978 – Enhancing the Understanding of Distribution Network Losses

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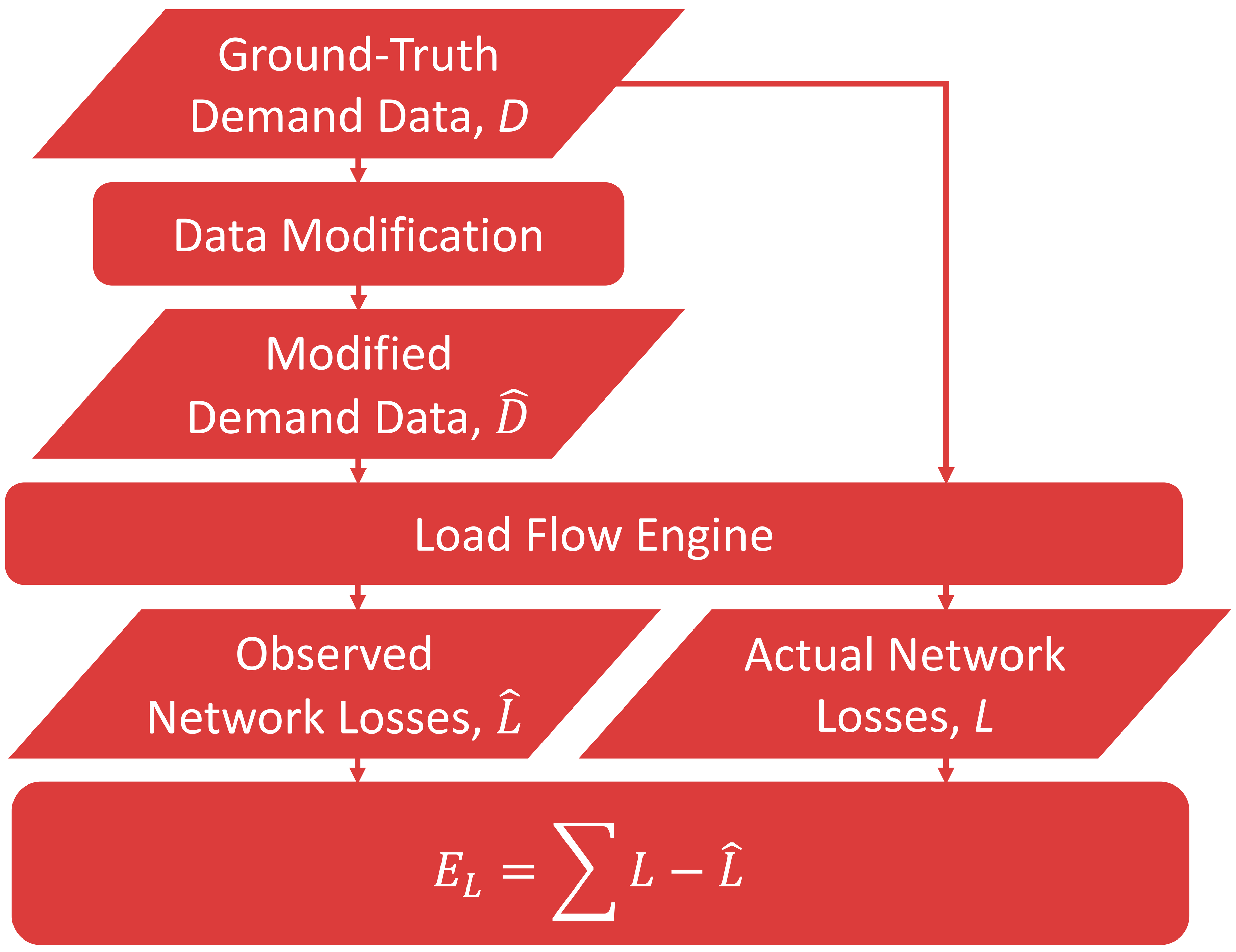
Introduction

Due to the size and complexity of distribution networks, estimation methods are used to calculate network losses; these inform network decision making and settlement of customer bills. Network losses are affected by many factors, including network topology, voltage, asset ratings, and variability of demand and generation. Estimation of losses is also affected by the information available due to issues such as missing data and measurement error. The goal of this project is to enhance the understanding of these losses, and the methods used for estimation, in the context of changing electricity demand.

