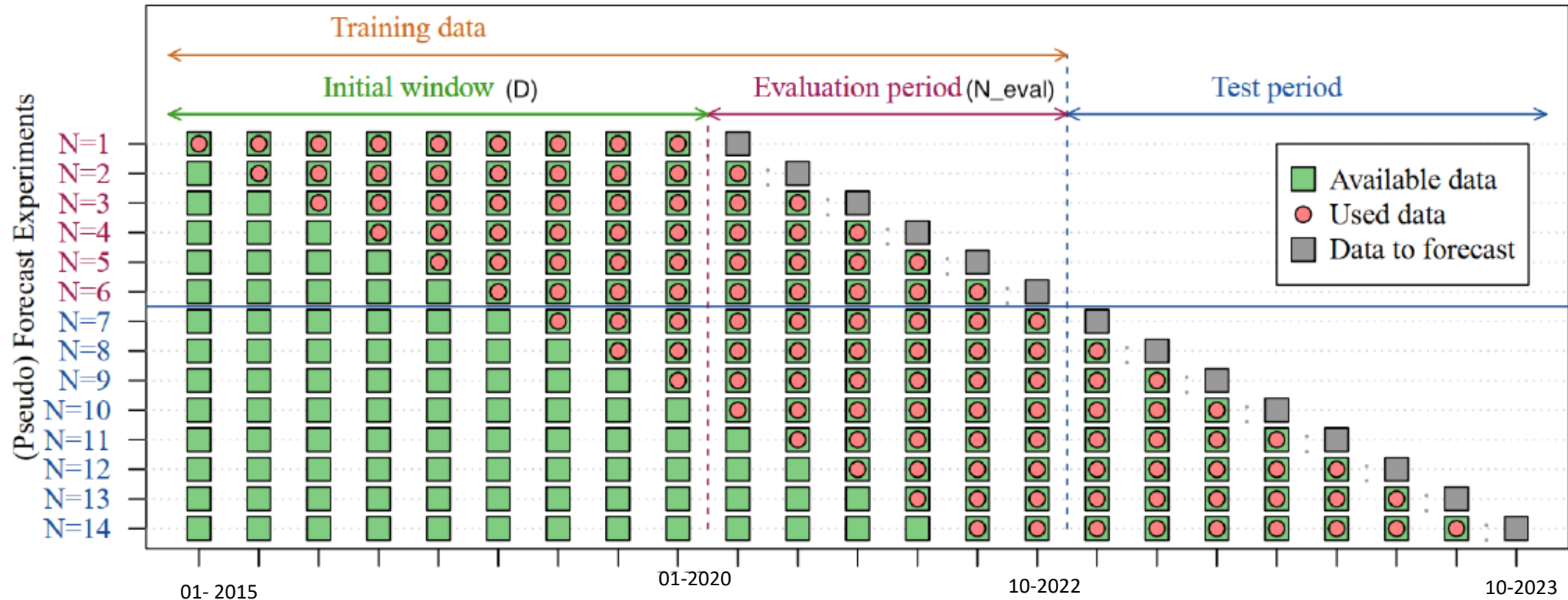


Figure 4b: Auto-correlation structure

Table 1: Summary statistics of the prices in France

Prices	Mean	Median	Standard Deviation	Minimum	Max
Statistics	80.41	46.52	95.26	-134.94	874.01

## 2. Data - Study Design



Splitting data and rolling forecast technique (Sources: Hansika Hewamalage, 2023)

- Total dataset: 76631 data points of 24 variables and its lagged values, hourly observations
- Data range: more than 8 years (from 2015-01-04 at 23:00:00 to 2023-10-02 at 21:00:00)
- Training set  $D = 5$  years, validation set:  $N_{eval} = 2$  years, and testing set = 1 year



### 3. Methods – Benchmark models



Naive Model

$$Y_{d,s} = \begin{cases} Y_{d-7,s} + \varepsilon_{d,s} & , d \text{ is Monday, Saturday, or Sunday} \\ Y_{d-1,s} + \varepsilon_{d,s} & , \text{other day } d \text{ of the week} \end{cases}$$



Expert Model

$$Y_{d,s} = \beta_{s,0} + \beta_{s,1}Y_{d-1,s} + \beta_{s,2}Y_{d-2,s} + \beta_{s,3}Y_{d-7,s} + \beta_{s,4}DoW_d^1 + \beta_{s,5}DoW_d^6 + \beta_{s,6}DoW_d^7 + \varepsilon_{d,s}$$

