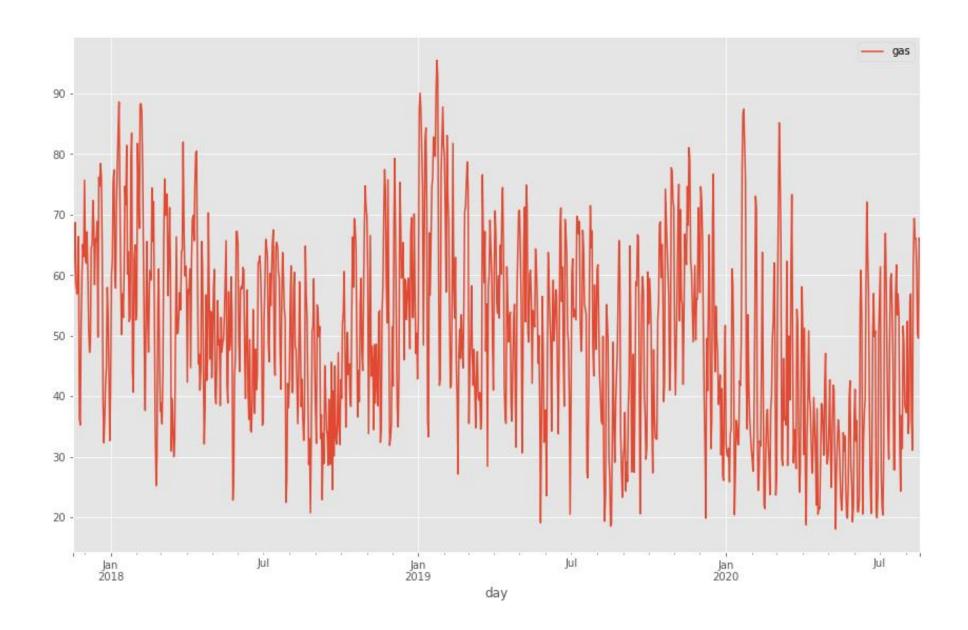
Short Term Power Burn Model

GAS Analytics

Rationale:

To produce short and long term forecast of gas demand for electricity production in the UK

Dependent Variable

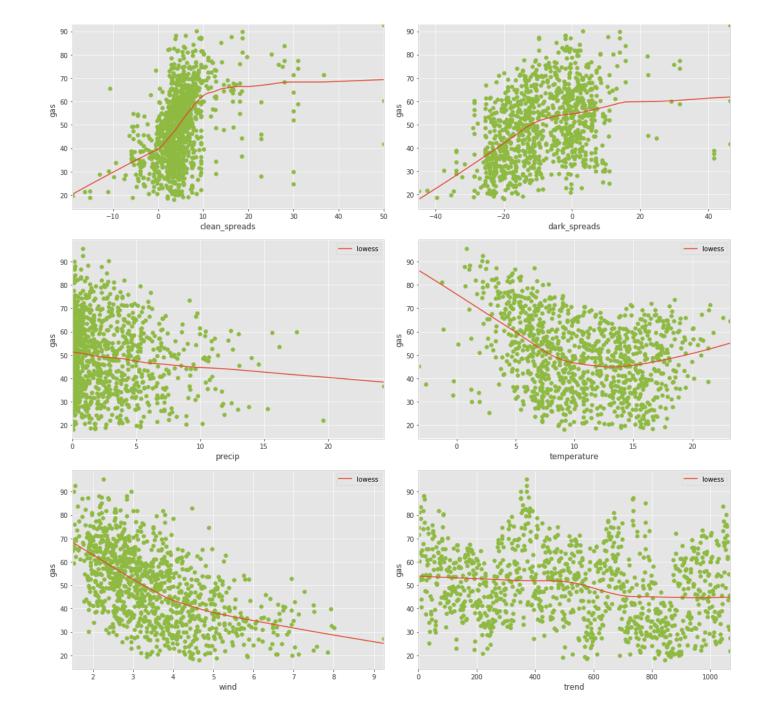


Covariates:

- clean spreads
- dark spreads
- temperature
- wind
- precipitation
- monday_thursday flag
- Fourier series

Data:

• 3 years daily sampling



Modelling Framework:

Design Matrix:

