UNC Workgroup 0754R

05/10/2021

Provided by:

Contents

- Workgroup Meeting 3 Recap (7th July 2021)
    - Background / Rationale
    - Key Discussion Points
- Update on Progress:
    - Approach to Analysis
    - Model Development
- Conclusions and Next Steps
- Timeline
- Next Steps

Contents

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

Glossary

- 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
    - UIG: Unidentified Gas
    - UNC: Uniform Network Code
    - WCF: Weather Correction Factor

Meeting 3 Re-cap (07th July 2021)

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 0754R:

- 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)

Meeting 3 Re-cap

Key Discussion Points

The main headlines from Meeting 3 of 754R were……

1.Areas to Investigate :

Focus will be on Area 1 (Fig. 1):

Trial EUCs and LDZ were proposed with details on the available datasets:

- LDZs: NW and SE will be used (north and south)
- EUCs: 01BND, 02BNI and 05B were proposed and agreed

2.Data Availability:

An update was provided on data availability including possibility of utilising some new / alternative weather data

i.e. precipitation and a classification called weather type are possibilities

3.Success Criteria and Measures:

For Area 1 the proposed success criteria is:

- Reduce Demand Modelling Error
  - Focus on higher volume periods between October and March and trade off between model accuracy and volatility
- Reduction in temporary Unidentified Gas Volumes
- To minimise impacts to Simulated Peak demand, maintaining Peak Load Factors and SOQ levels

4. Approach:

An initial Development / Test and evidence collection cycle was also presented (Fig. 2)

Fig. 1

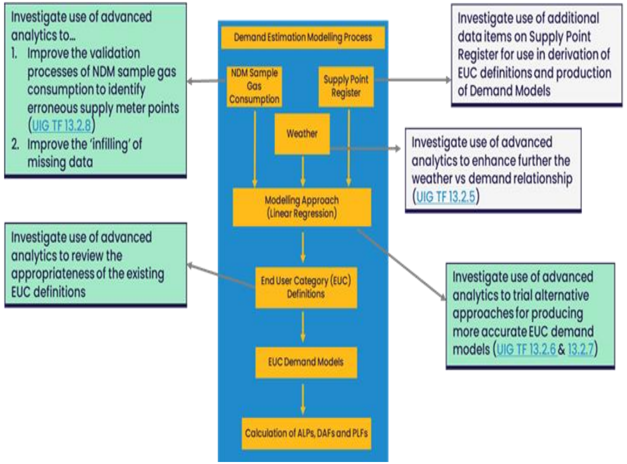
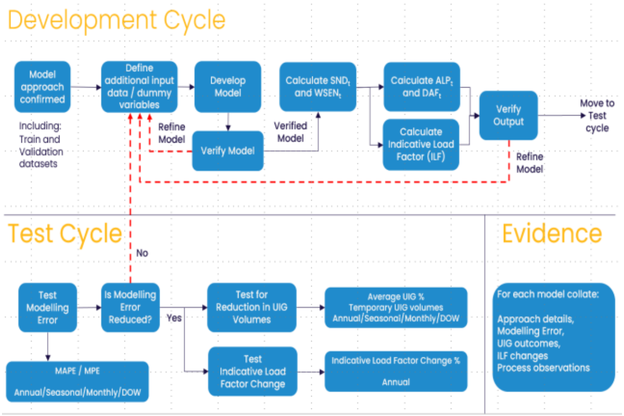


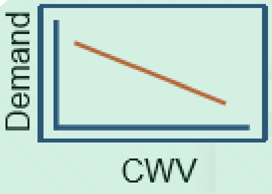
Fig. 2



Area 1

Update on Progress

Area 1: Trial alternative approaches to deriving SND_t



Linear Regression between NDM Sample Demand and Daily Composite Weather Variable

Current Approach

EUC Demand Models (39 per LDZ)

Model Smoothing, the process of averaging [3] individual models, is applied to create the final form of the EUC demand model.

$SND_t = P_t * (C1 + C2 * SNCWV_t)$,
$WSENS_t = P_t * C2$

P_t is a multiplicative factor which is set to 1 for a non-holiday Monday to Thursday and potentially a different value for weekend or holiday day.

C_1 is the constant from the (non-holiday) Monday to Thursday regression of daily demand against daily CWV.

C_2 is the slope of this regression line which represents the weather sensitivity of demand for (non-holiday) Mondays to Thursdays.

Annual Load Profiles

The ALP_t shall be determined as:

$$\mathrm{ALP}_t = \frac{SNDE_t}{\dfrac{[\sum_{t=1}^{N} SNDE_t]}{N}}$$

where

t denotes the value for a particular day

E denotes the EUC

N is the number of days in the Gas Year;

Daily Adjustment Factor

The DAF_t shall be determined as:

$$\mathrm{DAF}_t = \frac{WVCE_t}{SNDE_t}$$

where

E denotes the EUC

t denotes the value for a particular day

SND – Seasonal Normal Demand
WVC - Weather Variable Coefficient;

Peak Load Factor

The PLF for the EUC sample is calculated as:

$$\frac{\text{Aggregate AQ from the EUC model}}{\text{1 in 20 peak demand from the EUC model * 365}}$$

An aggregate AQ is derived from the smoothed EUC demand model by setting the composite weather variable to its seasonal normal level in the model and summing the resulting demand values over the 365 days of the forecast year (excluding any 29th February).

