Project: Forecasting France’s Day-ahead Electricity Price Using LASSO-Based Regression Models

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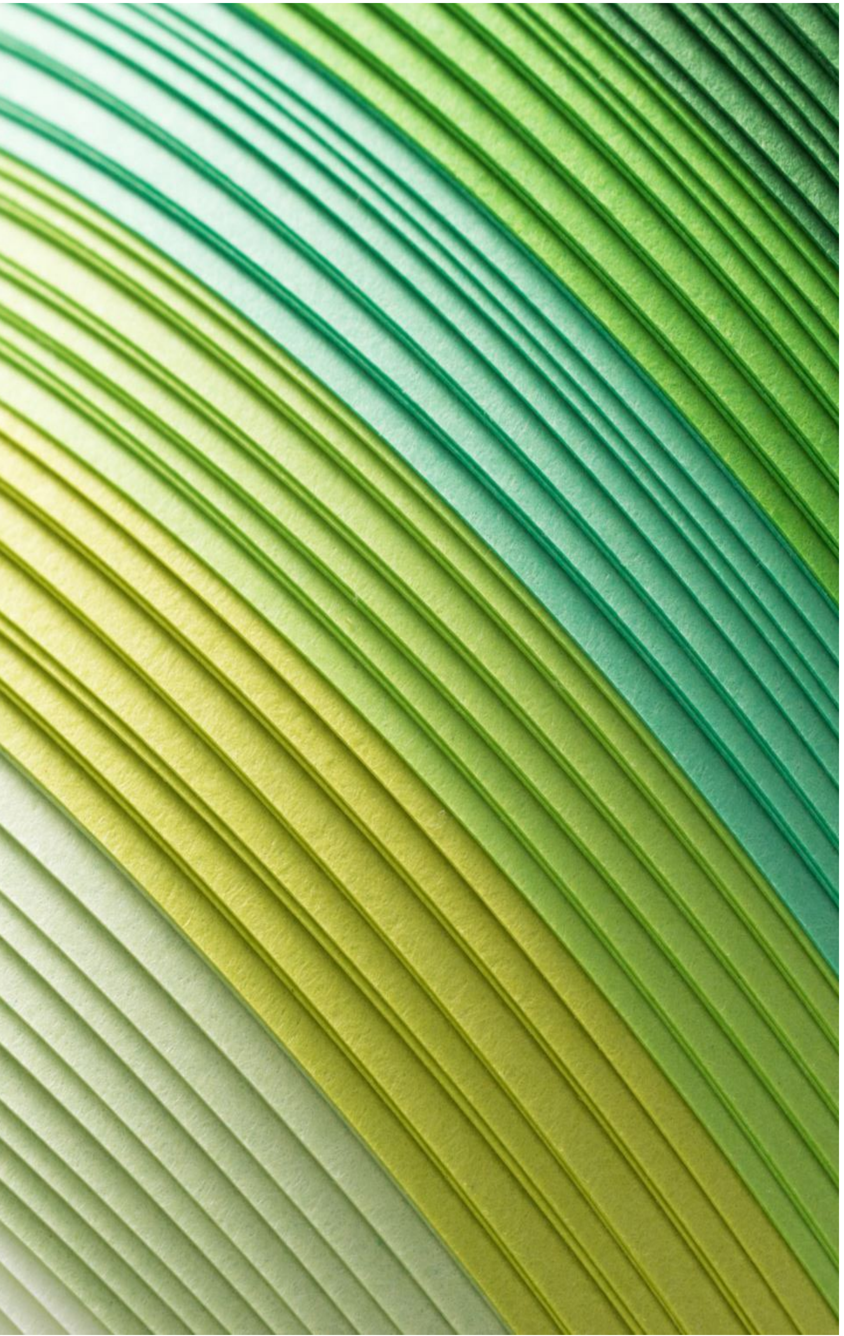

1- Introduction

- Challenges from the dynamic energy landscape and recent geopolitical events.
- 3 Shrinkage methods (Ridge Regression,LASSO, and Elastic Net) are employed
- Four benchmark model is utilized: Naive model, Expert model, the Extended Expert model **expert.last** and **expert.redav**

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2. Data – Regressors selection