- Imputations
- · Design Matrix:

$$t \mid y_t \xrightarrow{f} v_t, \mid x_t^1, x_t^2, \dots x_t^k \xrightarrow{g} g_1 x_t^1, g_2 x_t^2, \dots, g_k x_t^k$$

$$DM_t = DM_t(y_t, f, f^{-1}, \{x_t^i\}_{i=1,k}, \{g_t^i\}_{i=1,k})$$

Exploratory analysis

- · Autocorrelation:
 - $ACF(x_t)$
 - PACF(x_t)
- Scatter Plots:
 - y_t next to v_t and x_t^k next to g_kx_t^k
 - y_i vs. x_i^j for j = 1, k with LOWESS for dependency shape analysis
 - x_t vs. x_{t-h} with LOWESS for autocorrelation analysis
 - y_t vs. x_{t-h}^k for given k with LOWESS for lagged-leading relationship

Calibrator:

 $\mathbb{C}(\mathcal{H}yperParams) \rightarrow \mathbb{C}$

Model:

$$M = M(C, DM) \rightarrow {\{\hat{\theta}_l\}_{l=1,m}}$$

Model Specification

$$\{\hat{\theta}_l\} \xrightarrow{I(\theta): AIC, AICc, BIC} \{\hat{\theta}_l^*\}$$
GridSearch

Model Selection:

Cross Validation

 $CV = \mathbb{CV}(M, Partitioning, Performance Metric)$

$$\mathbb{C} \xrightarrow{\epsilon_{CY}} \mathbb{C}^*$$

Residuals Diagnostics:

$$\hat{\varepsilon}_t = v_t - \hat{v}_t; \ \hat{\varepsilon}_t^{std}; \ \hat{\varepsilon}_t^{stu}$$

$$RD = \mathcal{R}\mathcal{D}(\hat{\epsilon}_t, \hat{\epsilon}_t^{std}, \hat{\epsilon}_t^{stu})$$

Forecast:

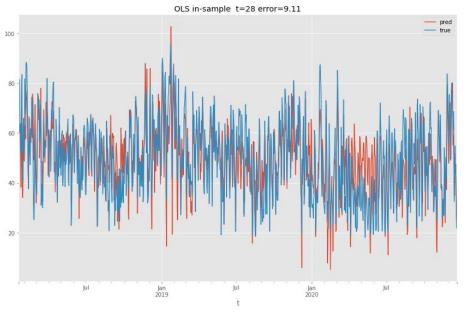
$$\mathbf{C}^*(DM_{t+1} = g_i(x_{t+1}^i)_{i=1,k} \mid \{\widehat{\theta^*}_t\}_{t=1,m}) = \widehat{v}_{t+1} \xrightarrow{f^{-1}, y_t} \widehat{y}_{t+1}$$

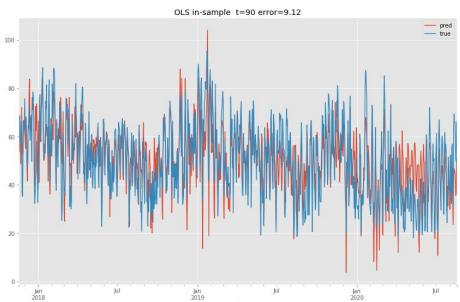
Data handling

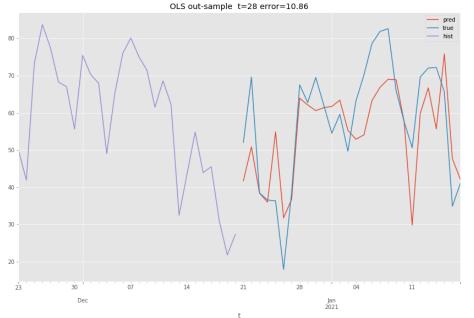
ALL DATA: IN TIME: ACTUALS 4y								OUT OF TIME: FUTURE	
IN SAMPLE 3y OUT SAMPLE 28days									
CROSS VALIDATION 3y:									
FOLD1 1y		FOLD2 1.5y		FOLD3 2.5y		FOLD4 3y			
train sample 0.8y	test sample 28days	train sample 1.3y	test sample 28days	train sample 2.3y	test sample 28days	train sample 2.8y	test sample28 days		
	error 1		error 2		error 3		error 4		
CV error = 1/4 * (error1 + error2 + error 3 + error4)									
CV std = Stand	CV std = Standard Deviation (error1, error2, error3, error4)								
IN SAMPLE ERROR								OUT SAMPLE ERROR	OUT OF TIME ERROR