For NDM EUCs a 1 in 20 peak day demand estimate is derived from each gas demand EUC model by simulation using the smoothed EUC demand model in conjunction with the database of historic daily composite weather variable values for the appropriate LDZ.

Development Cycle

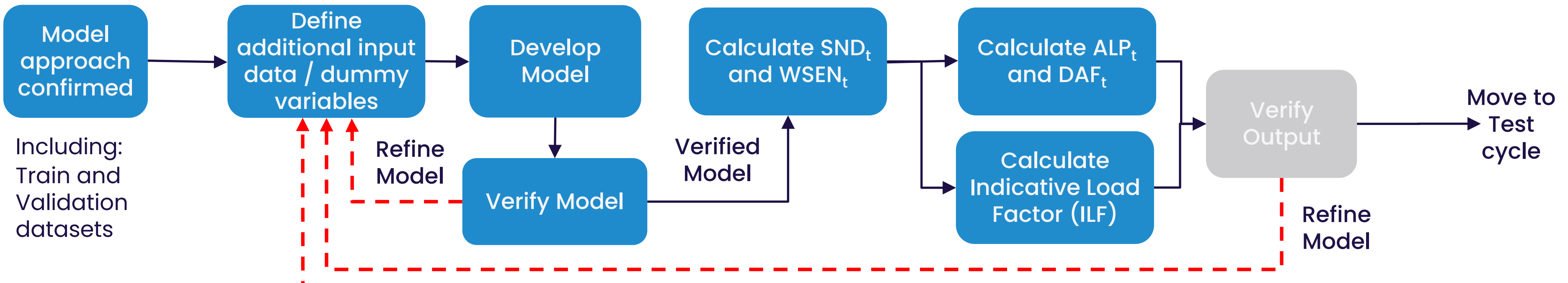
Progress on the approach and progress to date

- In meeting 3 we presented a development, test and evidence collection cycle approach to structure the investigations

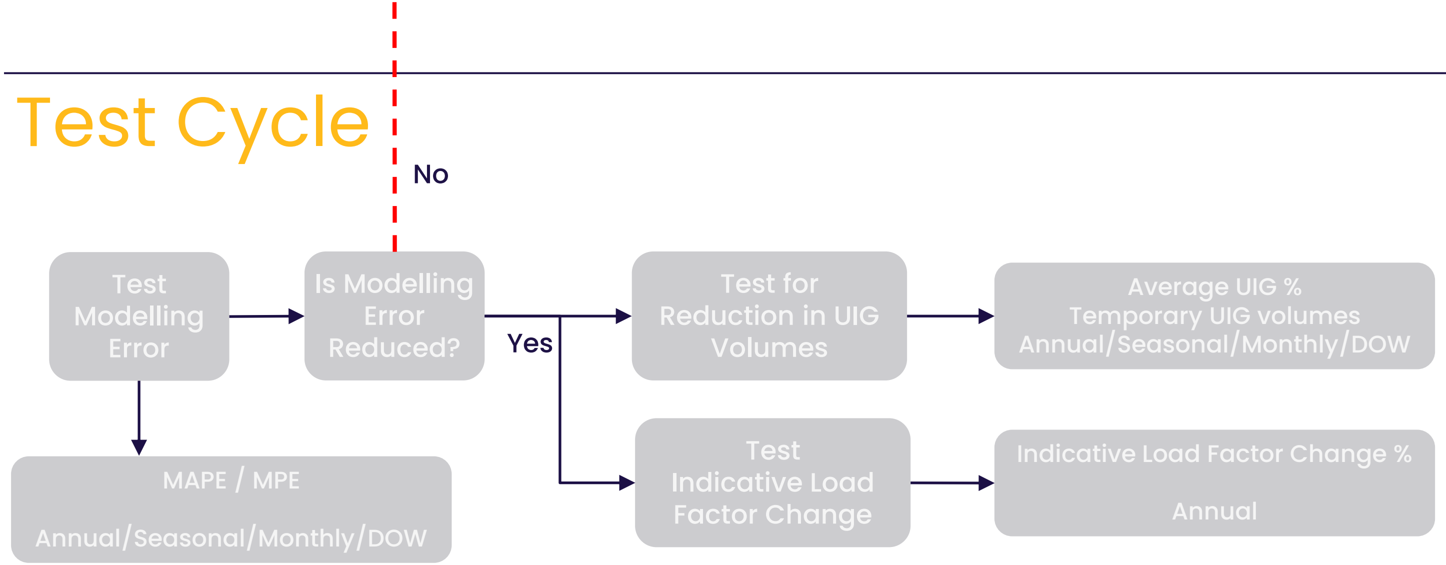
- The next slides will describe the progress to date

- The following slides will also capture some challenges we have identified from the initial development and investigation