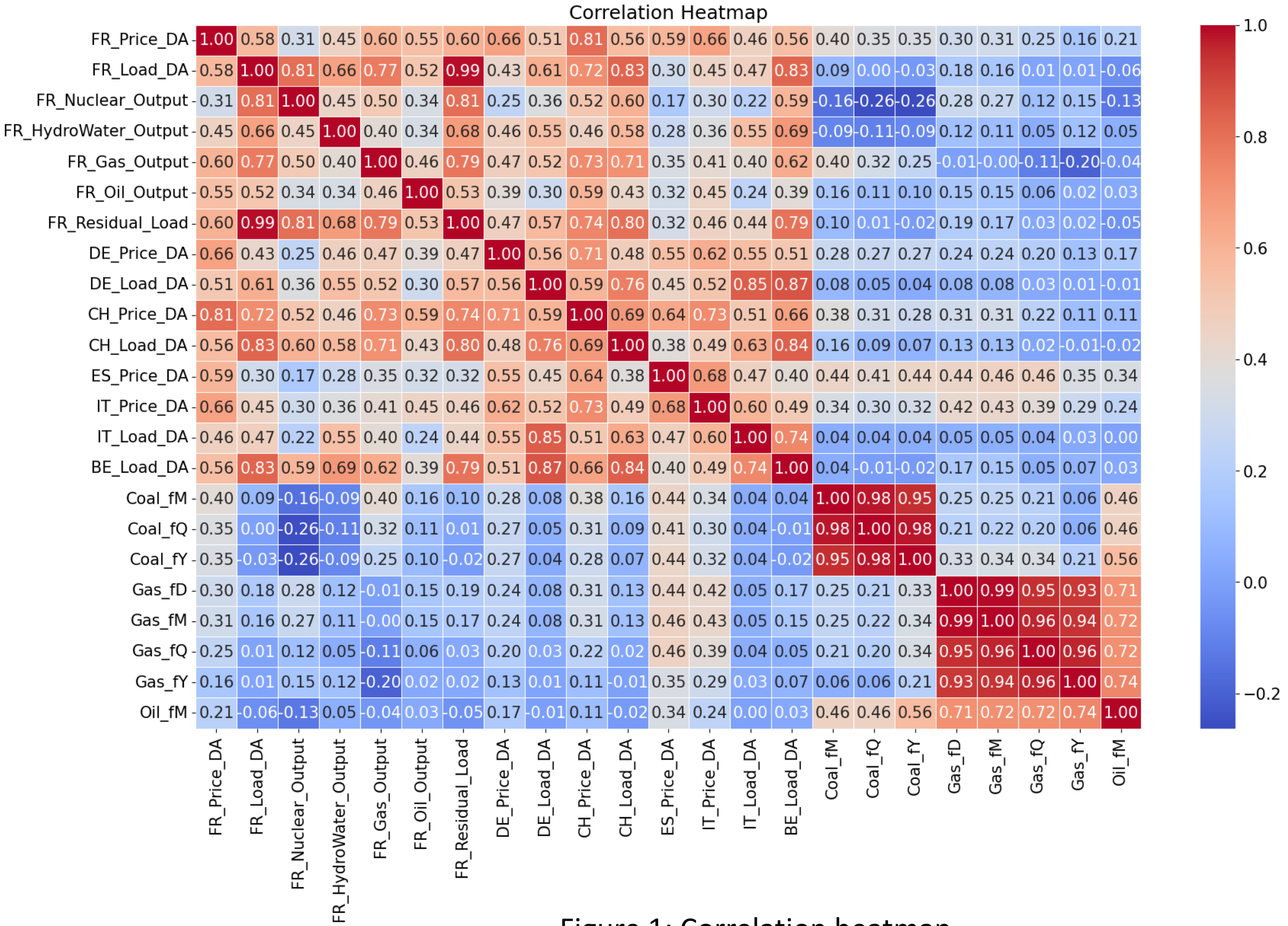

Figure 1: Correlation heatmap

Two main features:
- Feature of France: Price, Load, Output of France

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

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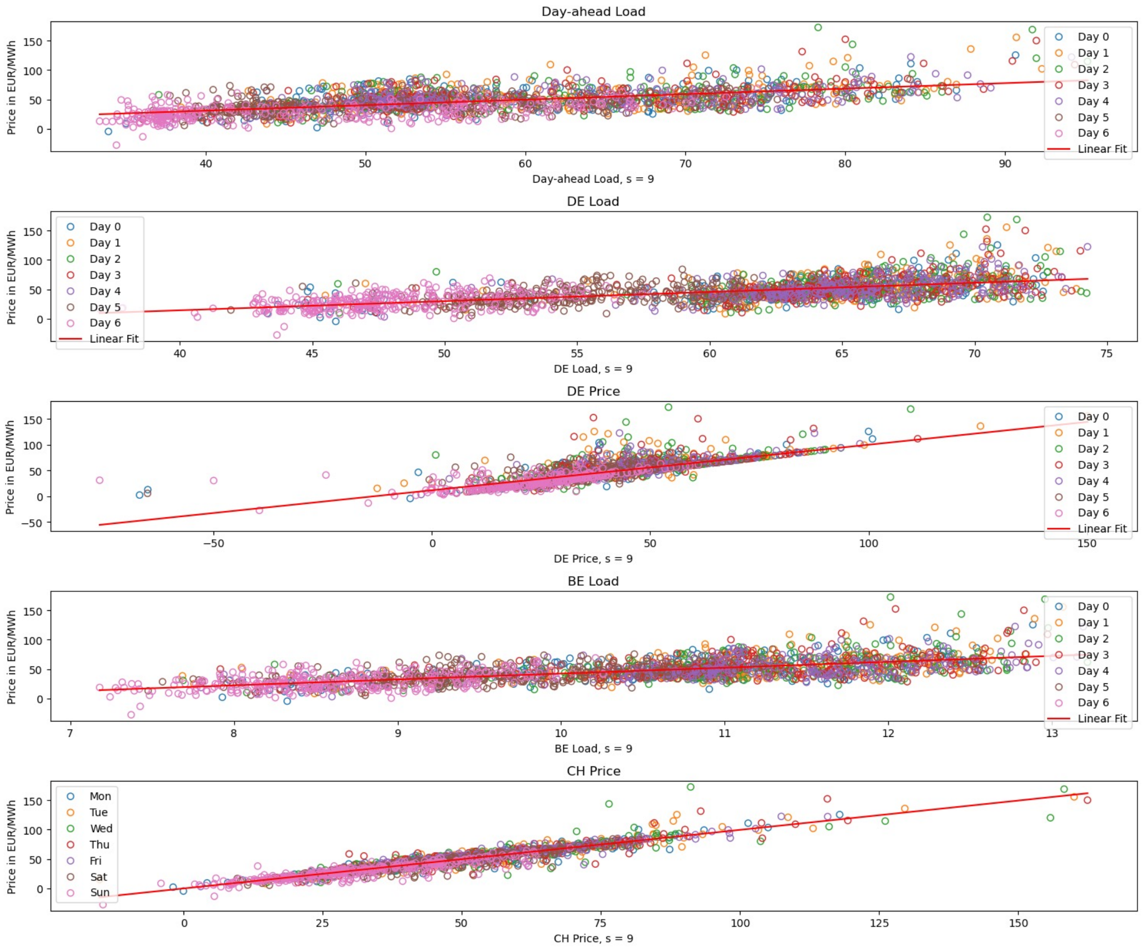