With  $Y_{d,s}$  is the DA electricity price,  $DoW_d^k$  is day-of-the-week dummies,  $k=1$  for Monday, and  $k=7$  for Sunday

### 3. Methods – LASSO-based models

#### LASSO

- Least Absolute Shrinkage and Selection Operator
- L1-regularization with L1-norm penalty term
- higher  $\lambda$  encourages sparsity, forcing more coefficients to become exactly zero
- Prevent overfitting and “get rid of” irrelevant variables => useful for variable selection

#### Ridge Regression

- Tikhonov regularization or L2 regularization
- Penalty term is as the “L2-norm” or Euclidean norm
- Shrinking the coefficients by reducing their magnitude but not becoming exactly zero

#### Elastic Net

- A combination of the L1-norm (LASSO) and the L2-norm (Ridge) in the penalty term
- Effective compromise between variable selection (sparsity) and regularization (shrinkage)



# 3. Methods – LASSO-based models

$$\hat{\beta}_{\lambda,s}^{\text{lasso}} = \arg \min_{\beta \in \mathbb{R}^D} \|Y_s - X_s \beta\|_2^2 + \lambda_s \|\beta\|_1$$

LASSO

Ridge Regression

$$\hat{\beta}_{\lambda,s}^{\text{ridge}} = \arg \min_{\beta \in \mathbb{R}^D} \|Y_s - X_s \beta\|_2^2 + \lambda_s \|\beta\|_2^2$$

$$\hat{\beta}_{\Omega_{\lambda_s},s}^{\text{elasticnet}} = \arg \min_{\beta \in \mathbb{R}^D} \|Y_s - X_s \beta\|_2^2 + \lambda_s \mathcal{P}_{\alpha}(\beta)$$

$$\mathcal{P}_{\alpha}(\beta) = \alpha \|\beta\|_2^2 + (1 - \alpha) \|\beta\|_1$$

Elastic Net

- $\beta$  is obtained by minimizing the loss function (SSR + penalty term)
- Parameter  $\lambda$  controls the strength of the L1 or L2 regularization for each hour  $s \in S$
- $\alpha$  is a mixing ratio which controls the balance of penalty

### 3. Evaluation Methods

#### Root Mean Squared Error

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (y_{s,t} - \hat{y}_{s,t})^2}$$

#### Diebold-Mariano test

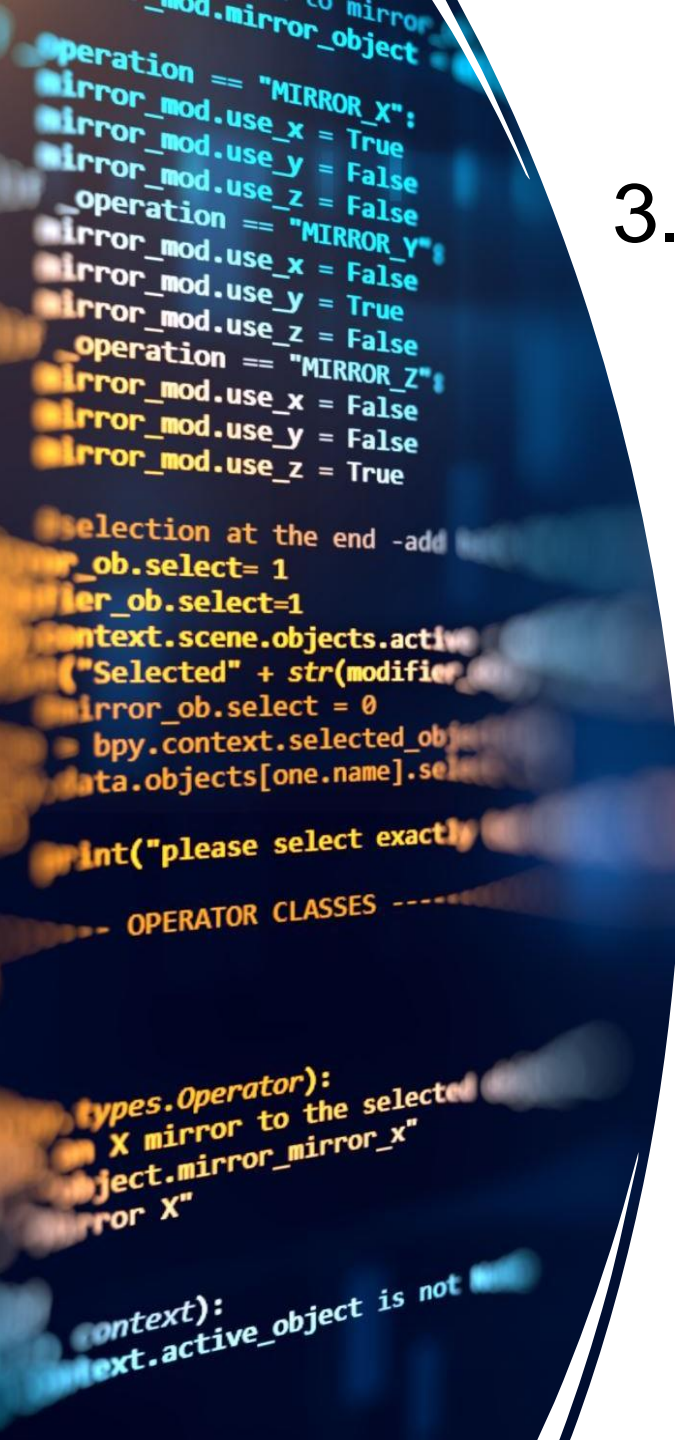
For comparing the forecast accuracy of two forecast model A and B  
Consider the difference loss function