Development Cycle



Test Cycle

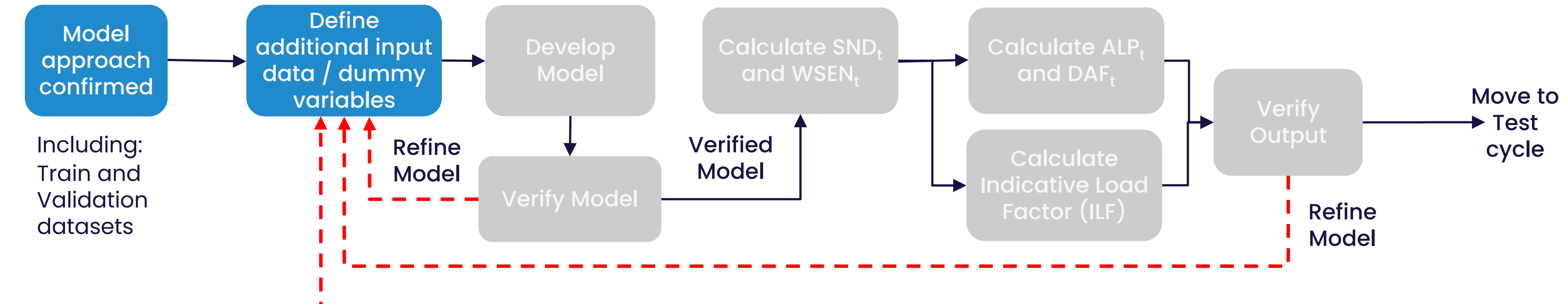


Evidence

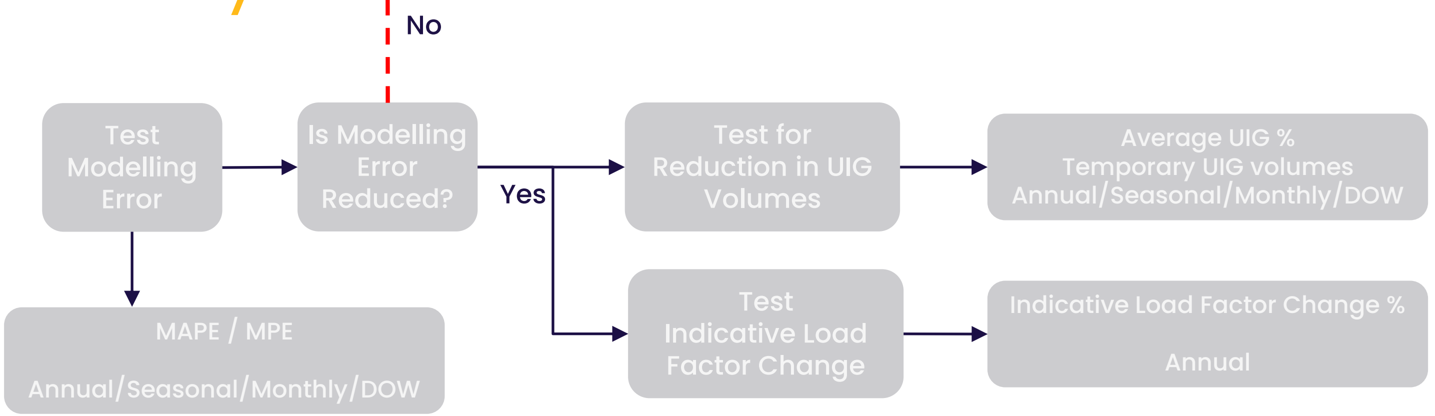
For each model collate:

Approach details,
Modelling Error,
UIG outcomes,
ILF changes
Process observations

Development Cycle



Test Cycle



Evidence

For each model collate:

Approach details,
Modelling Error,
UIG outcomes,
ILF changes
Process observations

Modelling decisions

Some high level decisions were made before commencing modelling to reduce the amount of data being processed.

Test areas were agreed as being EUC's 01BND, 02BNI and 05B for LDZs NW and SE

- Approach has been to focus the analysis on EUC segment NW 01BND, allowing us to learn the benefits and pitfalls of different modelling methods
- The focus was then expanded to the other test EUCs to see if different methods will suit different segments
- COVID years have been excluded from input
- The Data Period used in the analysis is from April 17 to March 20
- The data used in the analysis is the Sample Data collected for modelling

Observations from the Approach Phase

This table captures some of the data elements that were looked into during the approach phase and what insight was gained as a result

Data Set Up Considerations:

Data	Observation
Method for standardising Sample data	Needed this technique to allow training over multiple years
Tried individual years	To assess volatility (mimicking the current model smoothing approach)
Tried 3 year history	As an alternative to Model Smoothing
Sample data Apr 2020 to Mar 2021	Generally made the models worse (including the 01BND)
Solar Data	Solar is now used in the CWV, which has proven to be an improvement however it is possible not all Solar seasonal effects are being captured due to different reactions in winter and summer

