UNC Workgroup 0754R

March 2022

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Glossary

Useful Links

- Uniform Network Code Section H
- Demand Estimation Methodology
- Demand Modelling Approach (2021 version)
- UIG Task Force Findings
- NDM Algorithm Consultation Material
- UNC Request for 0754R Workgroup

For those not familiar with all the industry abbreviations please find full name of those used in this presentation below:

- ALP: Annual Load Profile
- AUGE: Allocation of Unidentified Gas Expert
- CDSP: Central Data Services Provider
- CWV: Composite Weather Variable
- DAF: Daily Adjustment Factor
- DESC: Demand Estimation Sub Committee
- DM: Daily Metered
- DOW: Day of Week
- EUC: End User Category
- ILF: Indicative Load Factor
- LDZ: Local Distribution Zone
- MAPE: Mean Absolute Percentage Error
- MPE: Mean Percentage Error
- NDM: Non-Daily Metered
- PLF: Peak Load Factor
- SNCWV: Seasonal Normal Composite Weather Variable
- SND: Seasonal Normal Demand
- UIG: Unidentified Gas
- UNC: Uniform Network Code
- WAR: Winter Annual Ratio
- WCF: Weather Correction Factor
- WSENS: Weather Sensitivity

Workgroup 0754R

Background

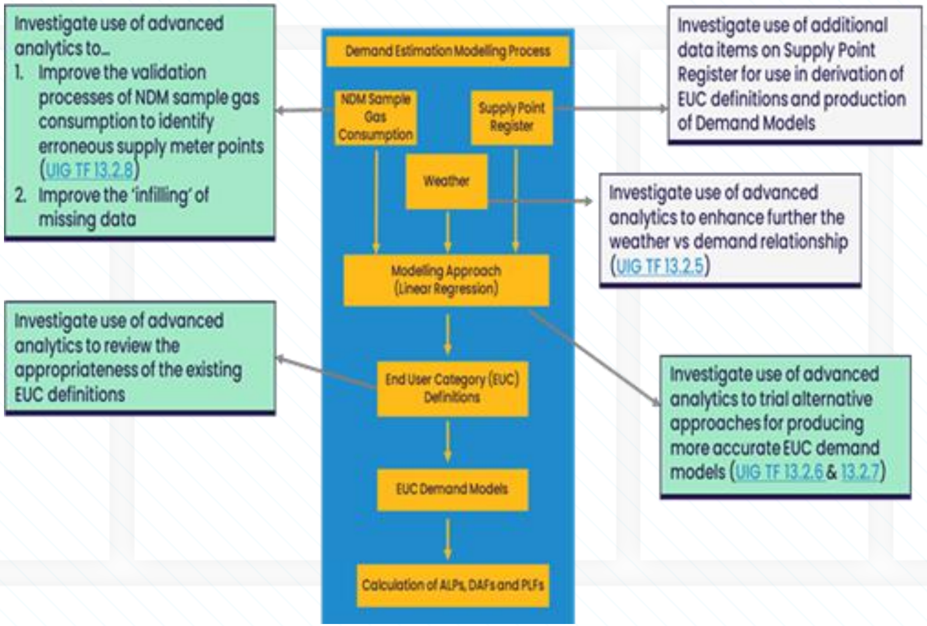
- UIG Task Force produced a number of recommendations to help reduce temporary UIG levels/volatility. This included findings associated with the modelling error within the NDM Algorithm
- DESC is responsible for the NDM Algorithm (UNC Section H) and has an obligation to review it every 3 years (UNC H 2.2.2)
- Prior to moving forward with the above a consultation was performed during Q4 of 2020 to assess the levels of support for making improvements to the NDM Algorithm
- A more detailed view of the background to this Workgroup and current state overview is provided in the March meeting papers here

Rationale for workgroup

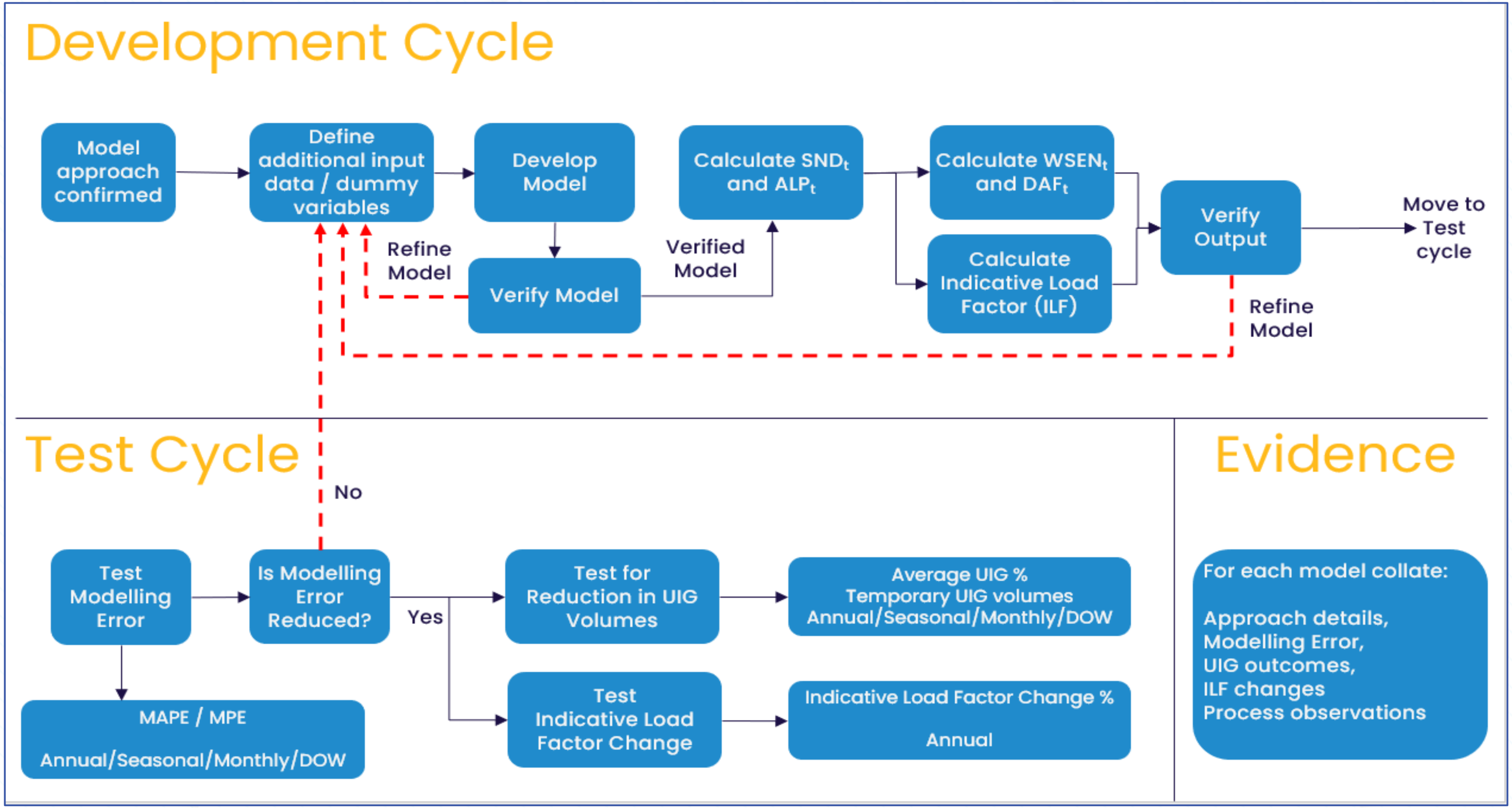
- Supports DESC's UNC obligation to review the NDM Algorithm
- UIG Task Force findings will be explored and progressed
- Clear industry support for investigating advanced analytical approaches
- A Workgroup maintains focus and increases visibility across the industry
- Improved NDM Allocation will result in a reduction in UIG volatility and subsequent Meter Point reconciliation/UIG volumes (temporary)

Workgroup 0754R: Investigation Areas

- The proposed areas of investigation



Workgroup 0754R: Area 1 Development Approach



Area 1: Test EUCs

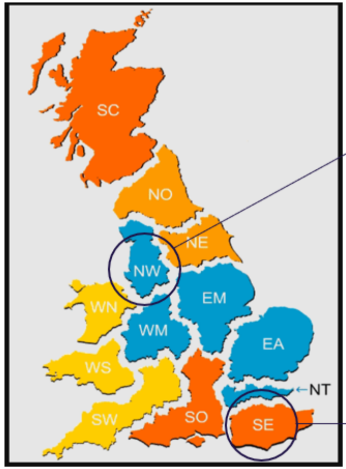
- Reminder of the LDZ and EUCs for trialing the approaches

Area 1: Trial LDZ Selection

It is proposed the following LDZs will be focussed on:

- North West (NW) represents a Northern LDZ and South East (SE) represents a Southern LDZ which is in line with the Workgroup's preference

The proposed EUC selections for both LDZs compare well as a representation of the total population – see tables below:



North West LDZ

EUC Band	EUC Type	Supply Point Count LDZ (Pop'n)	AQ LDZ (Pop'n)
"01BND"	Domestic Non-PPM	87% (88%)	75% (75%)
"02BNI"	I&C Non-PPM	0.6% (0.6%)	5% (5%)
"05B"	I&C Non-PPM	64% (65%)	26% (29%)

South East LDZ

EUC Band	EUC Type	Supply Point Count LDZ (Pop'n)	AQ LDZ (Pop'n)
"01BND"	Domestic Non-PPM	88% (88%)	77% (75%)
"02BNI"	I&C Non-PPM	0.6% (0.6%)	5% (5%)
"05B"	I&C Non-PPM	71% (65%)	36% (29%)

Meeting 5 Re-cap

(30th November 2021)

Meeting 5 Key Discussion Points

The main headlines from meeting 5 of 754R were…

- Provided an overview and background of the Advanced Analytics approaches being trialled, namely Neural Network (NN) and Gradient Boosting (GB). These approaches and their models have been labelled as follows:
  - NNGLM – Neural Network Generalised Linear Model (best result)
  - GBASE – Gradient Boosted model
- Discussed Model Verification methods
- Presented methodology for calculation of Daily Adjustment Factor (DAF), one of the key outputs from the Demand modelling process
- Provided visual of ALP and DAF profiles for test EUCs
- Provided initial Mean Average Percentage Error (MAPE) for test EUCs

Area 1:
Trial Alternative Approaches to Deriving SND_t

Indicative Load Factors

Indicative Load Factor: Development

Background:

- Indicative Load Factor (ILF) is a measure of the weather sensitivity of the model and provides a very important role in the assessment of demand models.
- It enables comparisons between models
  - For EUCs with Winter Annual Ratios (WAR) bands it highlights distinctions between the models.
  - Across years can highlight changes in an EUC’s profile

Objective:

- Can we calculate an Indicative Load Factor (ILF) for the new approaches?