$$\Delta_{A;B;t} = L_{A,t} - L_{B,t}$$

The null hypothesis

$$H_0 : E(\Delta_{A;B;t}) = 0 \quad \text{vs.} \quad H_1 : E(\Delta_{A;B;t}) \neq 0$$

The null hypothesis will be rejected if the computed DM statistic falls outside the range of  $-z_{\frac{\alpha}{2}}$  to  $z_{\frac{\alpha}{2}}$



## 4. Results - Hyperparameter

- Hyperparameter range:  $\Lambda = 2^{-10}, \dots, 2^2$  over 100 steps, tuning and selected using 5-fold cross-validation
- $\alpha$  ratio of Elastic Net is set at 0.5
- Best  $\lambda$  value for Lasso around 0.00097, for Ridge regression around 4, and Elastic Net model around 0.000976

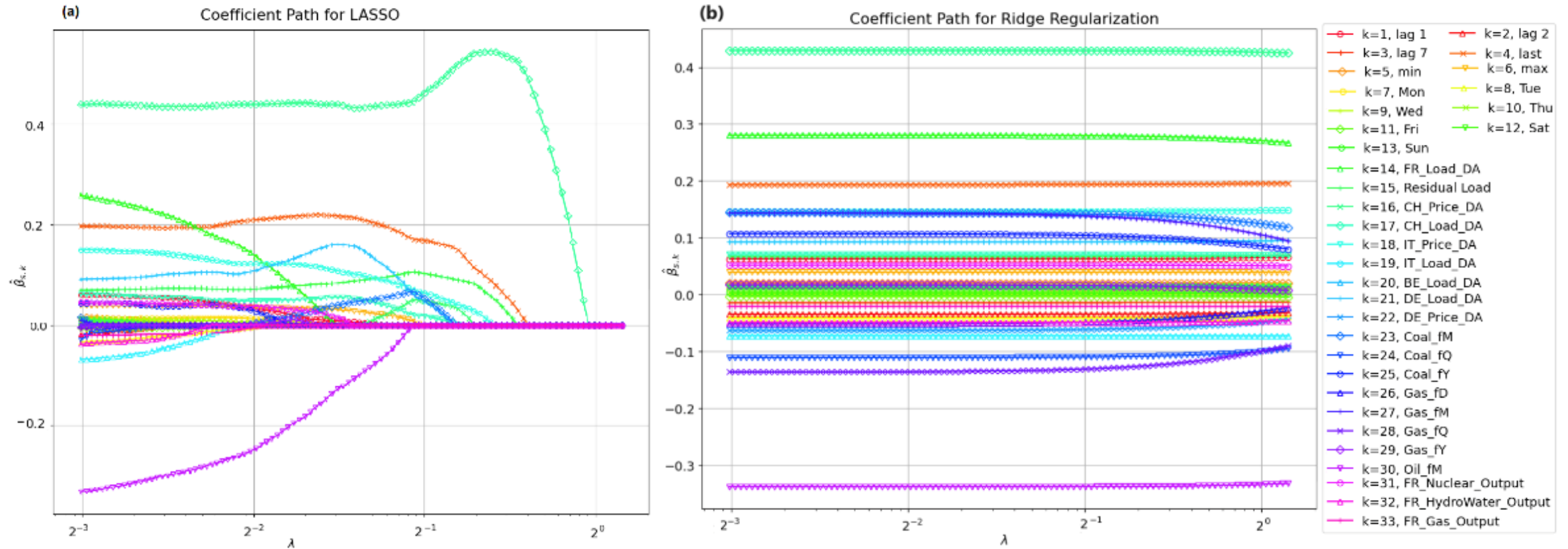


Figure 5: Shrinkage behavior of LASSO and Ridge regression.