Area 1: Trial alternative approaches to deriving SND_t

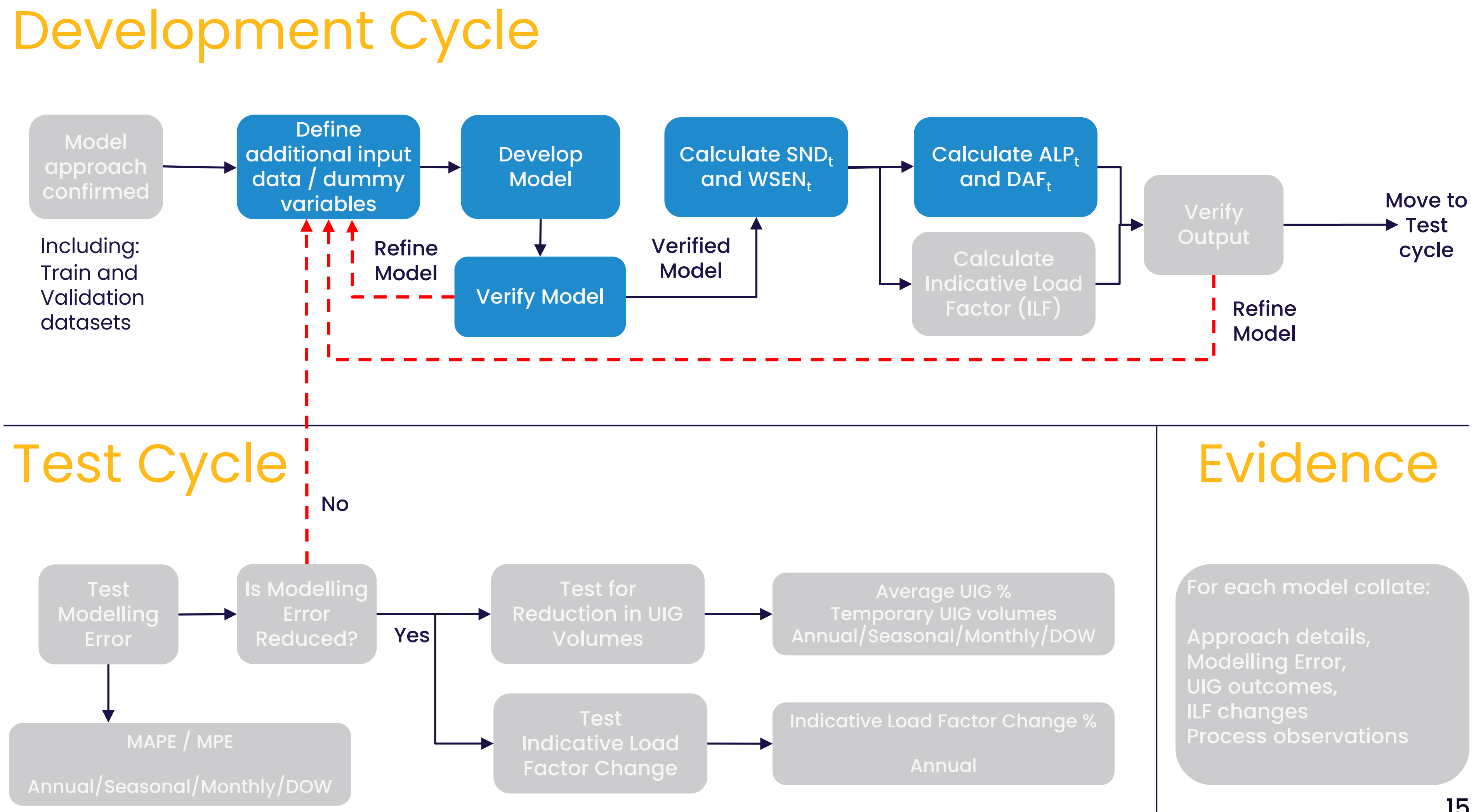
Objective:

Explore alternative modelling approaches (outside of linear regression) to identify whether a more accurate view of SND_t and subsequent ALPs, DAFs and PLFs exist

Identify any weaknesses, improvements and make recommendations which link to evidence of a reduction in NDM modelling error

Machine Learning has been used as well as tweaking parameters in the current modelling system, to understand significance of different factors