Figure 2: Relationship between some variables and DA price of France

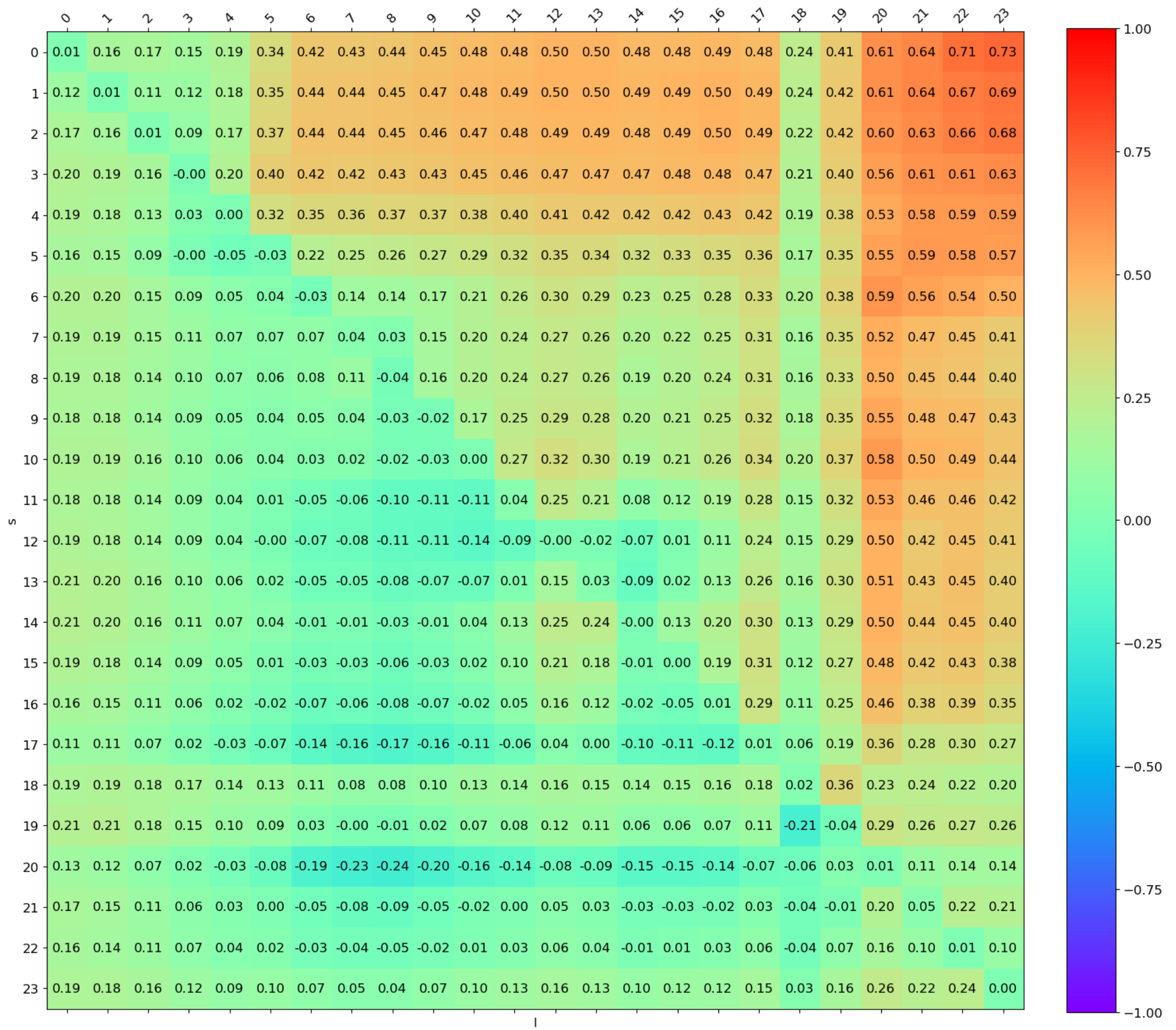

Figure 3: Correlation heatmap for all hours

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2. Data - Target variable

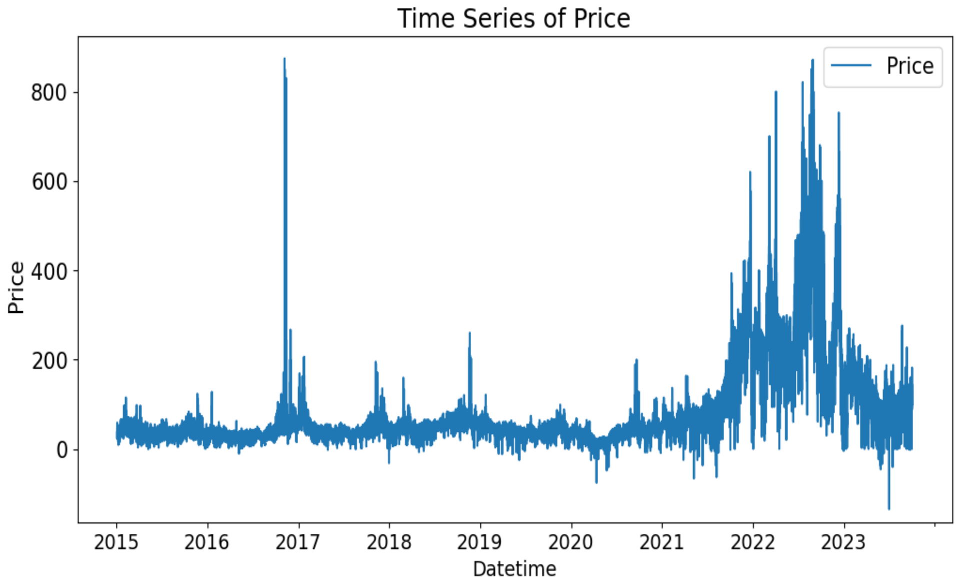

Figure 4a: Day-ahead price over time on traning set

(after oulier cleaning on 2022-04-04)

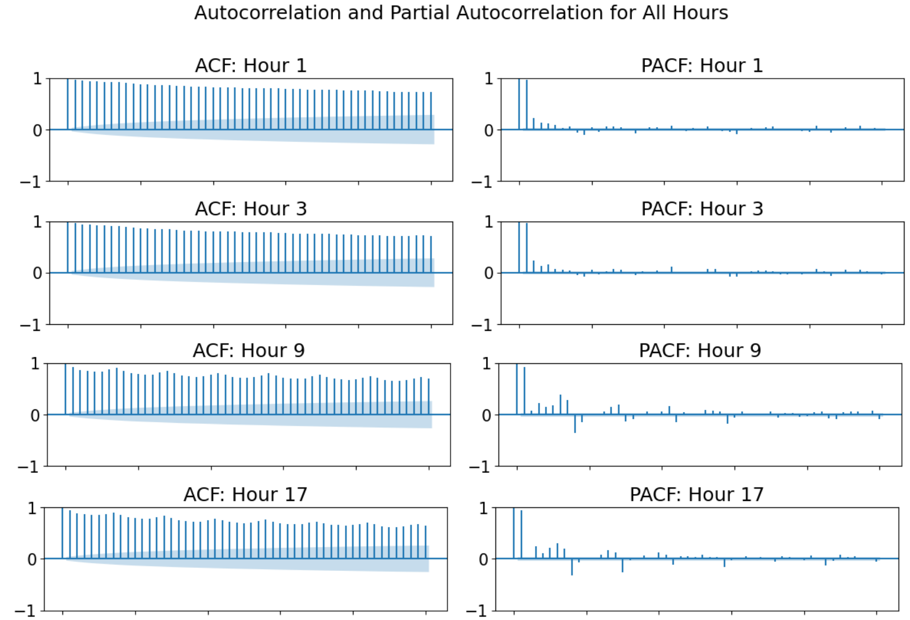

Figure 4b: Auto-correlation structure

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

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3. Methods – Benchmark models

Naive Model

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

Expert Model

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

Extended Expert Model (**expert.last**)

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

Extended Expert Model (**expert.redav**)

$$Y_{d,s} = \beta_{s,0} + \beta_{s,1} Y_{d-1,s} + \beta_{s,2} Y_{d-2,s} + \beta_{s,3} Y_{d-7,s} + \beta_{s,4} Y_{d-1,S-1} + \beta_{s,5} Y_{d-1,min} + \beta_{s,6} Y_{d-1,max} + \beta_{s,7} DoW_d^1 + \beta_{s,8} DoW_d^6 + \beta_{s,9} DoW_d^7 + \beta_{s,10} X_{d,s}^{Load} + \beta_{s,11} X_{d,s}^{DARES} + \beta_{s,12} X_{d,s}^{Coal} + \beta_{s,13} X_{d,s}^{Gas} + + \beta_{s,14} X_{d,s}^{Oil} + \varepsilon_{d,s}$$