Most important predictors: Switzerland's Load DA, price last hour of the day before, Oil price fm, Italy's Load DA, and France's Load DA and Germany's Load DA

# 4- Results - Model Performance

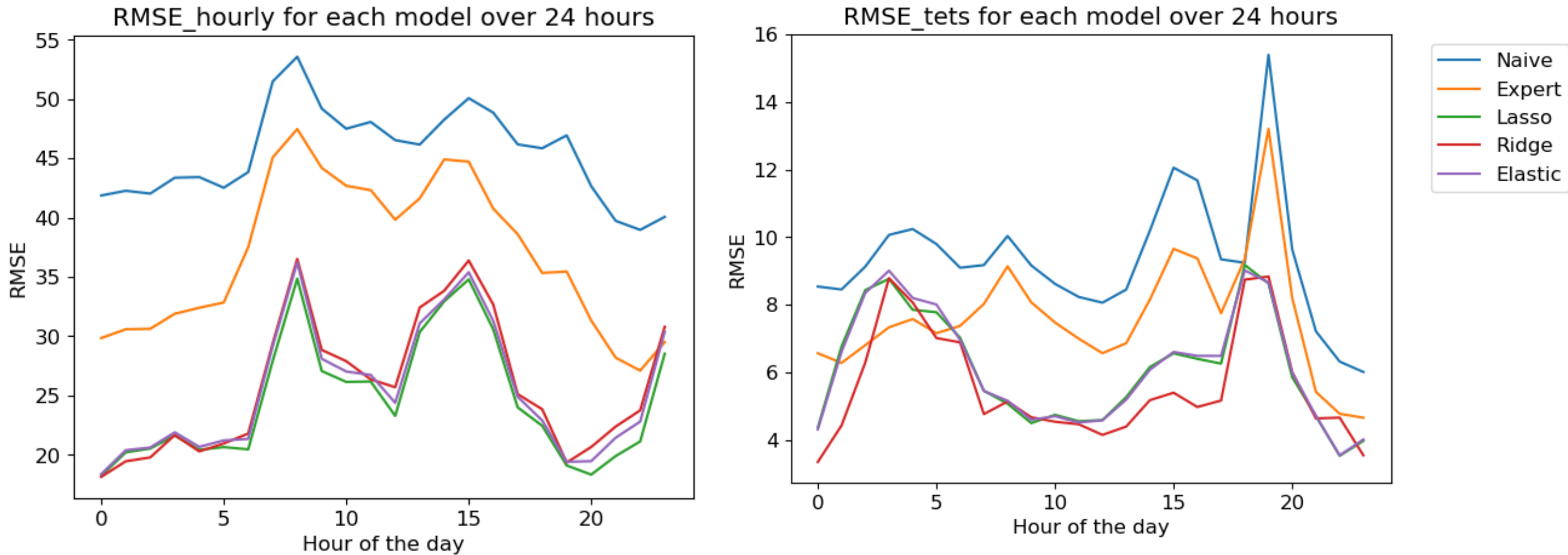


Figure 6: RMSEs by different models for different hours.