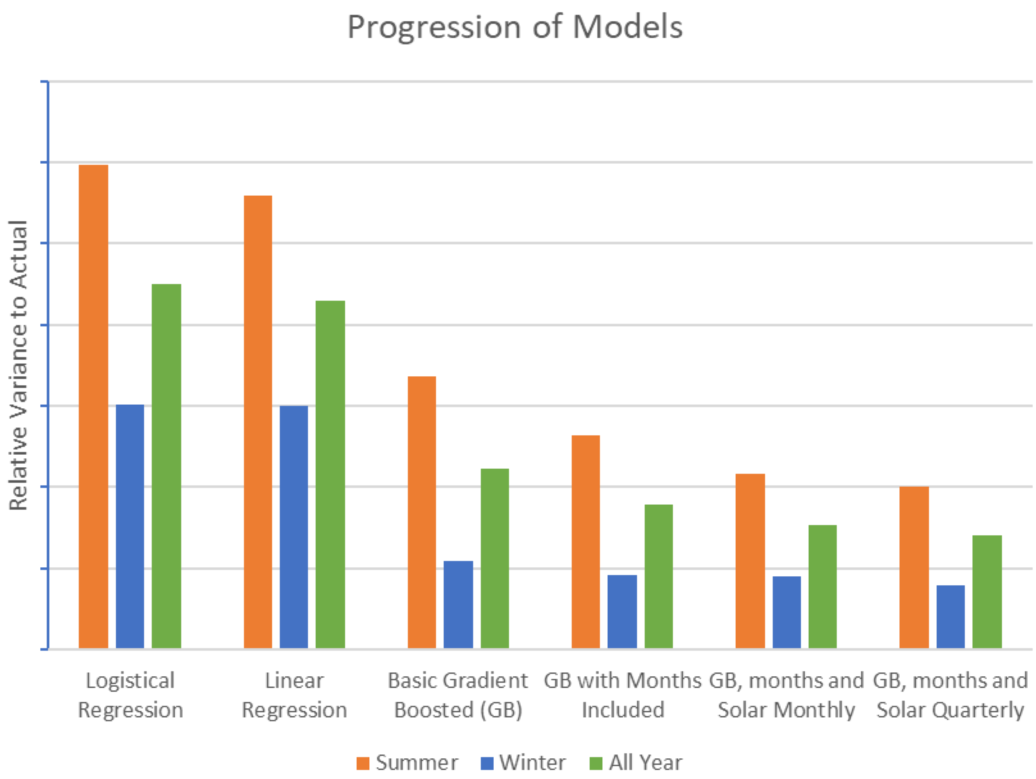
Approaches Tried	Description
Existing Model, Holidays included (all EUCs)	Opposite of current model (hols excluded). Examine significance of holidays on ALP
Existing Model, Summer Warm weather exclusion	To examine the significance of the warm weather exclusion i.e. allowing more warmer days into the models.
Machine Learning Regression	Both logistical and linear regression
Machine Learning Neural Networks	This is a Machine Learning method using a series of algorithms that work to understand the relationships between the data inputs (to emulate the way a brain operates)
Machine Learning Gradient Boosting	A Machine Learning method which produces a prediction model based from an "ensemble" of models
Additional Parameters	Adding data not currently used such as calendar month and additional weather information


Development Cycle
Model approach confirmed
Including: Train and Validation datasets
Define additional input data / dummy variables
Develop Model
Verify Model
Refine Model
Verified Model
Calculate SND_t and $WSEN_t$
Calculate ALP_t and DAF_t
Calculate Indicative Load Factor (ILF)
Verify Output
Refine Model
Move to Test cycle
Test Cycle
No
Test Modelling Error
MAPE / MPE
Annual/Seasonal/Monthly/DOW
Is Modelling Error Reduced?
Yes
Test for Reduction in UIG Volumes
Average UIG %
Temporary UIG volumes
Annual/Seasonal/Monthly/DOW
Test Indicative Load Factor Change
Indicative Load Factor Change %
Annual
Evidence
For each model collate:
Approach details,
Modelling Error,
UIG outcomes,
ILF changes
Process observations

Model Development

Progression of Modelling

- Gradient boosted was found to give the closest forecast to actuals (based on MAPE – Mean Absolute Percentage Error)
- Gas year 2018-2019 was used for scoring the models as this had no COVID impact skewing the results
- This means we are using some of the input data in scoring, however we are working on getting more data prepared so scoring can be independent
- Initial tests were run on NW 01BND and these results are shown in the chart
- Additional models were then run testing different scenarios.



Note on Linear Regression: This is a machine learning Linear Regression and not the current refined methodology

Initial view of ML for other test EUCs

- The remaining EUCs (01BND, 02BNI and 05B) and LDZ (NW and SE) have been run through ML
- These have not been refined but give an initial view of the model approach using the following parameters
  - Energy
  - CWV
  - Month
  - Holiday factors
  - Day of week
- There remains outstanding questions about determining a methodology for weather correction and calculation of a DAF

MAPE for data trained between 01/04/2017 and 31/03/2020
Machine Learning techniques used (with no refinement)

LDZ	EUC	Gradient Boosting (GB)	Least Angle Regression (Lars)	Linear Regression	Neural Network
NW	**01BND**	2.2%	8.7%	8.7%	27.9%
	02BNI	1.4%	8.1%	8.3%	25.8%
	05B	0.9%	6.9%	6.9%	22.7%
SE	**01BND**	1.4%	6.1%	6.2%	57.2%
	02BNI	1.4%	8.7%	8.7%	31.2%
	05B	1.2%	6.4%	6.4%	17.0%

- Initial results suggest Neural Networks had the poorest performance in the training of the data (although fine tuning parameters may bring improvements)
- The gradient boosting method generally showed the best MAPE values from all the runs.