3. Methods – LASSO-based models

$$\hat{\tilde{\beta}}^{\text{lasso}}_{\lambda,s} = \underset{\beta \epsilon \mathbb{R}^D}{\text{arg min}} \|\tilde{Y}_s - \tilde{X}_s\beta\|_2^2 + \lambda_s\|\beta\|_1$$

$$\hat{\tilde{\beta}}^{\text{elasticnet}}_{\Omega_{\lambda_s},s} = \underset{\beta \in \mathbb{R}^D}{\text{arg min}} \|\tilde{Y}_s - \tilde{X}_s\beta\|_2^2 + \lambda\mathcal{P}_\alpha(\beta)$$

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

Ridge Regression

LASSO

Elastic Net

$$\hat{\tilde{\beta}}^{\text{ridge}}_{\lambda,s} = \underset{\beta \epsilon \mathbb{R}^D}{\text{arg min}} \|\tilde{Y}_s - \tilde{X}_s\beta\|_2^2 + \lambda_s\|\beta|_2^2$$

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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: $\Lambda = 2^{-5}, \ldots, 2^{0.5}$ over 100 steps, tunning and selected using 5-fold cross-validation, α ratio in Elastic is set at 0.5

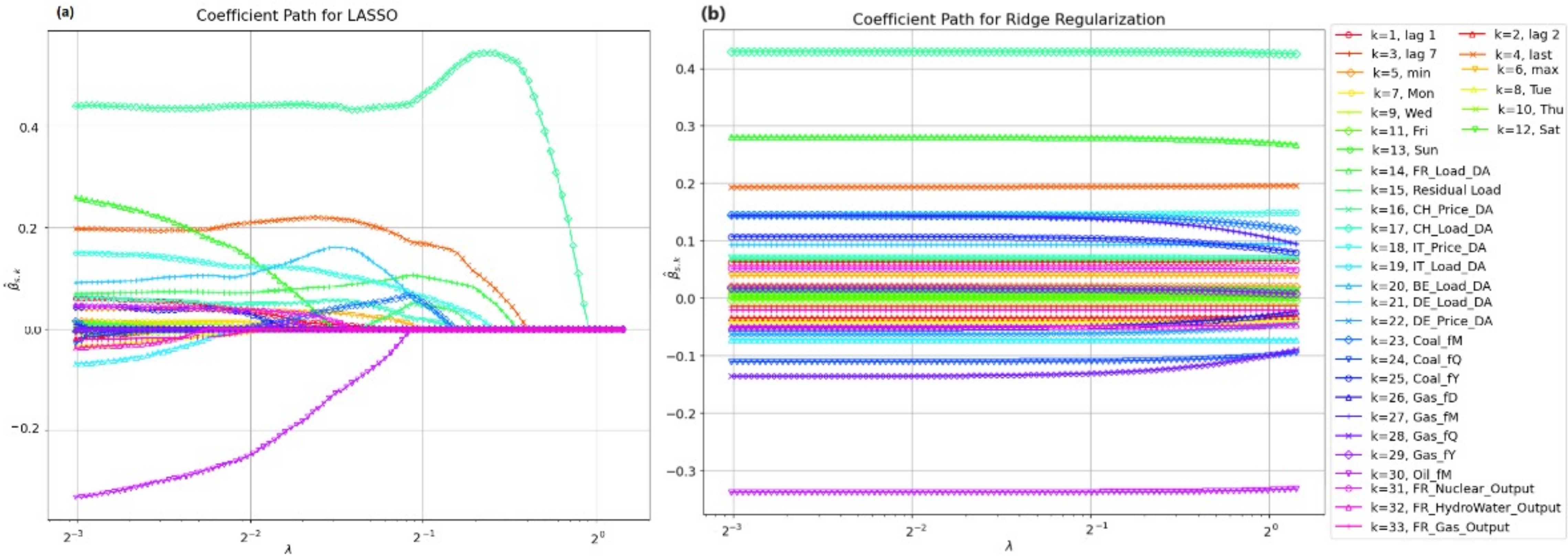

Figure 5: Shrinkage behavior of LASSO and Ridge regression.