Indicative Load Factor: Calculation

- The ILF Calculation is as follows:

  ILF = Average Demand / Peak Demand

- The Average Demand has been calculated as the mean of the predicted Seasonal Normal Demand.

- The Peak Demand is determined using

  – the Peak 1 in 20 CWV, which is a statistically calculated value (95% level) of the extreme cold weather in the gas industry history (from 1960). The values and further details are available in section 11 of the NDM Algorithm booklet

  – The dummy variables have been set to reflect the calculation taking place for “a non-holiday Monday to Thursday in January”

    - HOL_CODES set to ‘NONE’
    - MONTH = ‘JAN’
    - WKDAY_TYPE =‘MtoTh’

Indicative Load Factor: Results

- This table shows the initial values of the ILF calculated for the new approaches.

- Highlighted are some of the ILFs which are materially different from the live ILF

  Blue – small difference

  Yellow – materially different ILF

- The Gradient boost model produced a materially different ILF – which is being investigated to understand the drivers for the difference

LDZ_EUC	Live	NNGLM	GBASE
NW01BND	32.34	31.85	39.21
NW02BNI	33.57	40.21	51.65
NW05B	41.07	44.45	54.52
SE01BND	31.08	30.03	41.57
SE02BNI	33.15	37.75	50.11
SE05B	43.76	43.94	56.66

Indicative Load Factor: GB investigation

- Initial investigation of the differences in the ILF has shown:
  - Average Demand consistent for all Models
  - Peak Demand materially different for all GBASE results and NNGLM NW02BNI.

- Next steps to investigate why the peak is so different
  - A theory is that the Peak 1 in 20 CWV is quite low a value and the training data has very little observations that are even close to this level.

- The down side of Machine Learning (M/L) is the ‘black box’ nature and in some cases the influences may not be fully explainable.

Indicative Load Factor: Summary

- Conclusion – Yes, we can calculate ILFs however there is outstanding investigation into their levels especially Gradient Boosted approach.

- It should be noted if we cannot calculate an ILF for a particular M/L approach or can calculate it but cannot understand why it varies so much from the existing values then the approach is unlikely to be taken forward.

- While the focus is on ALP and DAFs to reducing impact on Modelling Error and also Temporary UIG, there are other downstream impacts such as on the Peak Load Factors

Area 1:
Trial Alternative Approaches to Deriving SND_t

Comparison with Live Models

Comparison with Live Models - Objective

- In meeting 5, high level results were provided for the new approaches
- This section explores the results in more detail
- This is to try and understand the strength and weaknesses of each approach and where they can be optimized
- This involved assessing trends by
  - Day of the Week (DOW)
  - Month
  - Holidays
- Reminder:
  - We are training using sample data from April 2017 to March 2020, excluding COVID affected days where possible
  - Testing is against October 2019 to September 2020 at present. COVID impacts results from end of March 2020

MAPE and MPE Calculations

- Mean Absolute Percentage Error (MAPE) is a measure of prediction accuracy of a forecasting method
  - It is calculated as Absolute(Actual Energy – Predicted Energy) / Actual Energy
  - The lower the MAPE value, the closer the prediction was to the actual value. For example, a MAPE of 3% means that, on average, the forecast is out by 3%.
- Mean Percentage Error (MPE) is a measure of the bias in the forecasting method
  - It is calculated as (Predicted Energy – Actual Energy) / Actual Energy
  - Where Actual Energy > Predicted Energy the models have under allocated, e.g. if MPE is -2% the model has under allocated by 2%
  - Where Actual Energy < Predicted Energy the models have over allocated e.g. if MPE is 2% the model has over allocated by 2%
- When comparing models, the preference is for the MPE and MAPE to be closer to zero

Initial MAPE 01BND

- Encouraging initial results with both machine learning models quite close to the current model

- Refining the ALP and DAF will hopefully improve this further

MAPE (Mean Absolute Percentage Error) Comparison
NW:E1901BND

	Summer	Winter	Full Year
Live Model	11.20%	4.05%	7.62%
Gradient Boosted	13.00%	4.10%	8.55%
Neural Network	12.37%	4.06%	8.22%

SE:E1901BND

	Summer	Winter	Full Year
Live Model	10.71%	3.58%	6.89%
Gradient Boosted	11.90%	3.60%	7.15%
Neural Network	11.72%	3.62%	7.32%

Monthly Trend MPE 01BND

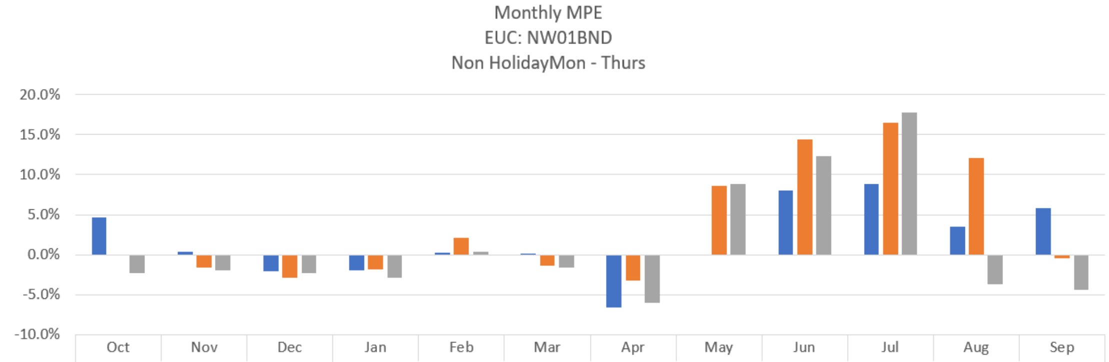
- The charts show the MPE error by month and also the direction of difference

- For NW
  - Live model was closer to zero in 8/12 months
  - NNGLM for 4/12 and
  - GBASE 0/12

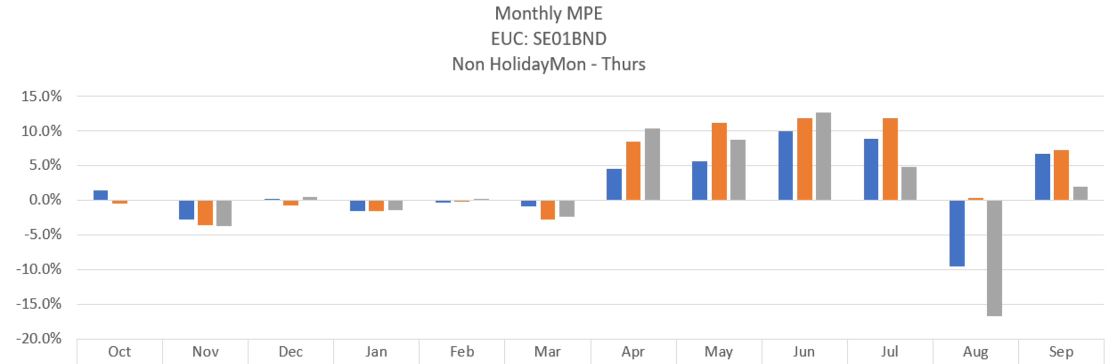
- For SE
  - Live model closer to zero in 6/12 months
  - NNGLM for 2/12 and
  - GBASE for 4/12

- MPE difference is larger in summer months

- SE for Aug 2020 stands out compared to the trends



	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
		2019						2020				
MODEL	4.6%	0.4%	-2.1%	-2.0%	0.2%	0.2%	-6.6%	0.0%	8.0%	8.8%	3.5%	5.8%
NNGLM	-0.1%	-1.6%	-2.9%	-1.9%	2.1%	-1.4%	-3.3%	8.6%	14.4%	16.5%	12.1%	-0.5%
GBASE	-2.4%	-2.0%	-2.3%	-2.9%	0.4%	-1.7%	-6.0%	8.8%	12.4%	17.8%	-3.7%	-4.4%



	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
		2019						2020				
MODEL	1.5%	-2.8%	0.2%	-1.6%	-0.3%	-0.8%	4.5%	5.6%	9.9%	8.8%	-9.6%	6.7%
NNGLM	-0.5%	-3.6%	-0.7%	-1.6%	0.0%	-2.8%	8.4%	11.1%	11.9%	11.9%	0.3%	7.3%
GBASE	0.1%	-3.7%	0.5%	-1.4%	0.2%	-2.4%	10.3%	8.7%	12.6%	4.8%	-16.7%	2.0%

MPE: negative = under allocation ; positive over allocation

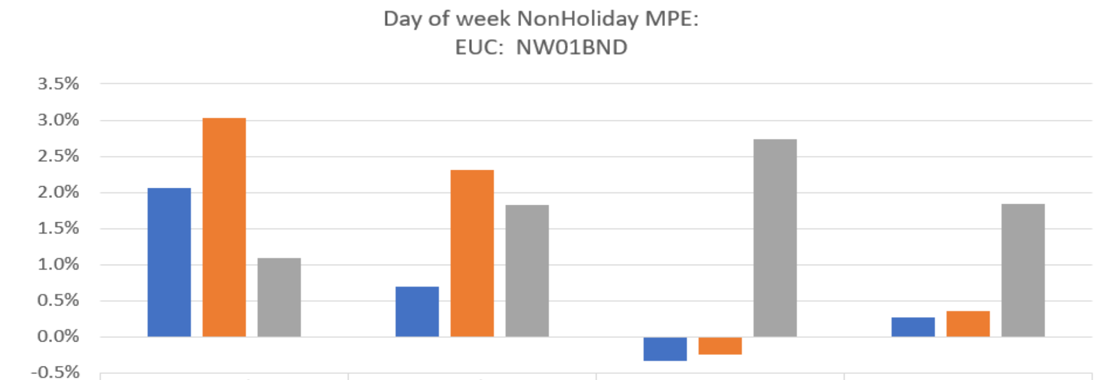
Day of the Week Trend NW01BND

- The MPE percentages are predominately positive.