Area 1: Summary of Deliverables

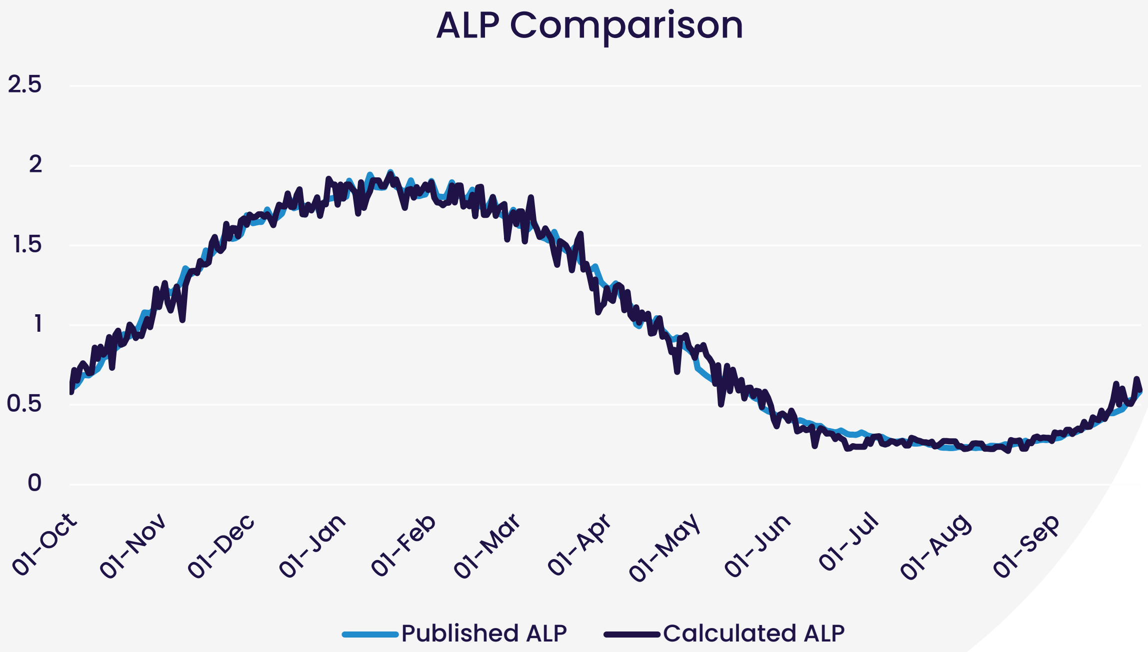
The key deliverables from Area 1 is the provision of ALP, DAF and Indicative Peak Load Factor.

This table summarises the success in producing these deliverables.

Modelling Methods Tried:

Area 1 Deliverables			
Methods Tried	ALP	DAF	Indicative Peak Load Factor
Existing Model Holidays included (all EUCs)	✔	✔	To be looked at later in process
Existing Model, Summer Warm weather exclusion	✔	✔	To be looked at later in process
Machine Learning Regression	✔	**Method unknown at present**	To be looked at later in process
ML Neural Networks	✔	**Method unknown at present**	To be looked at later in process
Machine Learning Gradient Boosting	✔	**Method unknown at present**	To be looked at later in process

Comparison of Calculated ALP to Published ALP



Example of an ALP produced with machine learning (Gradient Boosted with Months and Seasonal Solar Radiation)

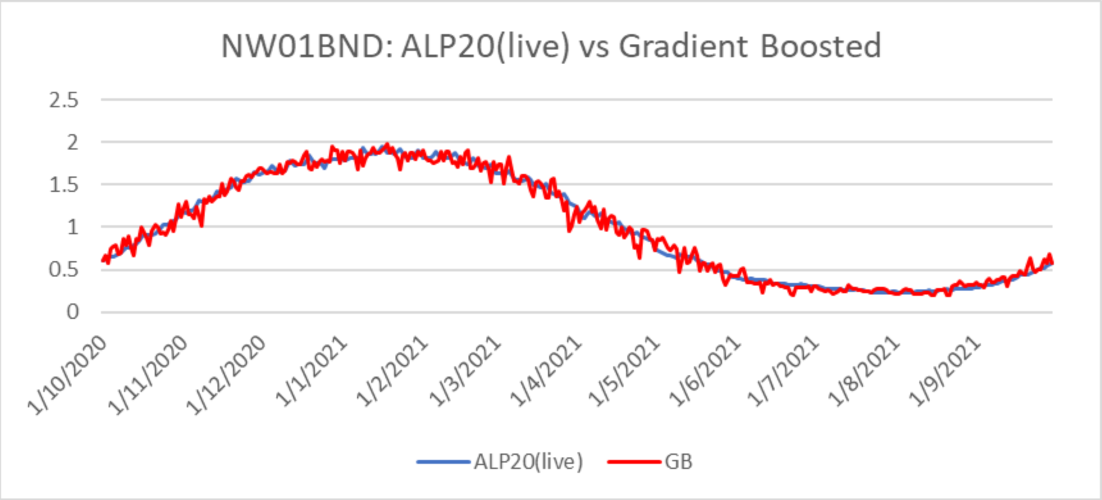
There are a number of areas where the newly calculated ALP differs from the published ALP