## 4. Results - Diebold-Mariano test

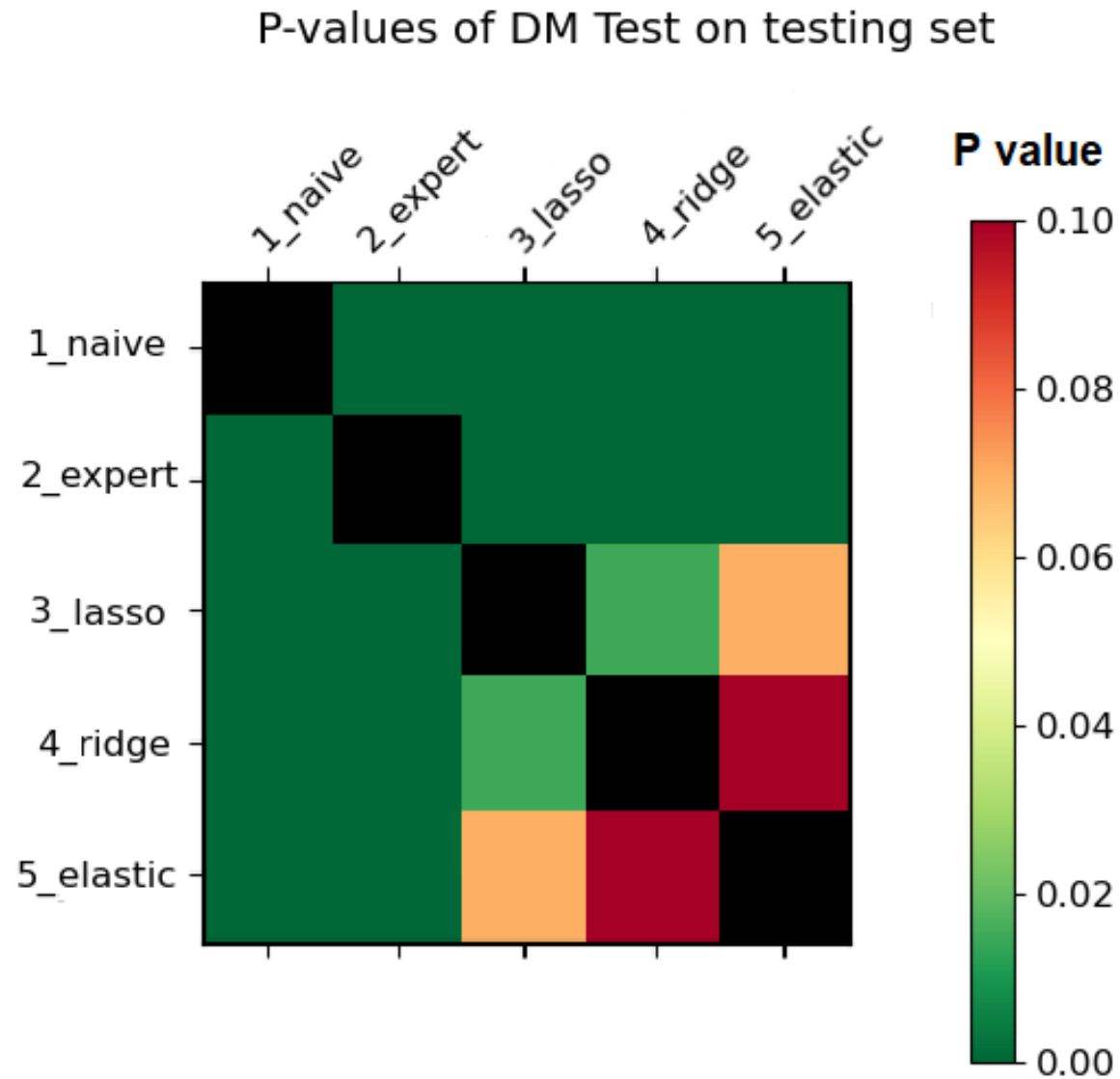
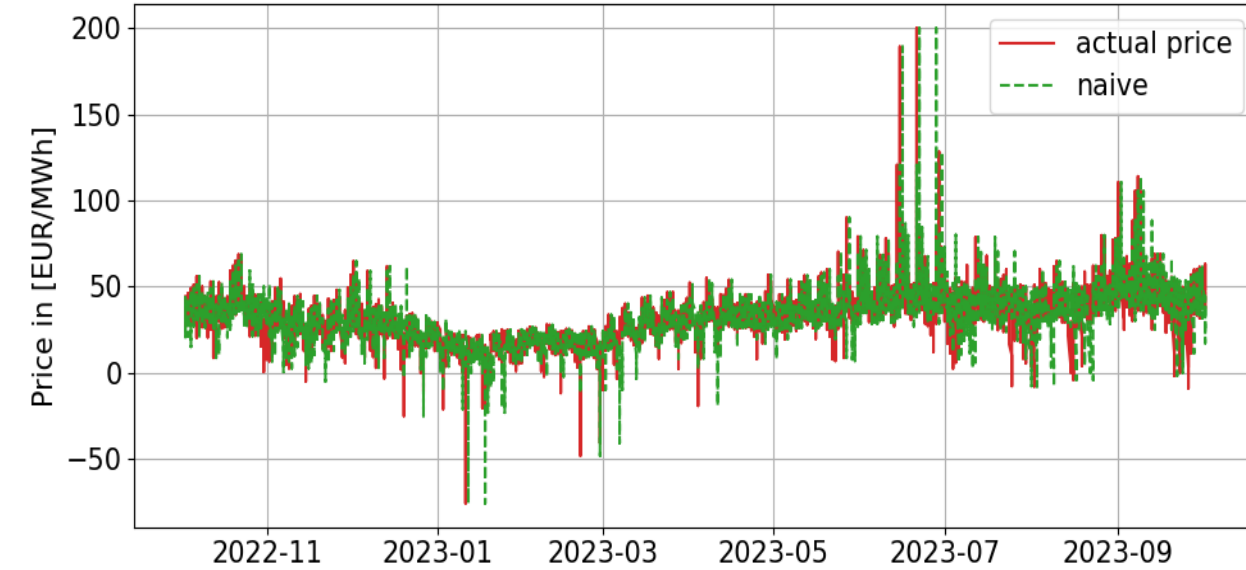