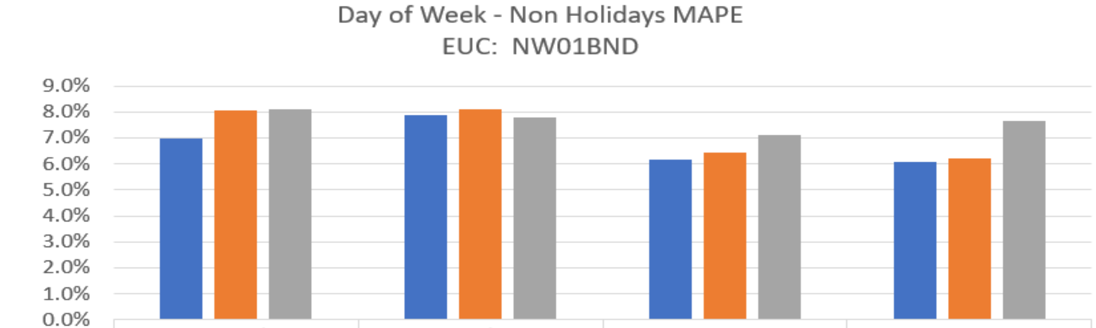
- All the GBASE values are positive (showing over allocation)

- Both the live and NNGLM model profiles resulted in a negative MPE for a Saturday (under allocation)

- The MAPE would tend to favour the Live model, as for this measure it is closest to zero in all DOW categories



	MonToThur	Fri	Sat	Sun
MODEL	2.1%	0.7%	-0.3%	0.3%
NNGLM	3.0%	2.3%	-0.2%	0.4%
GBASE	1.1%	1.8%	2.7%	1.8%



	MonToThur	Fri	Sat	Sun
MODEL	7.0%	7.9%	6.2%	6.1%
NNGLM	8.1%	8.1%	6.5%	6.2%
GBASE	8.1%	7.8%	7.1%	7.7%

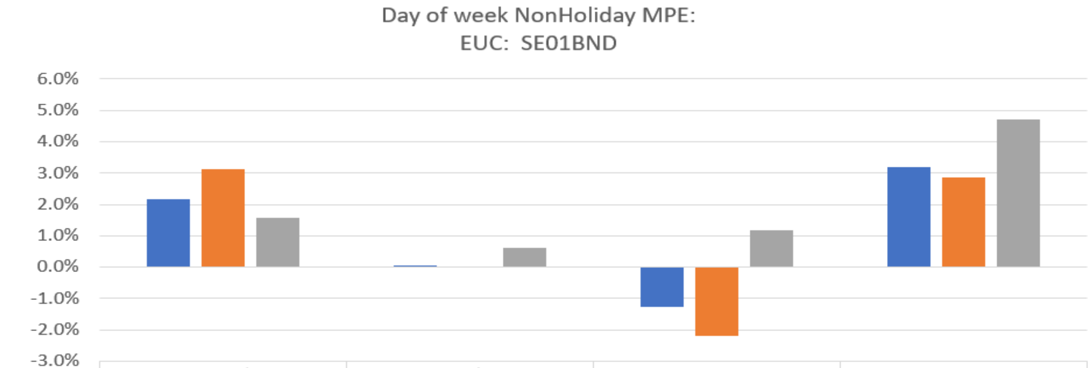
MPE: negative = under allocation ; positive over allocation

Day of the Week Trend SE01BND

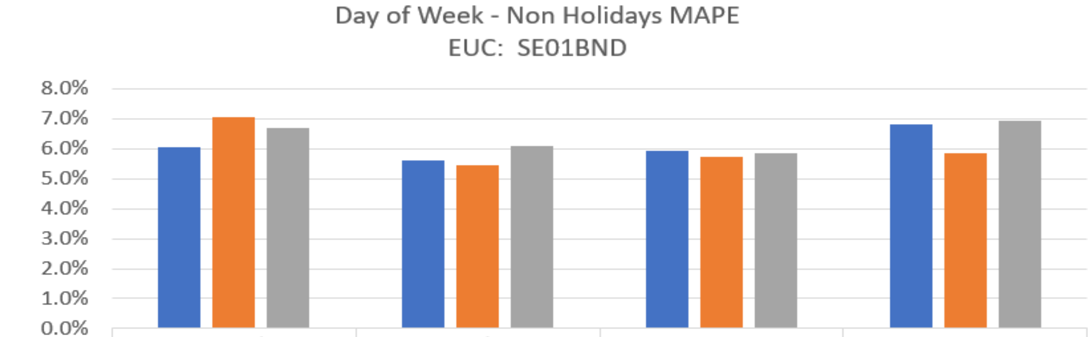
- The MPE percentages show some variation between the DOW.

- The Saturday MPE results for Live and NNGLM model stand out as being negative (under allocation – similar to LDZ NW)

- The MAPE shows all models are fairly close.



	MonToThur	Fri	Sat	Sun
MODEL	2.2%	0.0%	-1.3%	3.2%
NNGLM	3.1%	0.0%	-2.2%	2.9%
GBASE	1.6%	0.6%	1.2%	4.7%

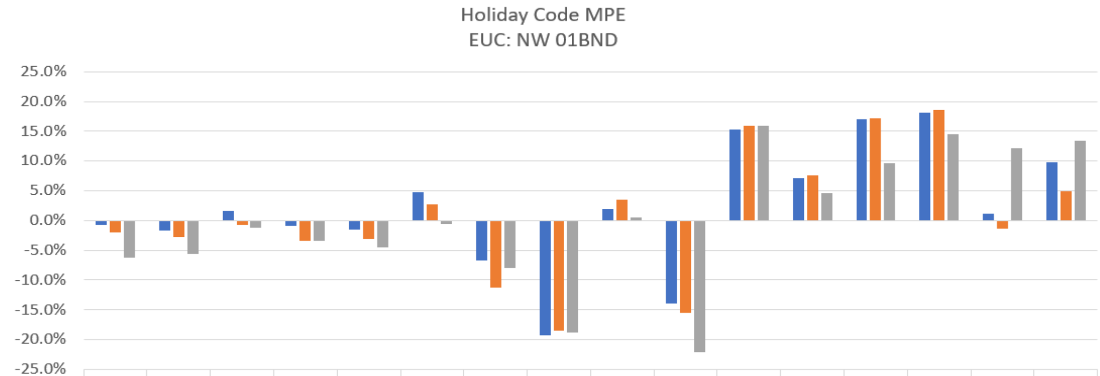


	MonToThur	Fri	Sat	Sun
MODEL	6.0%	5.6%	5.9%	6.8%
NNGLM	7.1%	5.4%	5.7%	5.9%
GBASE	6.7%	6.1%	5.9%	6.9%

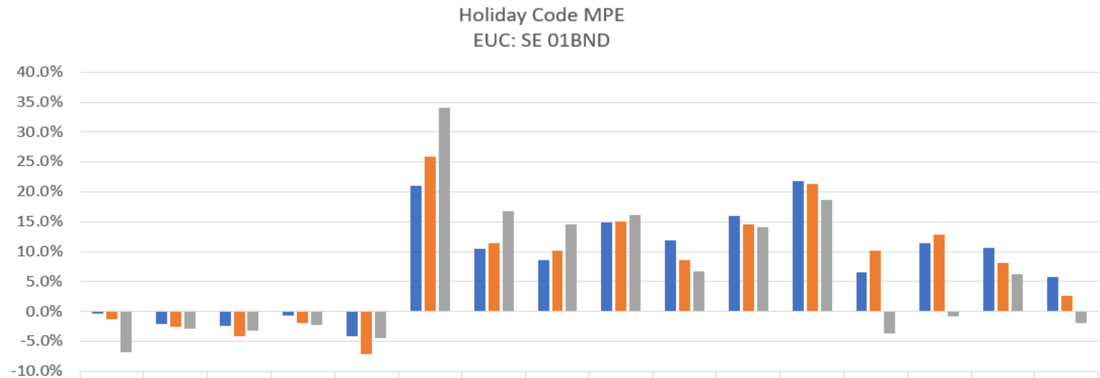
MPE: negative = under allocation ; positive over allocation

Holiday Code Trend MPE 01BND

- The charts show the MPE error by for each of the Holiday Codes
- The results were mixed
- The live model seemed to perform better over the Christmas holiday periods
- Easter was particular difficult for the models, especially the weekdays (code 8)
- SE seems to have an under allocation for the Christmas period but over allocation for the other holiday periods



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MODEL	-0.7%	-1.6%	1.6%	-0.9%	-1.5%	4.7%	-6.8%	-19.2%	2.0%	-14.0%	15.3%	7.1%	17.1%	18.2%	1.2%	9.8%
NNGLM	-2.0%	-2.8%	-0.7%	-3.5%	-3.1%	2.7%	-11.3%	-18.4%	3.4%	-15.5%	16.0%	7.6%	17.2%	18.6%	-1.3%	4.9%
GBASE	-6.2%	-5.7%	-1.2%	-3.5%	-4.5%	-0.5%	-7.9%	-18.9%	0.5%	-22.2%	15.9%	4.6%	9.7%	14.6%	12.1%	13.4%



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MODEL	-0.3%	-2.1%	-2.4%	-0.6%	-4.1%	21.0%	10.5%	8.6%	14.9%	12.0%	16.0%	21.8%	6.6%	11.5%	10.6%	5.8%
NNGLM	-1.3%	-2.5%	-4.1%	-1.9%	-7.2%	26.0%	11.5%	10.2%	15.0%	8.6%	14.6%	21.3%	10.2%	12.8%	8.2%	2.7%
GBASE	-6.8%	-2.9%	-3.1%	-2.2%	-4.5%	34.1%	16.7%	14.6%	16.2%	6.7%	14.1%	18.7%	-3.6%	-0.8%	6.3%	-1.8%