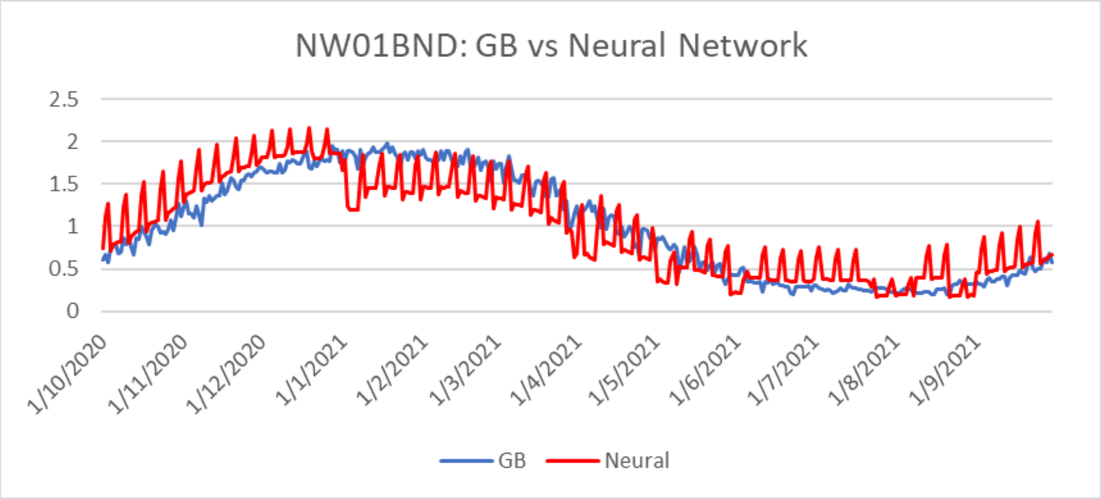
- Bigger peaks and troughs with the calculated ALP
- Actual consumption does experience peaks and troughs, challenge is separating 'normal' from the idiosyncrasies of the input data
- The calculated ALP has not reduced consumption in the May holiday period
- The calculated ALP has put a reduction in late June

These will be worked through to see what is driving the differences

Understanding trends NW01BND

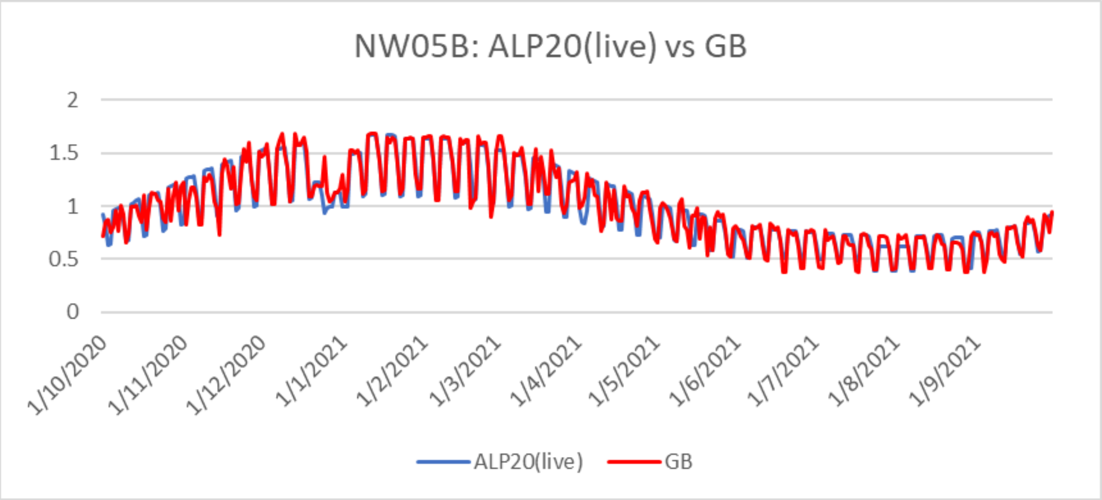
- The top chart shows the Gradient Boosted Machine Learning (as the most promising) model against the live Gas Year 2020 ALP.
- The model show parts of the year with noticeably different predictions. Further analysis to try and understand the differences
- The Gradient Boosted vs Neural Network model ALP is pictured in the 2nd chart. Neural network showed the poorest MAPE but visual comparison to the GB model shows quite an unusual pattern including a step change from 1st Jan. Next steps is to try and understand the step change.