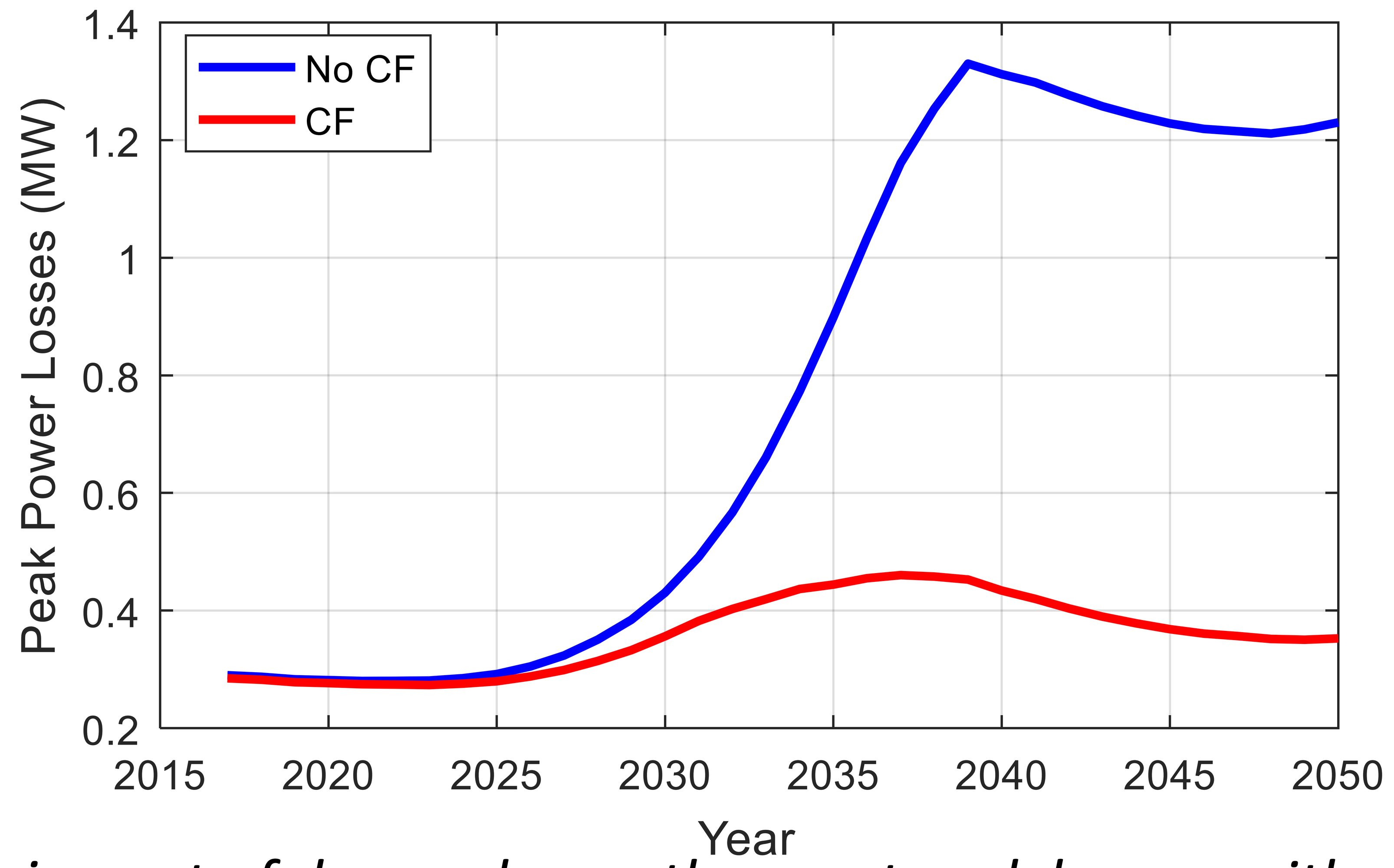
Methodology – Sensitivity Analyses

Sensitivity analyses allow us to study how a given parameter affects the estimation of network losses. The sensitivity analyses in this paper are carried out via sequential Montecarlo simulation using real network data and load flow simulations performed in MatPower.