MPE: negative = under allocation ; positive over allocation

Initial MAPE 02BNI

- Note: These datasets have COVID impacted days between April 2020 to September 2020 which explains the poor percentages for all the models
- The Gradient Boosted model is better than Neural Network for NW but not SE
- The live Model is still giving the best results for both areas

MAPE (Mean Absolute Percentage Error) Comparison

NW:E1902BNI

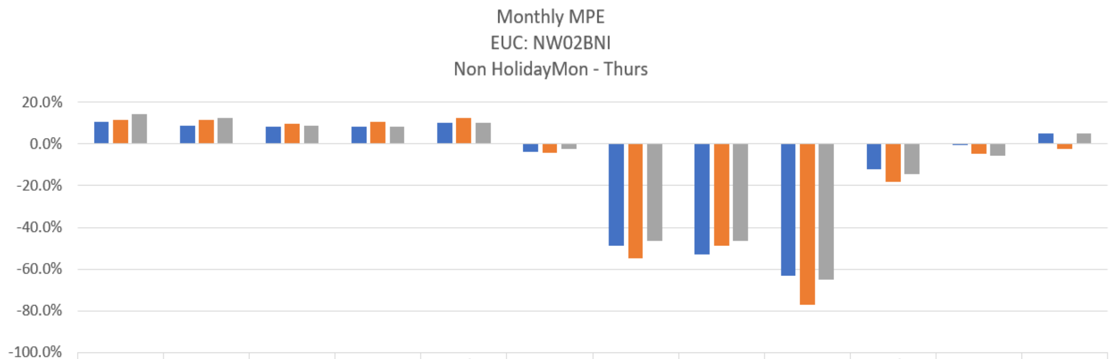
	Summer	Winter	Full Year
Live Model	32.64%	11.13%	21.89%
Gradient Boosted	34.02%	11.59%	22.80%
Neural Network	35.48%	11.77%	23.62%

SE:E1902BNI

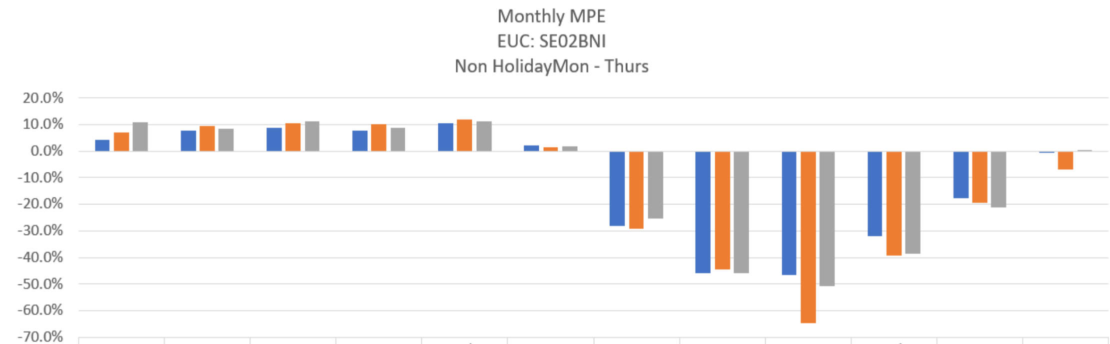
	Summer	Winter	Full Year
Live Model	26.65%	7.94%	17.29%
Gradient Boosted	31.90%	8.84%	20.37%
Neural Network	29.95%	8.70%	19.33%

Monthly Trend MPE 02BNI

- The charts show the MPE error by month
- For NW
  - Live model was closer to zero in 7/12 months
  - NNGLM for 1/12 and
  - GBASE 5/12
- For SE
  - Live model closer to zero in 8/12 months
  - NNGLM for 2/12 and
  - GBASE for 2/12
- MPE difference is larger in summer months



	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
		2019						2020				
MODEL	10.5%	8.9%	8.3%	8.2%	10.4%	-3.8%	-48.9%	-53.2%	-63.3%	-12.1%	-0.2%	4.8%
NNGLM	11.4%	11.4%	9.5%	10.4%	12.5%	-4.1%	-54.8%	-48.8%	-77.0%	-18.3%	-4.6%	-2.2%
GBASE	14.5%	12.3%	8.8%	8.4%	10.1%	-2.5%	-46.3%	-46.5%	-65.0%	-14.4%	-5.4%	5.2%

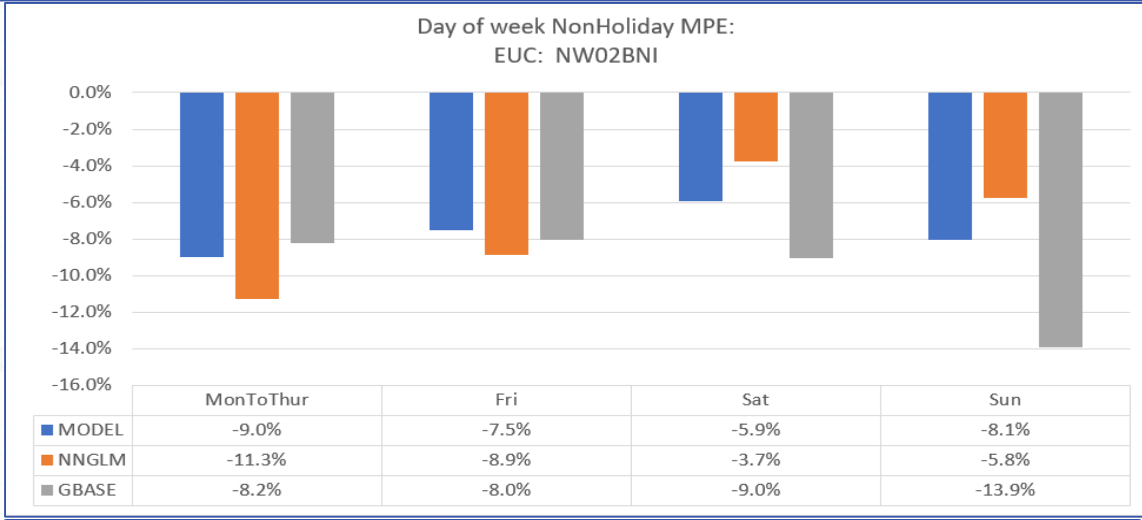


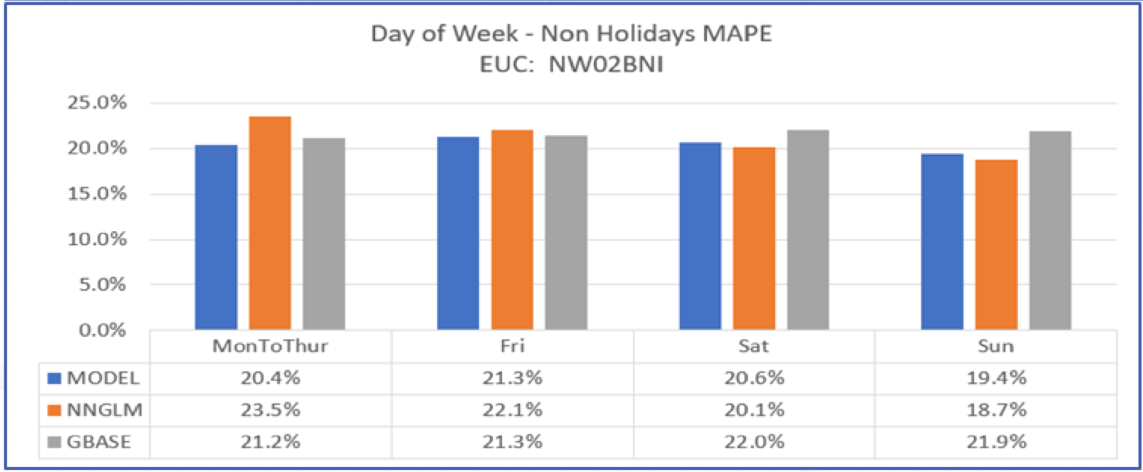
	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
		2019						2020				
MODEL	4.4%	7.8%	8.7%	7.6%	10.6%	2.3%	-28.0%	-45.8%	-46.5%	-31.8%	-17.8%	-0.7%
NNGLM	7.1%	9.4%	10.4%	10.0%	12.0%	1.6%	-29.1%	-44.5%	-64.6%	-39.4%	-19.4%	-7.0%
GBASE	10.9%	8.5%	11.4%	8.8%	11.4%	1.8%	-25.4%	-45.9%	-50.7%	-38.7%	-21.2%	0.2%

MPE: negative = under allocation ; positive over allocation

Day of the Week Trend NW02BNI

- The MPE chart suggests an under allocation in terms of the DOW trends which is unusual
- We are currently identifying months where the under allocation is significant to further investigate.
- A scenario was identified in Algorithm Performance where the Sample AQ used in analysis was COVID impacted and skewed some of the analysis





MPE: negative = under allocation ; positive over allocation

Day of the Week Trend SE02BNI

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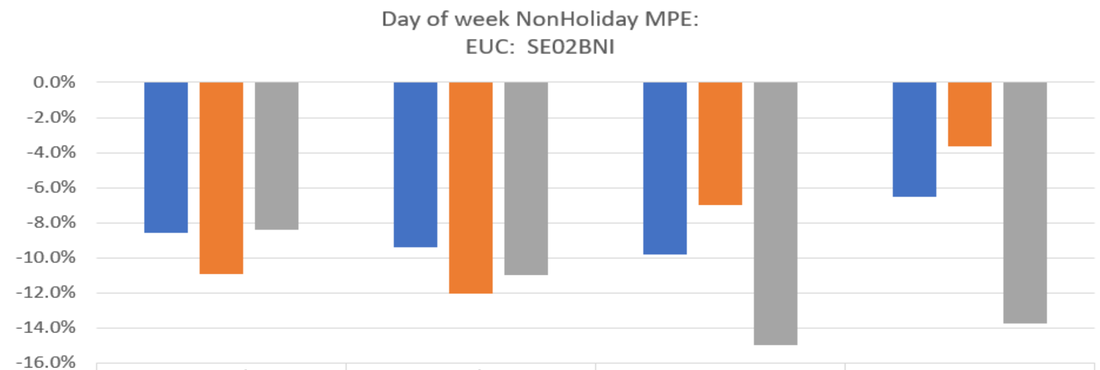
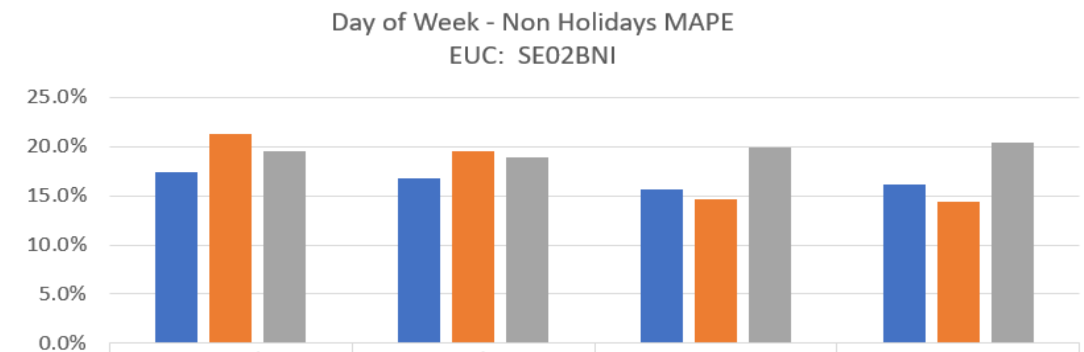
- We are currently identifying months where the under allocation is significant to further investigate.