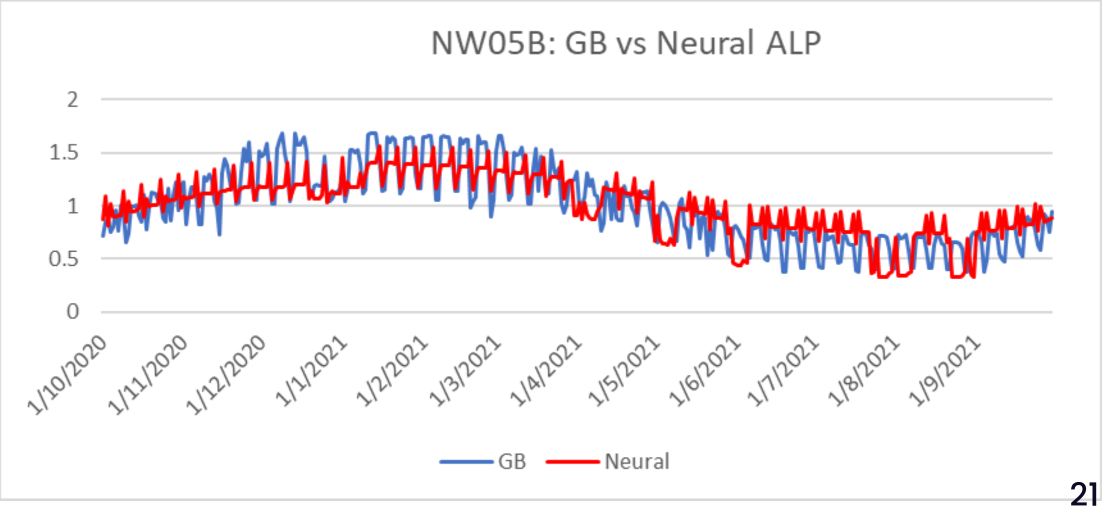




Understanding trends NW05B

- The top chart shows the GB ML (as the most promising) model against the live Gas Year 2020 ALP.
- The model show very similar peak and troughs, suggesting similar understanding of weekday and holiday patterns to the current methodology.
- The GB vs Neural Network model ALP is pictured in the 2nd chart. Neural network showed a MAPE of 22.7%. Visual comparison suggests it is producing a less peaky model (flatter). Also some periods seem to have the opposite reaction to either the live ALP or the one derived from the GB model.
- There seems to be a similar jump around the 1st Jan. Its not as pronounced as in the NW01BND model but looks like it exists. Next steps is to try and understand the step change.





Challenges from the Model Development phase

This table captures some of the challenges seen during the model Development phase

Challenges:

Challenges	Comment
Machine Learning methods produce a target value (in this case energy)	The ML techniques produce an "energy" figure which can be used to calculate an ALP. The is no obvious way of producing a weather correction and therefore a DAF or ILF value (still being investigated)
Current Modelling output i.e. Day of week, holiday factors, ILFs, Modelling Parameters	No obvious way of providing these outputs from Machine Learning (still being investigated)
Describing the outcome (metrics) of the models runs.	Some of the Machine Learning result metrics don't give a view of whether the ALP is reflective.
Understanding days with coexisting Holiday and weekend effects.	The Machine Learning models are overlapping weekend and holiday effects where they occur together. (Current modelling system gives preference to holiday factors)
Machine Learning is a 'Black Box' process	Unless we can get a clear ALP and DAF from the process there is difficulty applying the results to the population

Conclusions and Next Steps

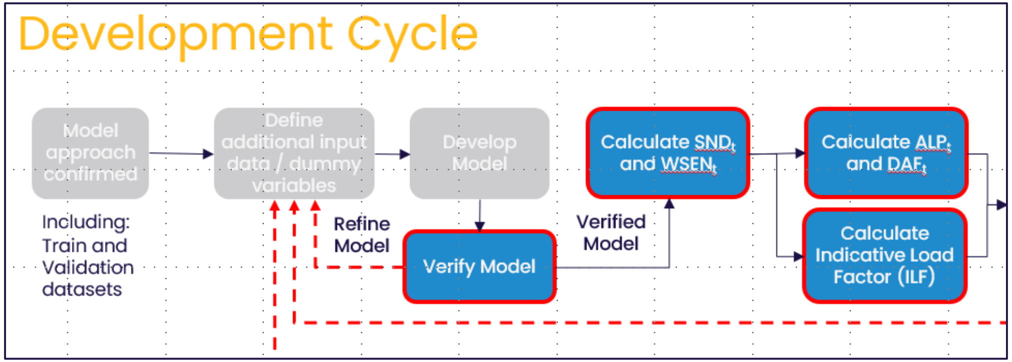
Conclusions and Next Steps

Adding calendar months and an element of ranked Solar Radiation into the input data improved the results

Gradient Boosting has given some really promising results

The next focus will be on

- Delivering DAFs and Load Factors
  These are fundamental as they present a risk to not being able to deliver a Machine Learning solution
- Improvement to models
  Including further investigation into previously visited methodology such as Neural Networks



- To investigate / develop a weather correction (DAF) methodology for the models.
- To further refine the models, including whether different methods will suit different EUCs
- To understand how to describe to the group the model principles and the metrics for assessing them (assuming they will require different explanation / support information to the current method (for example alternatives to R^2 and ILF values.
- Meeting 5 preparation

Timeline

Workgroup 0754R Timeline

March 2021

WG Meeting 1 (23rd)
- Scope/Objective
- High Level Principles
- Resources/Support
- Potential Areas to Investigate

May 2021

WG Meeting 2 (12th)
- Top 3 Areas to Investigate
- Data Availability
- Resourcing / Costs

July 2021

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

Sept 2021

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

WG Meeting 6 (TBC)

Apr 2022

Demand Estimation Team

Core Demand Modelling work takes place between April and June, so focus for team during Q2 has been on the production of Gas Demand Profiles for Gas Year 2021/22

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

ON BEHALF OF xoserve