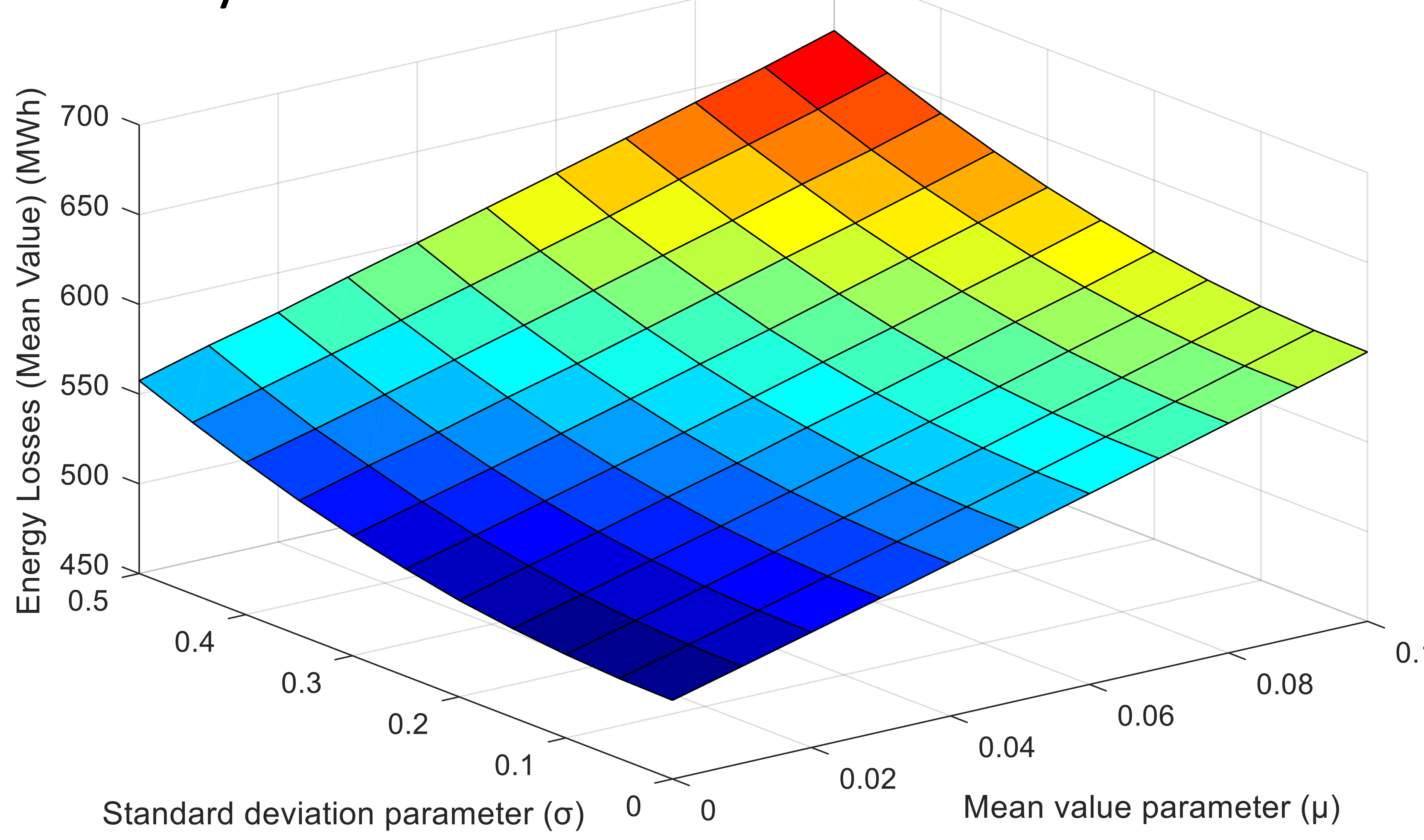
A flow chart illustrating the sensitivity analyses process

Future network scenarios: temporal & spatial variation of demand, demand growth, new technology uptake.



The impact of demand growth on network losses, with and without Customer Flexibility (CF)

Measurement accuracy: impact of the uncertainty inherent in loss estimation; ways to mitigate measurement uncertainty.



The impact of measurement error on loss estimation

Data aggregation and time resolution: Impact of data resolution; aggregation of data from available measurements; impact of voltage level.