	MonToThur	Fri	Sat	Sun
MODEL	-8.6%	-9.4%	-9.8%	-6.5%
NNGLM	-10.9%	-12.0%	-7.0%	-3.6%
GBASE	-8.4%	-11.0%	-15.0%	-13.8%

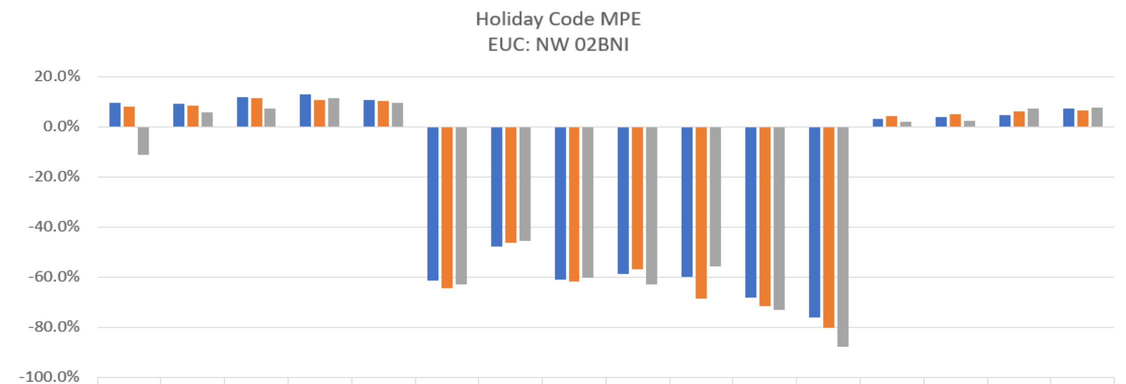


	MonToThur	Fri	Sat	Sun
MODEL	17.4%	16.8%	15.6%	16.1%
NNGLM	21.3%	19.6%	14.7%	14.4%
GBASE	19.5%	18.8%	19.9%	20.4%

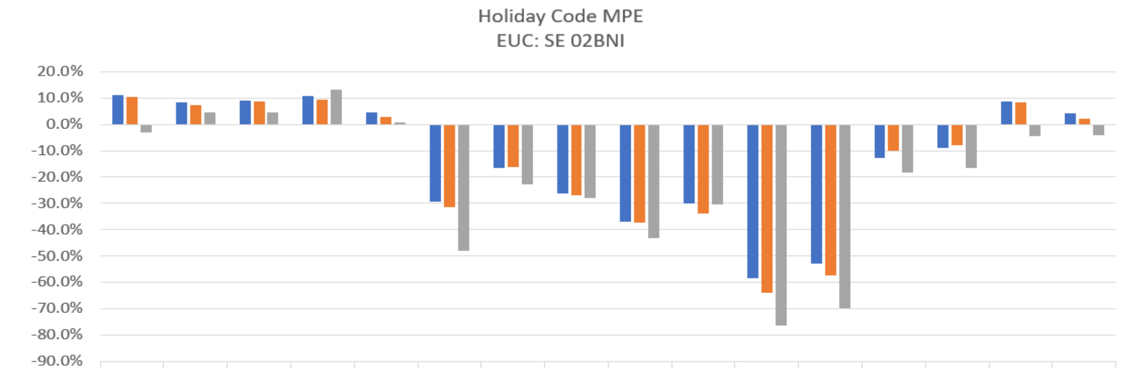
MPE: negative = under allocation ; positive over allocation

Holiday Code Trend MPE 02BNI

- The charts show the MPE error by for each of the Holiday Codes
- The results were mixed
- Each of the models showed as the better model for different holiday periods
- The models tended to over allocate for Easter(6,7,8) and both sets of May Holiday periods (9,10,11,12)



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MODEL	9.4%	9.2%	11.8%	12.9%	10.5%	-61.3%	-47.7%	-61.0%	-58.6%	-59.7%	-68.1%	-76.1%	3.3%	3.8%	4.6%	7.3%
NNGLM	8.0%	8.4%	11.5%	10.7%	10.3%	-64.5%	-46.4%	-61.8%	-56.8%	-68.7%	-71.7%	-80.1%	4.2%	4.9%	6.1%	6.6%
GBASE	-11.3%	5.9%	7.2%	11.3%	9.7%	-62.8%	-45.6%	-60.1%	-63.0%	-55.8%	-73.0%	-87.6%	2.0%	2.5%	7.3%	7.7%



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MODEL	11.2%	8.2%	8.9%	10.9%	4.7%	-29.3%	-16.6%	-26.4%	-36.8%	-30.1%	-58.3%	-53.0%	-12.7%	-8.9%	8.7%	4.3%
NNGLM	10.5%	7.3%	8.7%	9.4%	2.8%	-31.6%	-16.1%	-26.8%	-37.1%	-33.9%	-64.1%	-57.4%	-10.2%	-7.8%	8.4%	2.2%
GBASE	-3.2%	4.5%	4.4%	13.0%	0.7%	-47.9%	-22.8%	-27.8%	-43.3%	-30.5%	-76.2%	-69.8%	-18.4%	-16.6%	-4.5%	-4.2%

MPE: negative = under allocation ; positive over allocation

Initial MAPE 05B

- Note: These dataset have COVID impacted days between April 2020 to September 2020 which explains the poor percentages for all the models
- The Neural Network model is quite close to the live model for both areas
- The Neural Network model is slightly better for NW and better for Summer in SE
- Gradient Boosted results were not as good

MAPE (Mean Absolute Percentage Error) Comparison

NW:E1905B

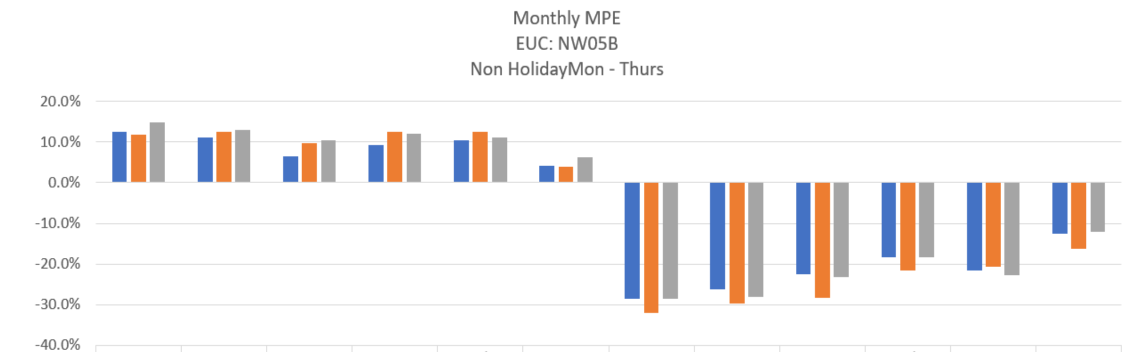
	Summer	Winter	Full Year
Live Model	24.14%	10.89%	17.52%
Gradient Boosted	23.39%	10.92%	17.16%
Neural Network	21.71%	10.61%	16.16%

SE:E1905B

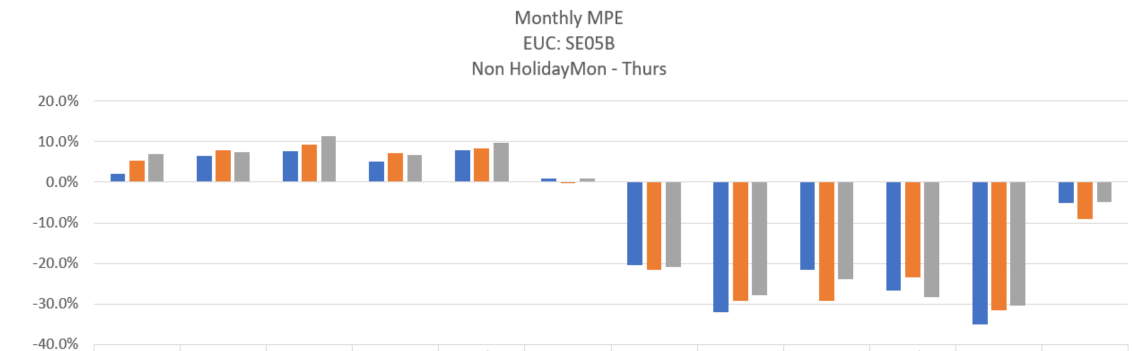
	Summer	Winter	Full Year
Live Model	19.83%	6.62%	13.23%
Gradient Boosted	22.07%	7.59%	14.83%
Neural Network	19.77%	7.12%	13.44%

Monthly Trend MPE 05B

- The charts show the MPE error by month
- For NW
  - Live model was closer to zero in 8/12 months
  - NNGLM for 3/12 and
  - GBASE 1/12
- For SE
  - Live model closer to zero in 7/12 months
  - NNGLM for 2/12 and
  - GBASE for 3/12
- MPE difference is larger in summer months