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4. Results - Model Performance

4.2

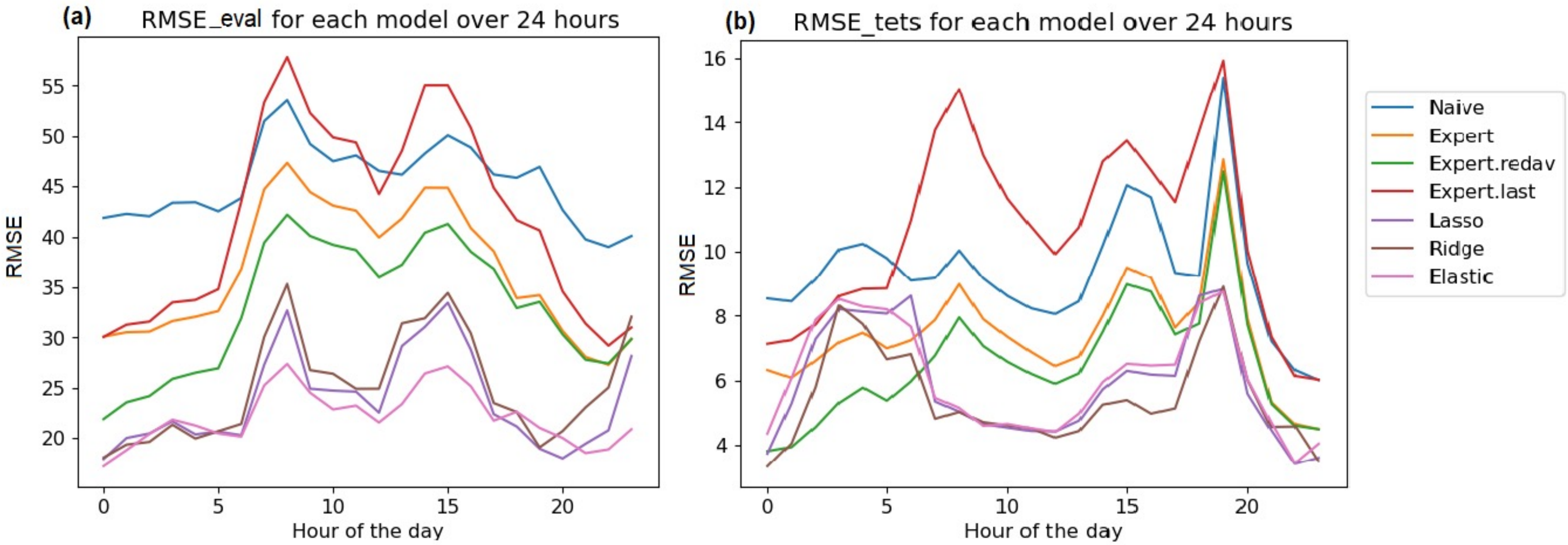

Figure 6: RMSEs by different models for different hours.

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4. Results - Diebold-Mariano test