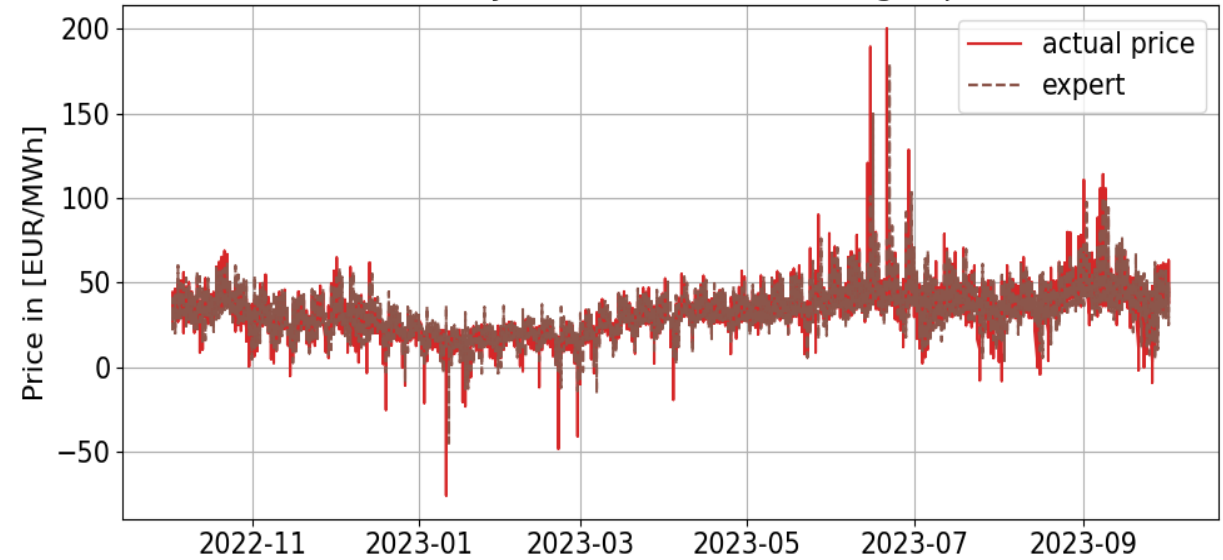
Figure 7: DM test results

## 4. Results – Forecast visualization

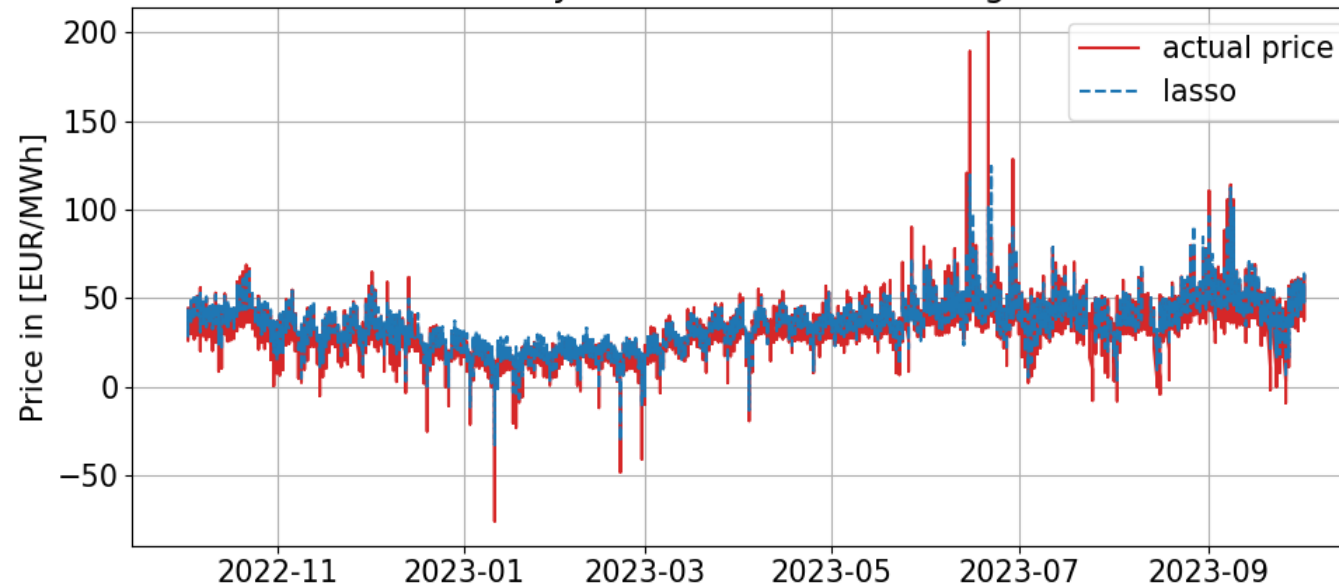
France Day-ahead Price Forecasting Naive