	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
		2019						2020				
MODEL	12.5%	11.0%	6.6%	9.3%	10.4%	4.3%	-28.5%	-26.2%	-22.6%	-18.3%	-21.5%	-12.5%
NNGLM	11.9%	12.4%	9.7%	12.6%	12.4%	4.0%	-32.1%	-29.7%	-28.3%	-21.6%	-20.6%	-16.4%
GBASE	14.8%	13.0%	10.5%	12.0%	11.3%	6.2%	-28.5%	-28.1%	-23.2%	-18.4%	-22.9%	-12.1%



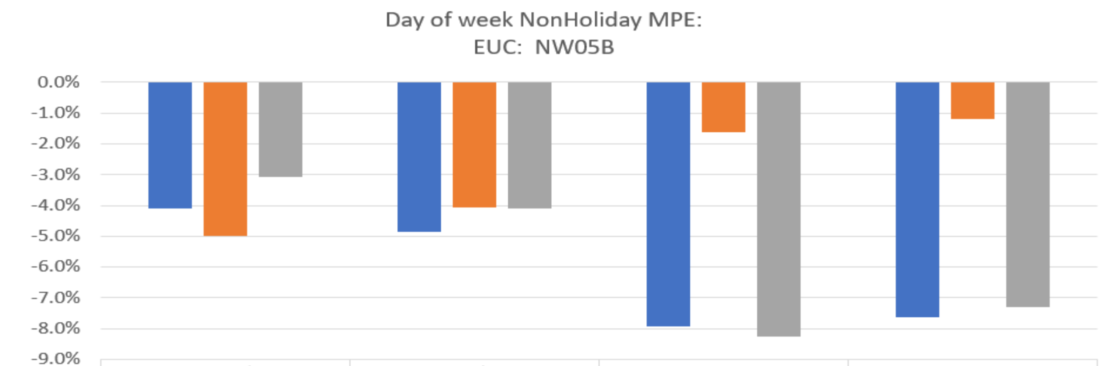
	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
		2019						2020				
MODEL	2.1%	6.4%	7.7%	5.1%	7.8%	0.9%	-20.5%	-32.0%	-21.6%	-26.7%	-35.1%	-5.2%
NNGLM	5.2%	7.8%	9.4%	7.2%	8.4%	-0.2%	-21.6%	-29.2%	-29.2%	-23.5%	-31.6%	-9.0%
GBASE	7.0%	7.5%	11.3%	6.8%	9.8%	1.0%	-21.0%	-27.9%	-23.9%	-28.2%	-30.4%	-4.9%

MPE: negative = under allocation ; positive over allocation

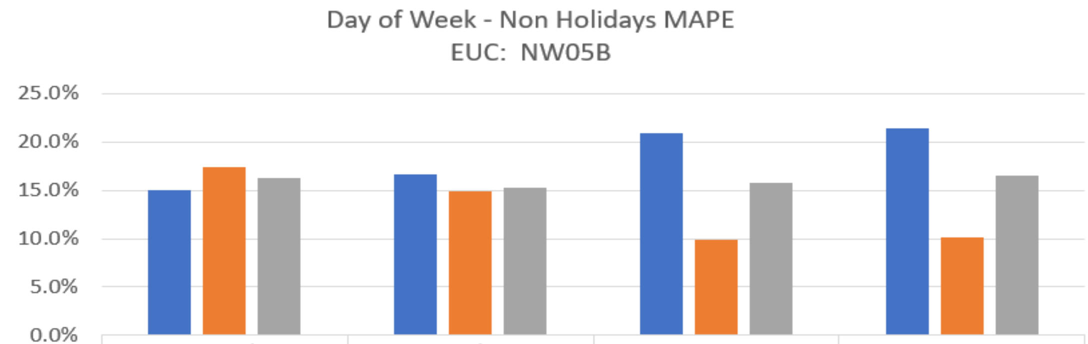
Day of the Week Trend NW05B

- The MPE chart suggests an under allocation in terms of the DOW trends which is unusual

- We are currently identifying months where the under allocation is significant to further investigate.



	MonToThur	Fri	Sat	Sun
MODEL	-4.1%	-4.9%	-7.9%	-7.6%
NNGLM	-5.0%	-4.1%	-1.6%	-1.2%
GBASE	-3.1%	-4.1%	-8.3%	-7.3%



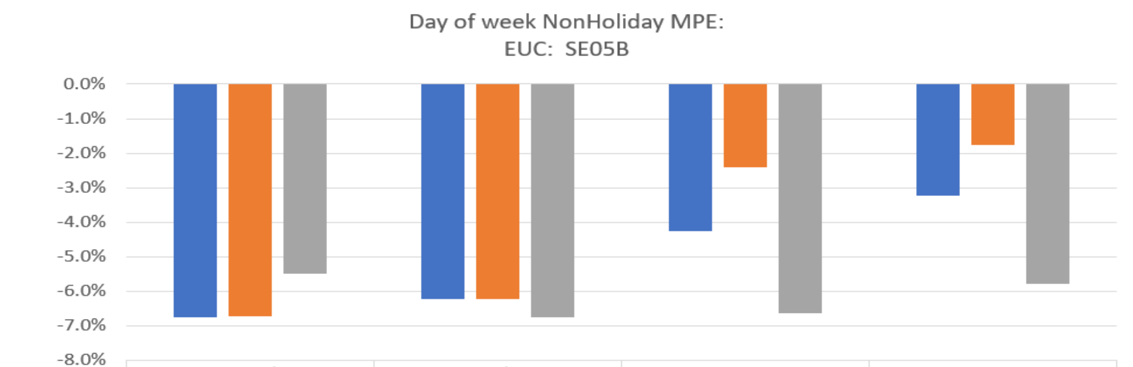
	MonToThur	Fri	Sat	Sun
MODEL	15.0%	16.6%	20.8%	21.4%
NNGLM	17.4%	14.9%	9.9%	10.2%
GBASE	16.3%	15.3%	15.7%	16.5%

MPE: negative = under allocation ; positive over allocation

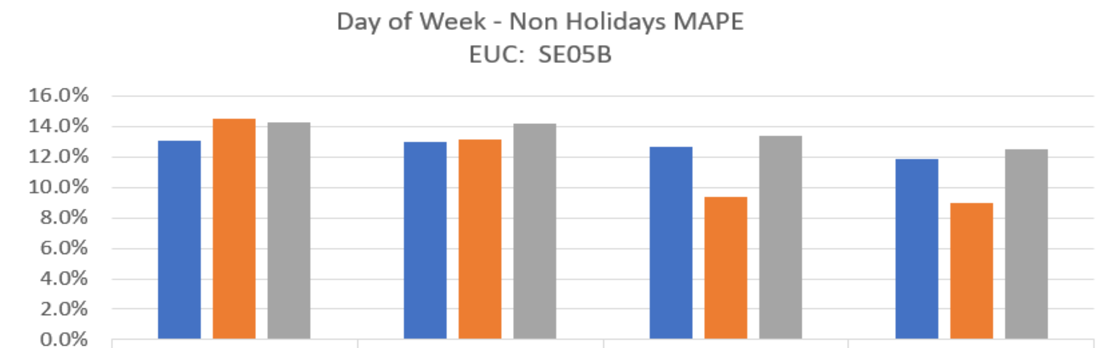
Day of the Week Trend SE05B

- The MPE chart suggests an under allocation in terms of the DOW trends which is unusual

- We are currently identifying months where the under allocation is significant to further investigate.



	MonToThur	Fri	Sat	Sun
MODEL	-6.8%	-6.2%	-4.3%	-3.2%
NNGLM	-6.7%	-6.2%	-2.4%	-1.8%
GBASE	-5.5%	-6.8%	-6.6%	-5.8%

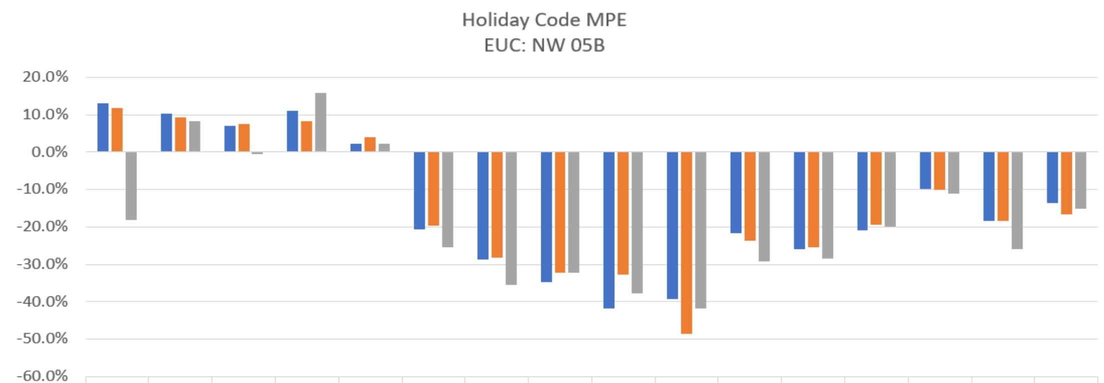


	MonToThur	Fri	Sat	Sun
MODEL	13.0%	13.0%	12.7%	11.9%
NNGLM	14.5%	13.2%	9.3%	9.0%
GBASE	14.2%	14.2%	13.4%	12.5%

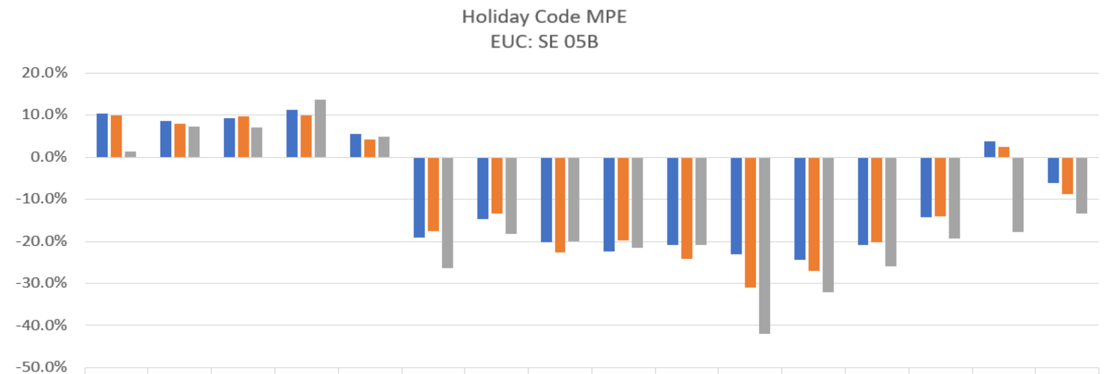
MPE: negative = under allocation ; positive over allocation