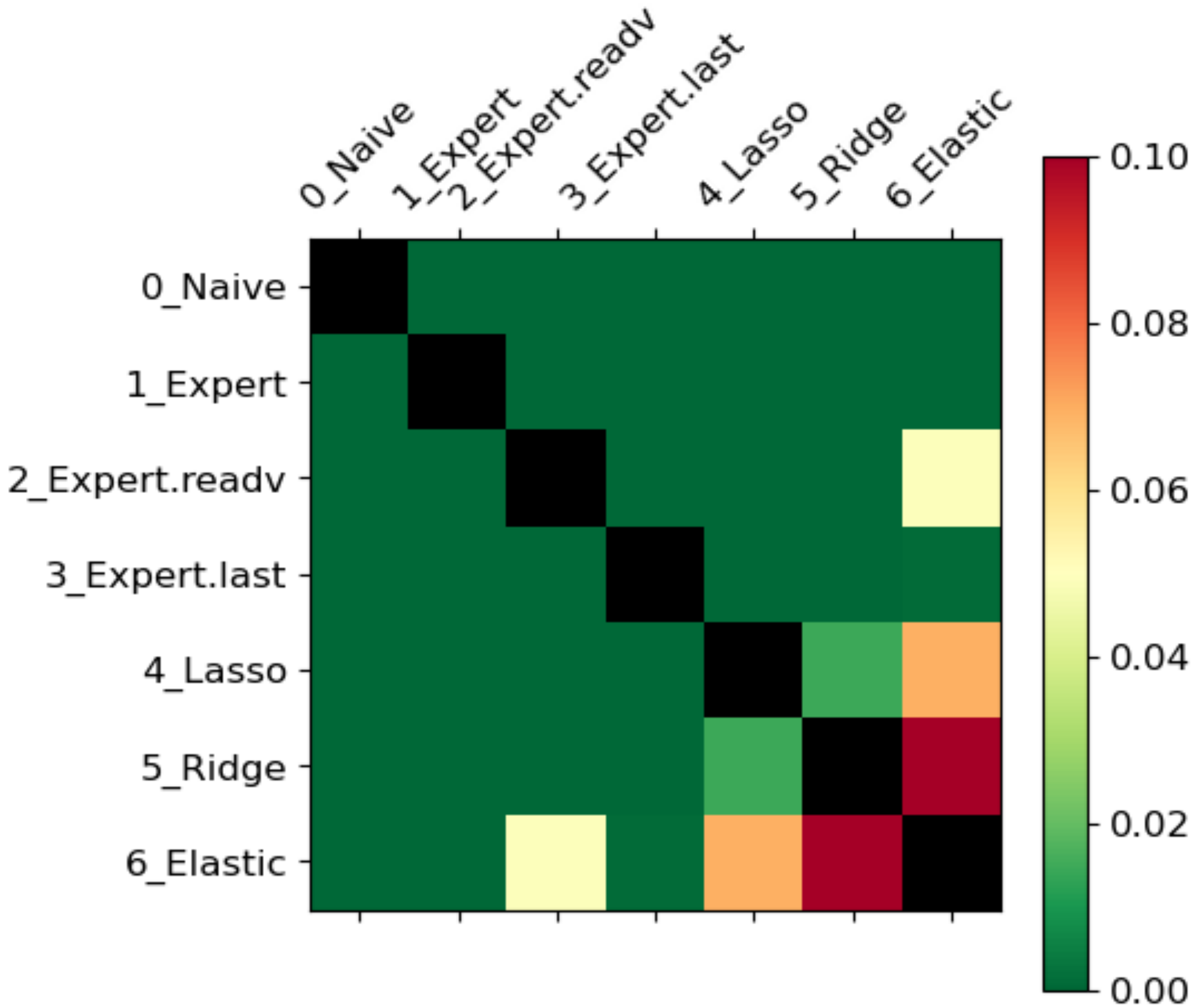

Figure 7: DM test results

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4. Results – Forecast visualization