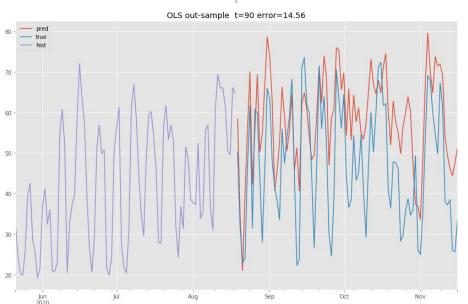
error = Root Mean Square Error

Calibrator (exog): Linear Regression





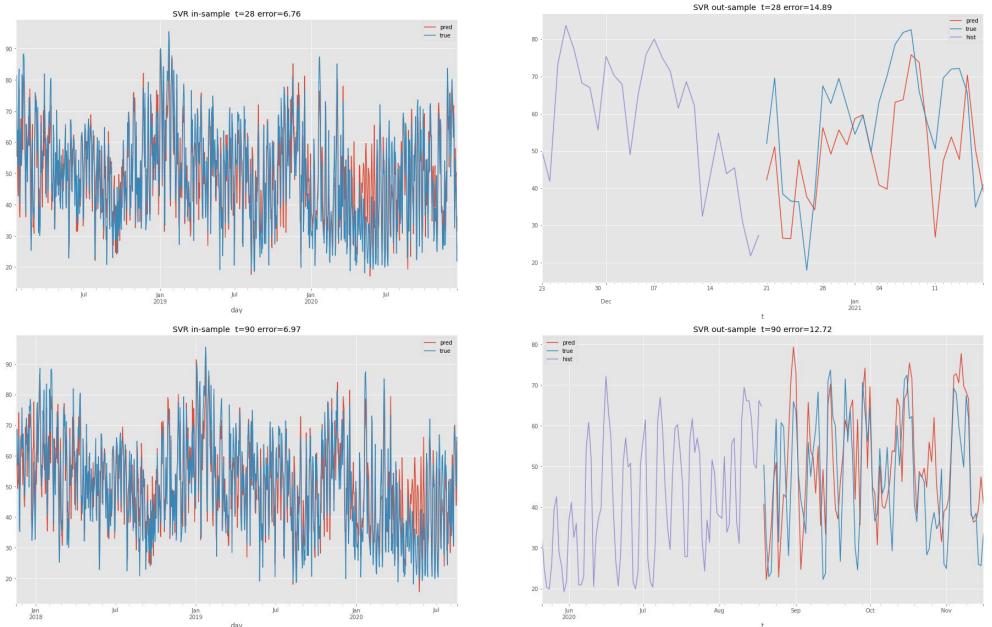




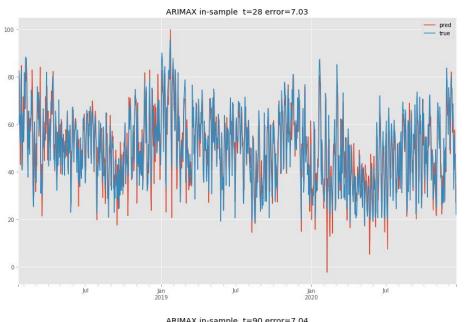
CV= 9.43 (2.08)

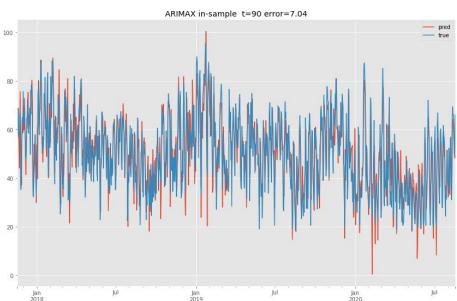
CV= 10.57 (1.79)