France Day-ahead Price Forecasting Expert

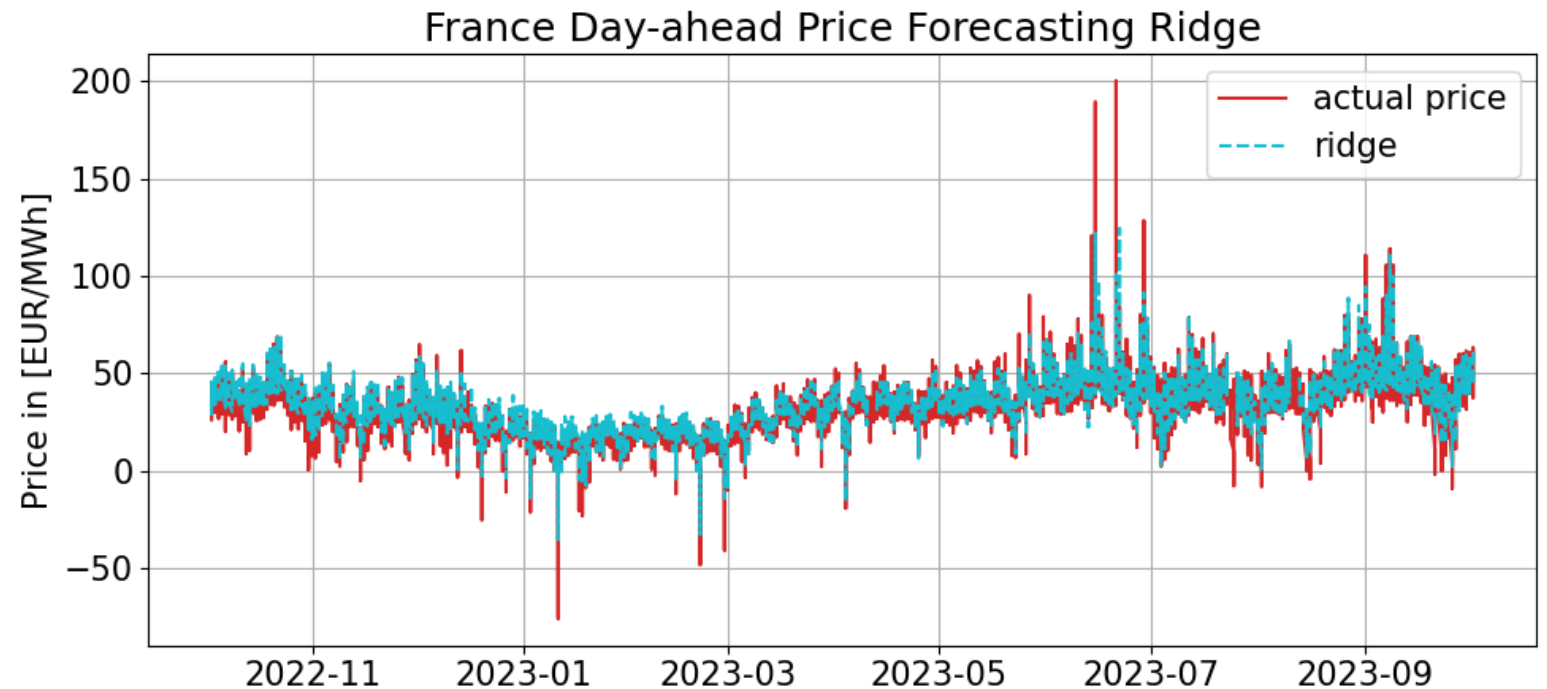
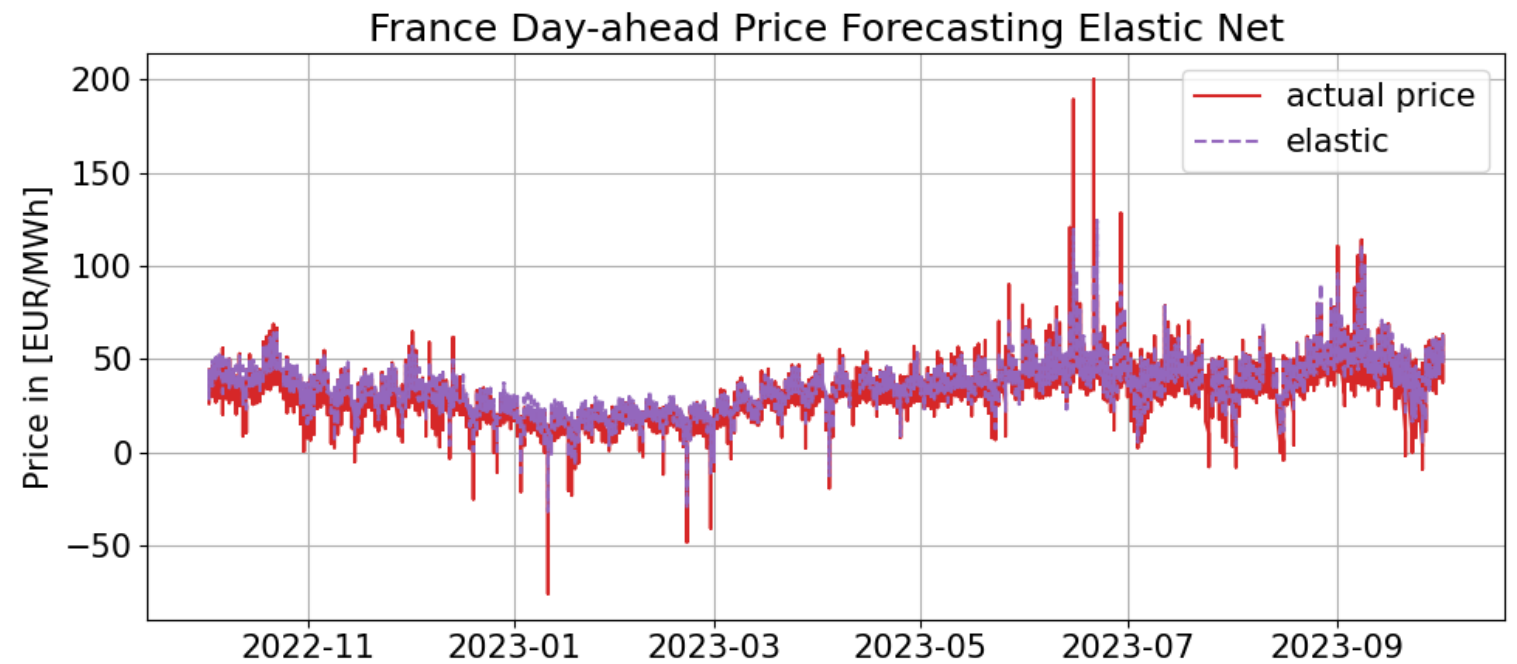


France Day-ahead Price Forecasting Lasso



## 4. Results

Forecast visualization



# 5 - Conclusions



- LASSO-based models have close RMSE results
- LASSO outperforms other models in the validation set.
- Ridge regression stands out as the best performer in out-of-sample testing set
- The naive and expert has the worst performance, the need for more sophisticated model with other predictors than only use the historical DA price
- The Diebold-Mariano test emphasizes the forecast power of Ridge regression in practical scenarios
- The study underscores the importance of incorporating covariates and the advantage of LASSO-based models in forecasting





Thank You

# 6 - Bibliography

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