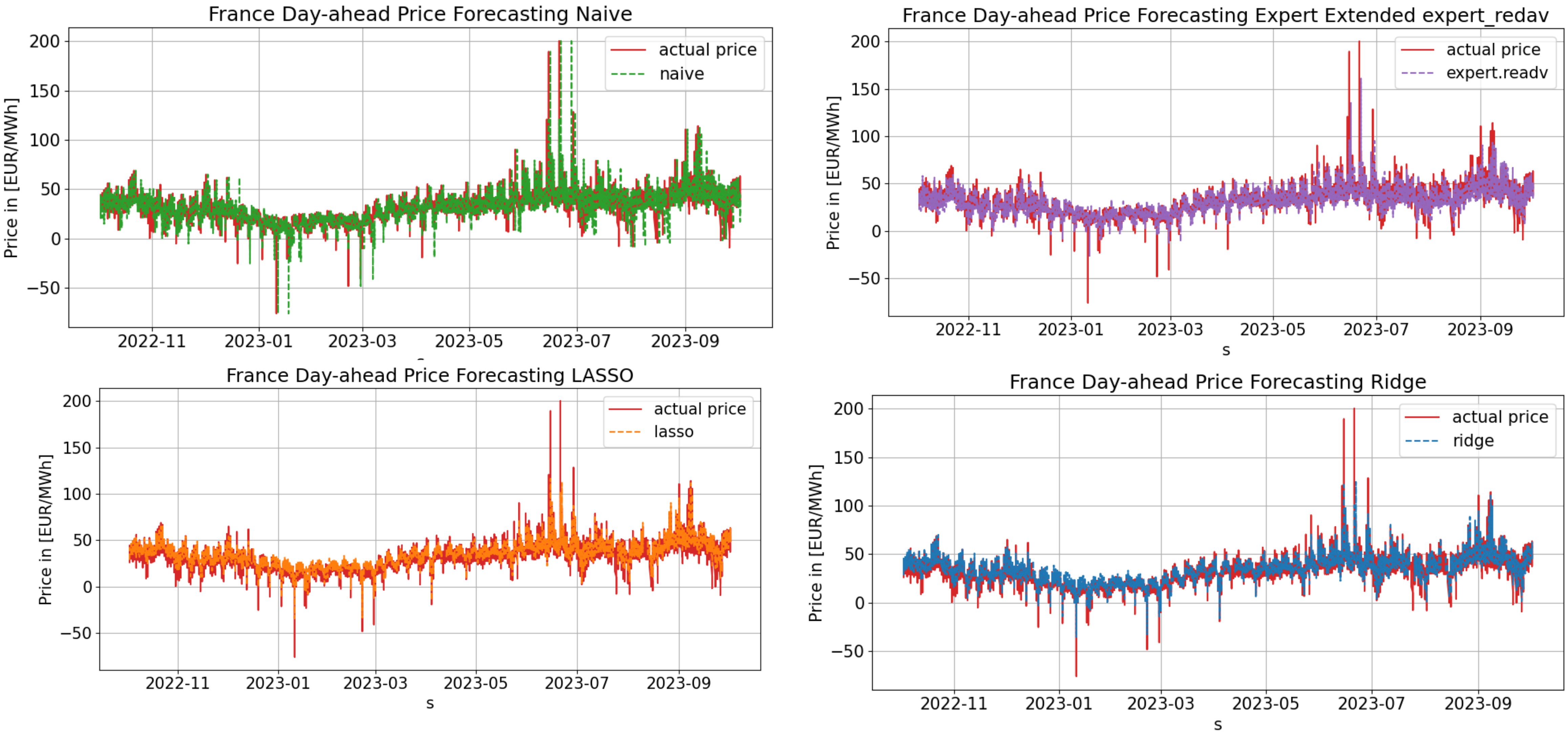

Figure 8: Forecast visualization

4. Results – Forecast visualization

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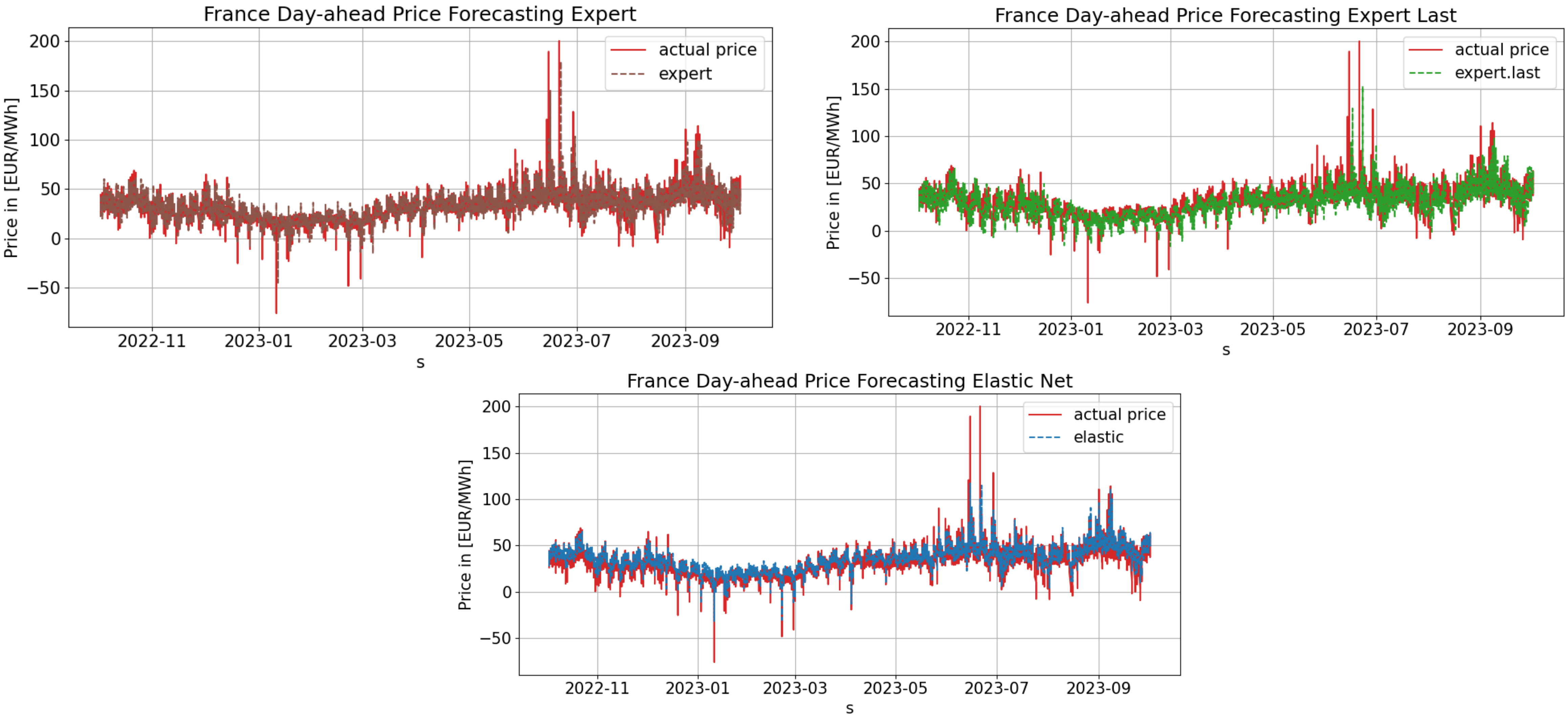
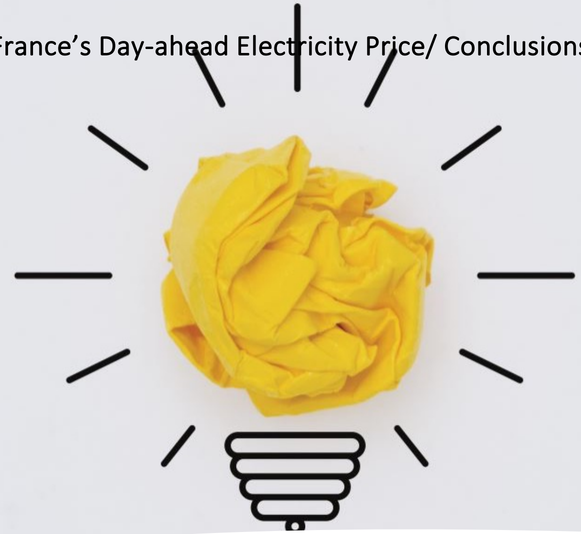


Figure 9: Forecast visualization



5 - Conclusions

- LASSO-based models have close RMSE results
- Elastic Net, with the combination of LASSO and Ridge regression, outperforms other models in the validation set.
- Ridge regression stands out as the best performer in out-of-sample testing set
- The naive, expert.last and expert has the worst performance, expert.redav has better results
- The Diebold-Mariano test emphasizes the forecast power of Ridge regression in practical scenarios
- The study underscores the importance of incorporating covariates in forecasting

Thank You

6 - Bibliography

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