Calibrator (exog): Support Vector (kernel) Regression

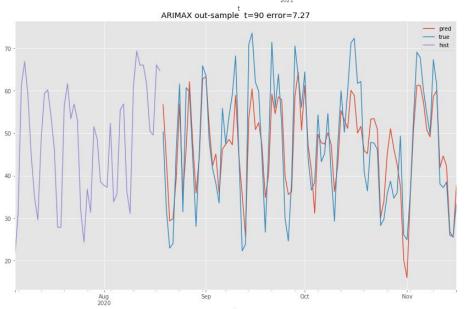


Calibrator (exog): SARIMAX





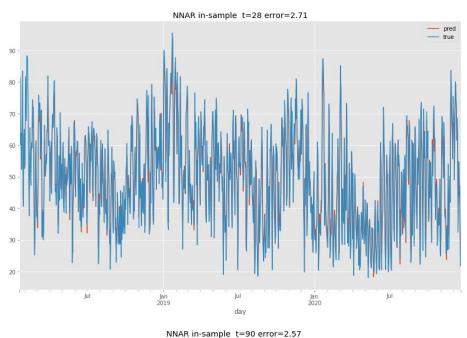


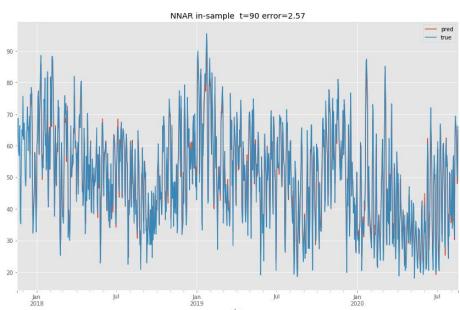


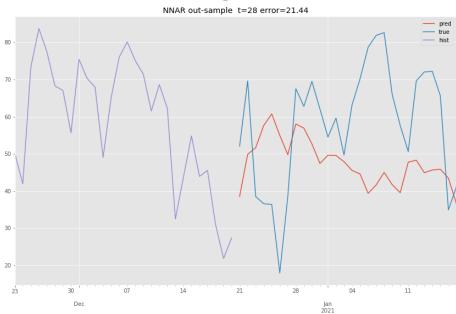
CV= 8.44 (1.71)

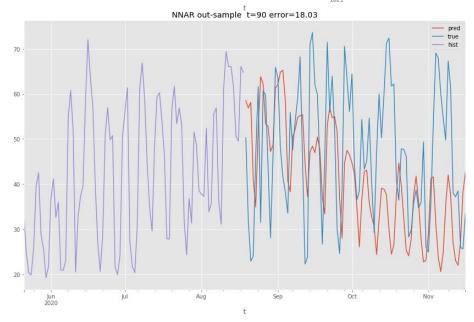
CV= 10.37 (2.41)

Calibrator (endog): Neural Network Autoregression

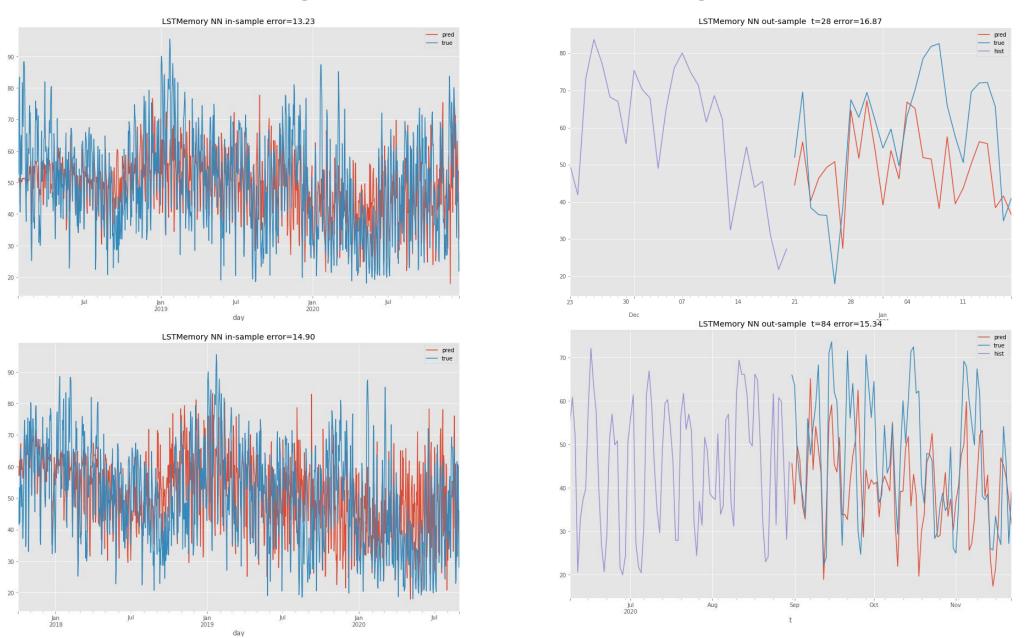








Calibrator (endog): Neural Network Long Short Term Memory



Appendix A:

Model	Parameters	Description
EXOGENEOUS RELATIONSHIP:		
Linear Regression	const, trend, clean_spreads, precipitation, temperature, wind, S1-7, C1-7, S2-7, C2-7, S3-7, C3-7, mo_th_yes	Modelling in levels Exog variables: grid search with BIC criterion 3 terms of Fourier series at weekly frequency
SARIMAX	SARIMAX(1, 0, 1)x(1, 0, 1, 7)	Modelling in levels
	const, dark_spreads, precipitation, temperature, wind,	Specification: grid search with BIC criterion
		Exog variables: grid search with BIC criterion
Support Vector Regression	type="eps-regression" kernel='radial'	Dependent variable and features scaling: standardization
	cost= 8gamma= 0.0625epsilon= 0.3	Specification: grid search with 10-fold CV
ENDOGENEOUS RELATIONSHIP:		
Neural Network Autoregression	 Model: NNAR(29,1,15)[7] Average of 20 networks, each of which is a 29-15-1 network with 466 weights options were - linear output units 	Dependent variable scaling: standardization
Long Short Term Memory Neural Network		