Holiday Code Trend MPE 05B

- The charts show the MPE error by for each of the Holiday Codes
- Christmas holidays tended to be an over allocation where as the other holidays were under allocations
- For NW Christmas day, the GBASE model was a significant under allocation when compared to the other models



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MODEL	13.1%	10.2%	6.9%	11.1%	2.3%	-20.7%	-28.7%	-34.6%	-41.7%	-39.2%	-21.8%	-25.9%	-20.8%	-9.8%	-18.5%	-13.6%
NNGLM	11.8%	9.2%	7.6%	8.1%	3.9%	-19.6%	-28.3%	-32.2%	-32.7%	-48.6%	-23.8%	-25.4%	-19.4%	-10.0%	-18.5%	-16.8%
GBASE	-18.3%	8.2%	-0.6%	15.9%	2.2%	-25.4%	-35.4%	-32.2%	-37.8%	-41.7%	-29.2%	-28.6%	-20.0%	-11.1%	-26.1%	-15.1%



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MODEL	10.3%	8.7%	9.3%	11.3%	5.4%	-19.1%	-14.7%	-20.1%	-22.3%	-20.8%	-23.0%	-24.3%	-20.8%	-14.2%	3.7%	-6.2%
NNGLM	9.9%	7.9%	9.6%	9.9%	4.3%	-17.6%	-13.3%	-22.7%	-19.7%	-24.2%	-31.0%	-27.0%	-20.2%	-14.0%	2.5%	-8.7%
GBASE	1.3%	7.4%	7.0%	13.7%	4.9%	-26.5%	-18.2%	-20.0%	-21.5%	-20.9%	-42.0%	-32.1%	-25.9%	-19.4%	-17.7%	-13.4%

MPE: negative = under allocation ; positive over allocation

Area 1
Understanding the Principles of the M/L models

Understanding the Models - Objective

Objective:

- To look closer at the approaches and the mechanics of the models to get a better understanding of how they work.
- To understand the influencing factors in order to improve and optimise the models
- To understand and interpret the results
  - For example to investigate the ILF differences highlighted earlier

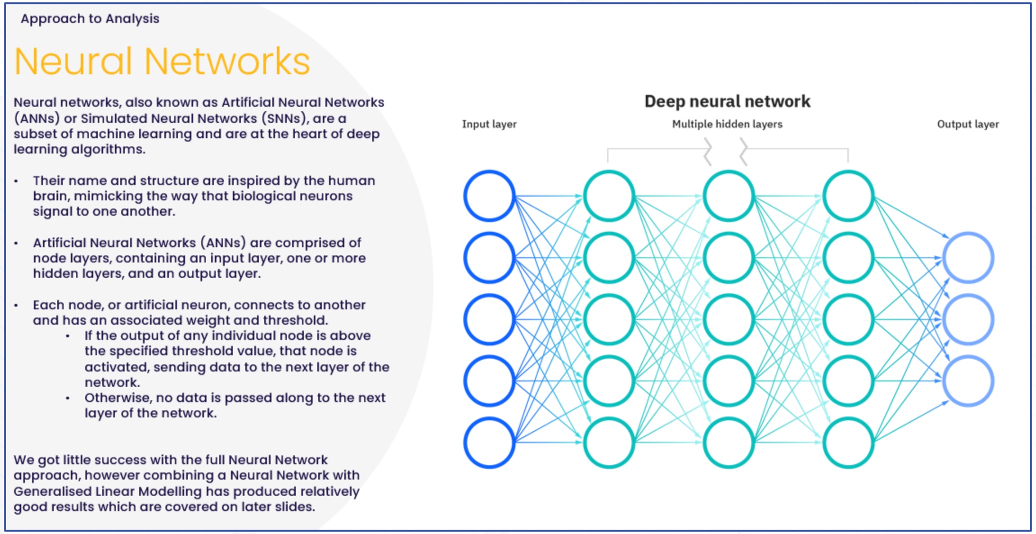
Understanding the Models

- For Workgroup 0754, in addition to the Live Model, we have produced
  - Neural Network and
  - Gradient Boosting models

- As a control we have also ran a Regression Model
  - Regression is the model currently being used and arguably most understood

Understanding the Models – Neural Networks

- In meeting 5 we provided a high level overview of the different models.
- This diagram shows the principle of Neural Networks
- We tried multiple NN approaches
- The ‘Generalised Linear Model (GLM) approach produced the best results (referred to as NNGLM)

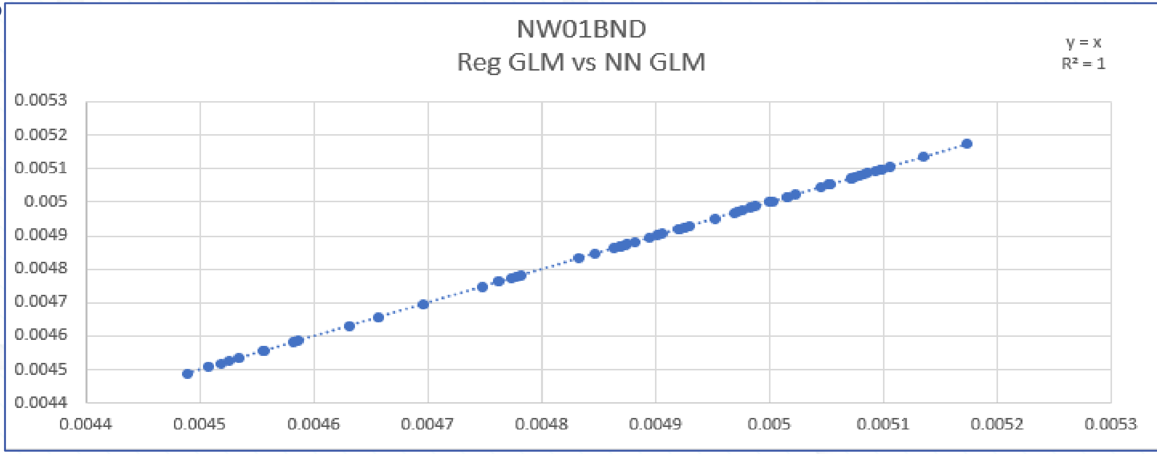


Understanding the Models - Comparison

- The comparison produced some interesting results
- The Neural Network model produced identical results as the Regression model
- The values matched for
  - Predicted Values (SND_t)
  - Indicative Load Factors
  - And this was for all the test EUCs

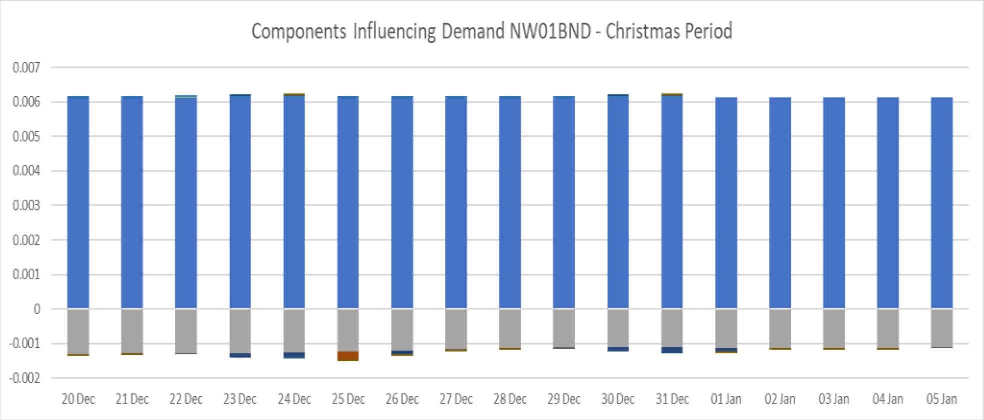
Understanding the Models - Reg vs NNGLM

- The Chart shows the predicted values for EUC NW01BND
- The plot is given as y=x or in this case NNGLM = Reg
- Investigating the underlying coefficients and weightings highlighted the approaches were the very similar.
- The main difference was the way the Neural Network model categorised and set the dummy variables.



Understand the Models – Key Influences (1)

- The chart shows Neural Network coefficients / weights for EUC NW01BND for the Xmas period



- This is the building blocks of the predicted Seasonal Normal demands and shows the interactions between the variables

- The NN GLM model takes the form:

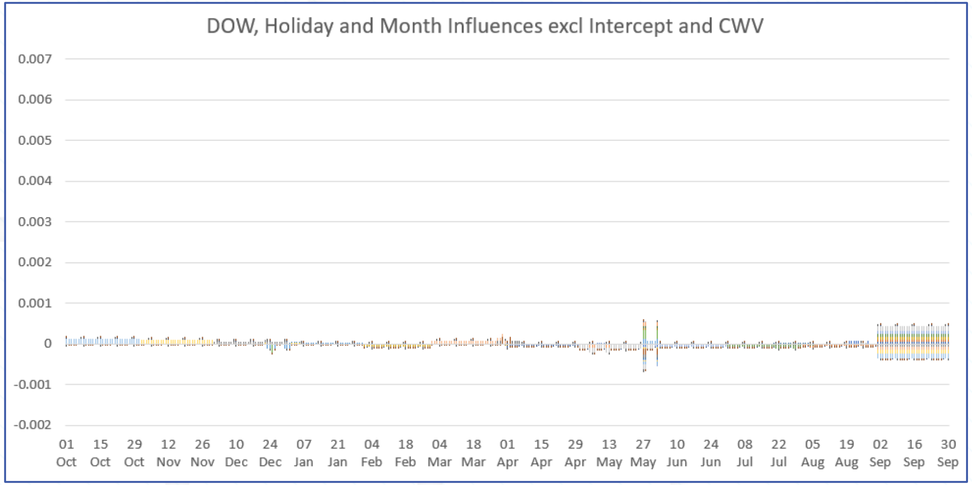
  Y=Intercept + CWV effect + dummy variables * weight
  - Blue = Intercept
  - Grey = CWV influence

- Other colours represent DOW, Holiday, Month weightings (legend has not been added as it the number of components are too small to read)

Understand the Models – Key Influences (2)

- The key inputs to the demand shape (and those that have the most influence) are:
  - Intercept
  - CWV influence

- As a contrast this chart shows the influence of DOW, Holiday and Month variables across a Gas Year



- To optimise the models :
  - One focus will be to look at the demands and CWV with an option to add extra years of data to the training datasets.
  - Look at how to influence the trends with further / other dummy variables

- Any suggestions of dummy variables welcome

Introduction to
Area 2: Improve Validation processes

Objective & Background

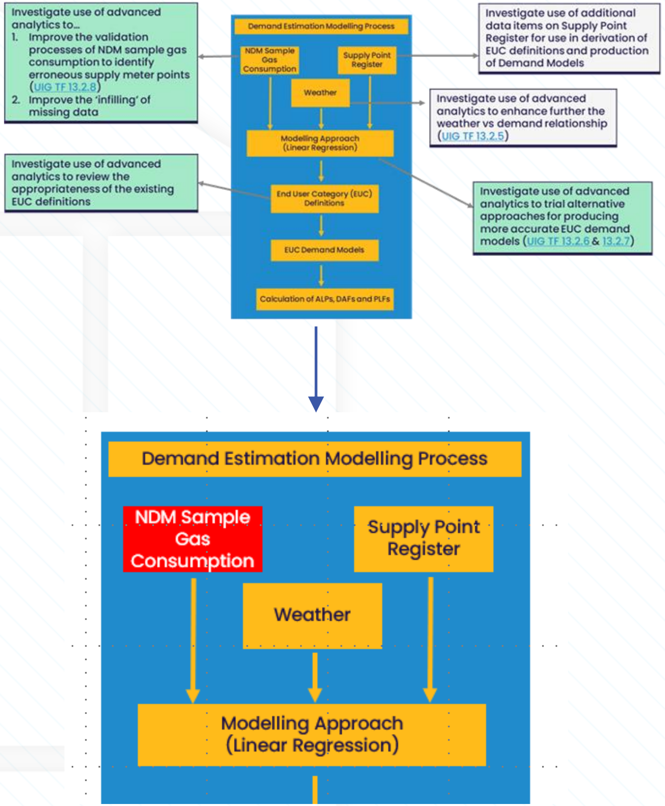
- Explore the use of advanced analytics techniques to develop and improve validation process prior to modelling

- Identify potential weakness, development opportunities and make recommendations which link to evidence of reduction in NDM modelling error.

Potential Approach	Data	Systems
Investigate latest data cleansing techniques/scripts 'Uncertainty Estimation' UIG TF 13.2.8 Compare current post validation results to revised methods - both 'infill' approach and ability to identify suspicious demand patterns	Daily Gas Consumption Daily Weather Supply Point Attributes (AQ, MSC, Correction Factor)	SAS Demand Estimation Modelling

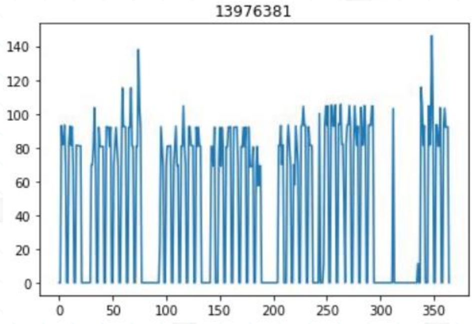
Modelling Process Flow

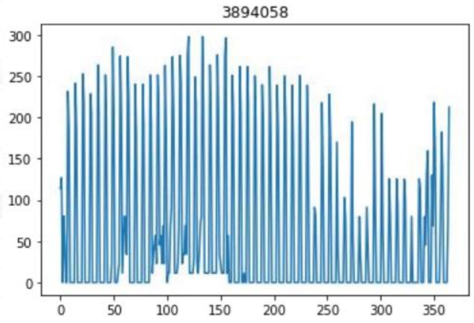
- In this Modelling process flow the key inputs are:
  - NDM Sample consumption data.
  - Weather data
  - Supply Point register
- Poor data leads to poor models and interpretation
- Supply Point Register is provided from the Shippers
- Weather data is consistent
- Our focus is on ensuring the validation of the Sample data produces quality inputs for the models

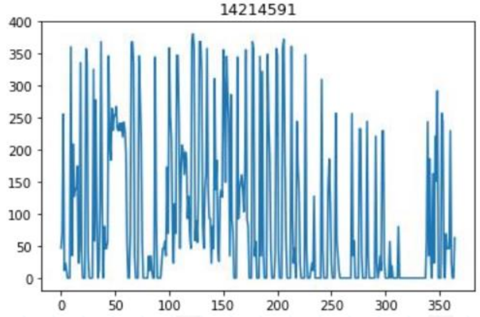


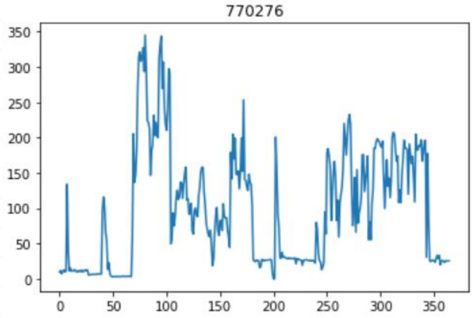
Sample data - Task Force Findings

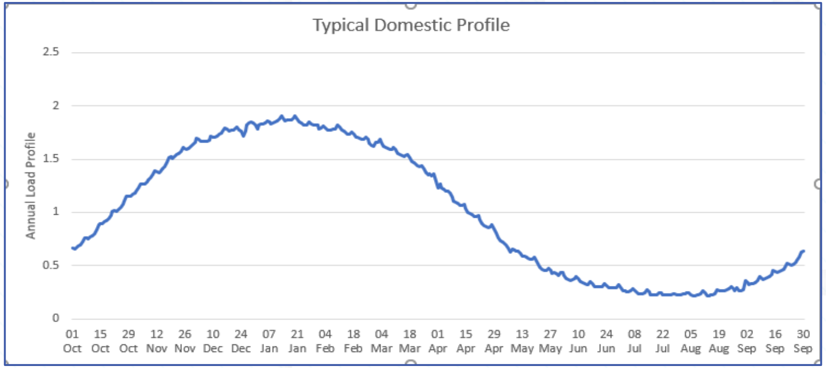
- The UIG task force produced an assessment of Sample MPRs
- These charts are a selection of demand patterns that:
  - Passed validation
  - Were believed to be domestic
- Visually they do not seem to match a typical domestic profile.











Note the reference numbers above are anonymized IDs and not MPRs

Sample Data - Intended plan

- Utilise Machine Learning (M/L) to enhance our existing validation routines (see table)
  - To help identify suspicious demand patterns in assessing sample MPRs

- Infilling:
  - Assess whether M/L can assist with infilling of missing data

- We are going to investigate:
  - Techniques for identifying demand patterns and difference including:
    - Uncertainty estimation (as suggested by the task force)
    - Others to be determined

Appendix 2 –Daily Gas Consumption Data Validation

The following provides the proposed validation criteria for use against the Daily Gas Consumption Data in the 2021 Gas Demand EUC Modelling. Section 1 of the NDM Algorithms Booklet will contain further details of the validation process and outcomes

Small NDM: 0 to 2,196 MWh p.a.

Source	EUC Bands	Missing Days		Consecutive Zeros		Spike Ratios	
		Summer	Winter	Summer	Winter	Summer	Winter
Xoserve Managed sample (and any third party data)	01 and 02	15 or more	15 or more	N/A	33 or more	15:01	08:01
Network Managed sample (and any third party data)	02, 03	28 or more	28 or more	N/A	20 or more	13:01	05:01

Large NDM: >2,196 MWh p.a.

Source	EUC Bands	Missing Days		Consecutive Zeros		Spike Ratios	
		Annual	Winter	Annual	Winter	Annual	Winter
Network Managed sample (and any third party data)	05, 06, 07 and 08	40 or more	20 or more	N/A	20 or more	08:01	N/A

Where:
Summer period is defined as 1st April 2020 to 30th September 2020.
Winter period is defined as 1st October 2020 to 31st March 2021.
Annual period is defined as 1st April 2020 to 31st March 2021

Conclusion and Next Steps

Conclusion:

- ILFs can be calculated but further analysis needed for non linear model suitability
- Time has been spent on understanding the models their characteristics and which elements are influencing the shape of demands that are produced
- Further analysis and understanding required if we are to succeed in identifying significant improvements

Next Steps:

- Area 1: Investigate Peak Demand calculation for GB model
- Area 1: Investigate the Day of the week trends for the 02BNI and 05B datasets and test it against non-covid datasets.
- Area 1: Try other dummy variables
- Area 2: Investigate methods to support validation identifying suspicious demand patterns
- Next meeting preparation

Workgroup 0754R: Timeline

March 2021

WG Meetings 1&2
- Scope/Objective
- High Level Principles
- Resources/Support
- Potential Areas to Investigate

- Top 3 Areas to Investigate
- Data Availability
- Resourcing / Costs

July 2021

WG Meeting 3 (7th)
- Area 1 Focus
- Measures/Success Criteria
- Timescales

Oct 2021

WG Meeting 4 (5th)
- Area 1 Progress - Initial Results

Nov 2021

WG Meeting 5 (30th)
- Develop DAF methodology
- Further refine models

Jan 2022

Mar 2022

WG Meeting 6 (22nd)
Area 1 refinement
Area 2 introduction

TBC 2022

WG Meeting 7 (TBC)
Area 1 and 2 progress

Nov 2022

WG Conclusion

Demand Estimation Team

Core Demand Modelling work will take place between April and June, 2022 for the production of Gas Demand Profiles for Gas Year 2022/23

Thank you