Smart and non-Smart Technology, including demand, generation, and network technology, in both controlled and uncontrolled deployments.

Enhanced understanding of losses **Improved Calculation** **Losses in a DSO environment**

Conclusion: Future networks, with higher utilisation and increased peak demand, will have higher losses than those experienced today. It is therefore vital that DSOs understand how and where these losses occur, how they will evolve with changing a system, and how accurately they can be estimated with available information. This project provides initial investigation into how demand growth and customer flexibility will affect losses, and will deliver a broader methodology to enable accurate load estimation without the need for computationally intensive studies.

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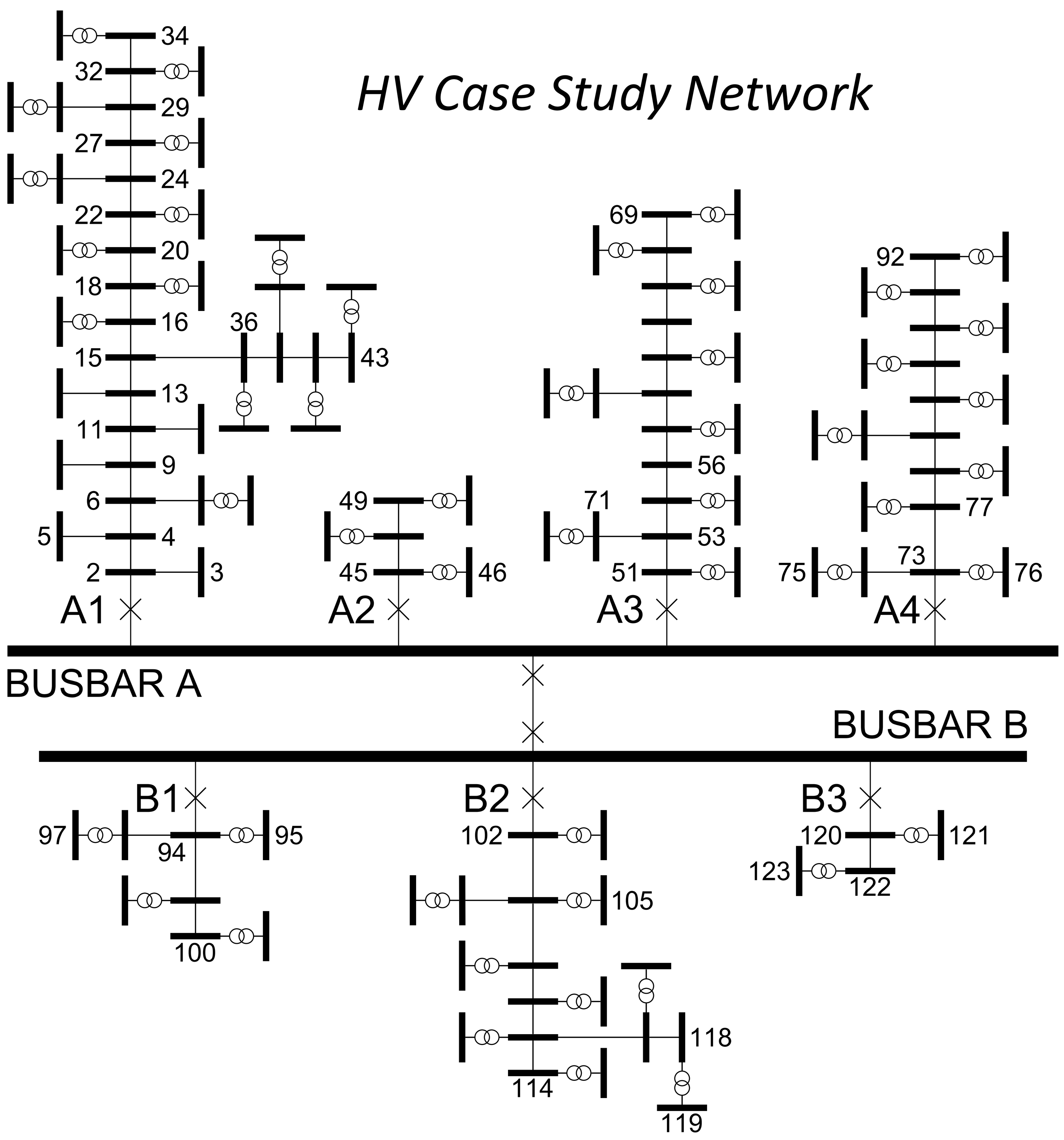
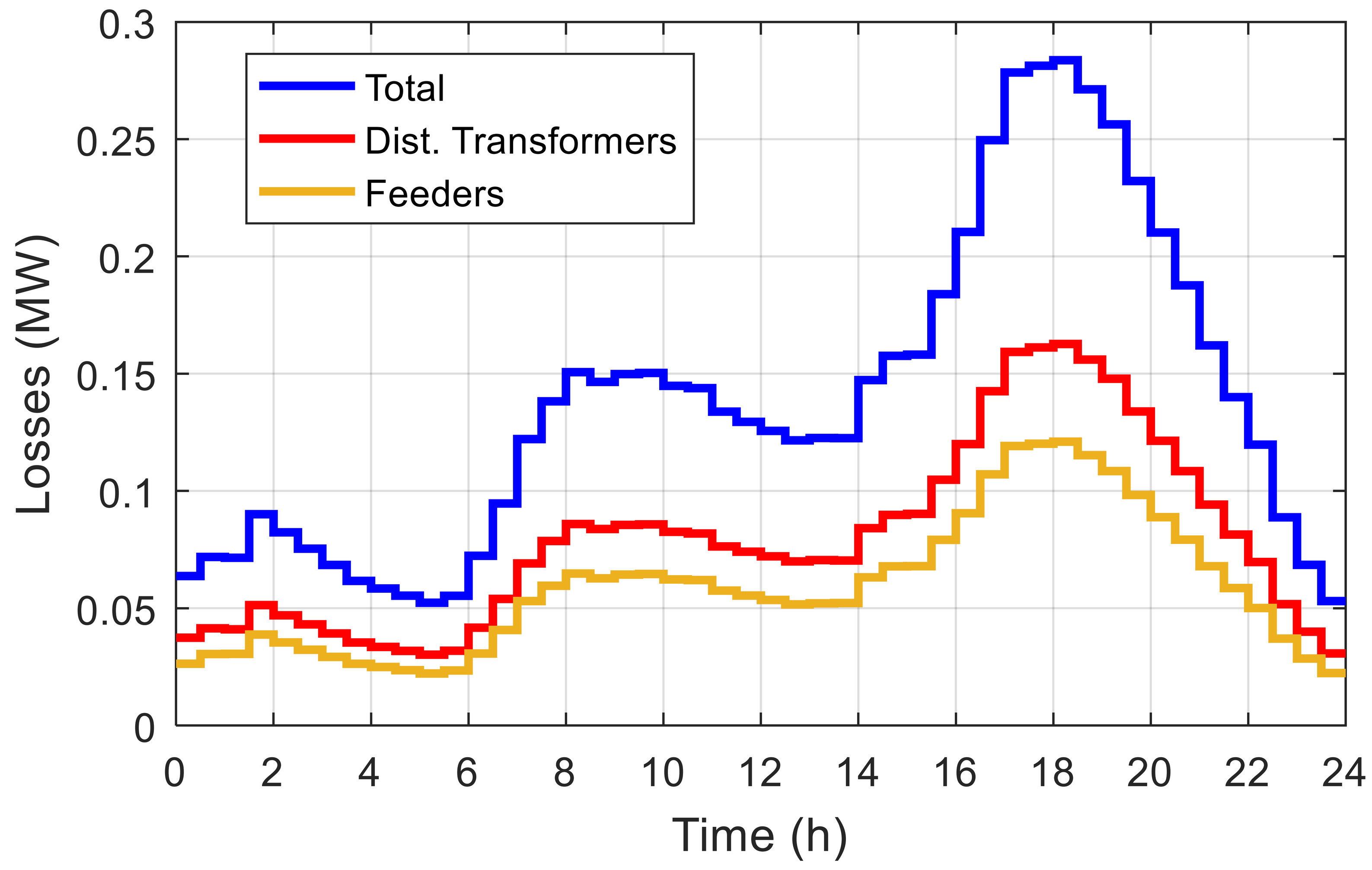
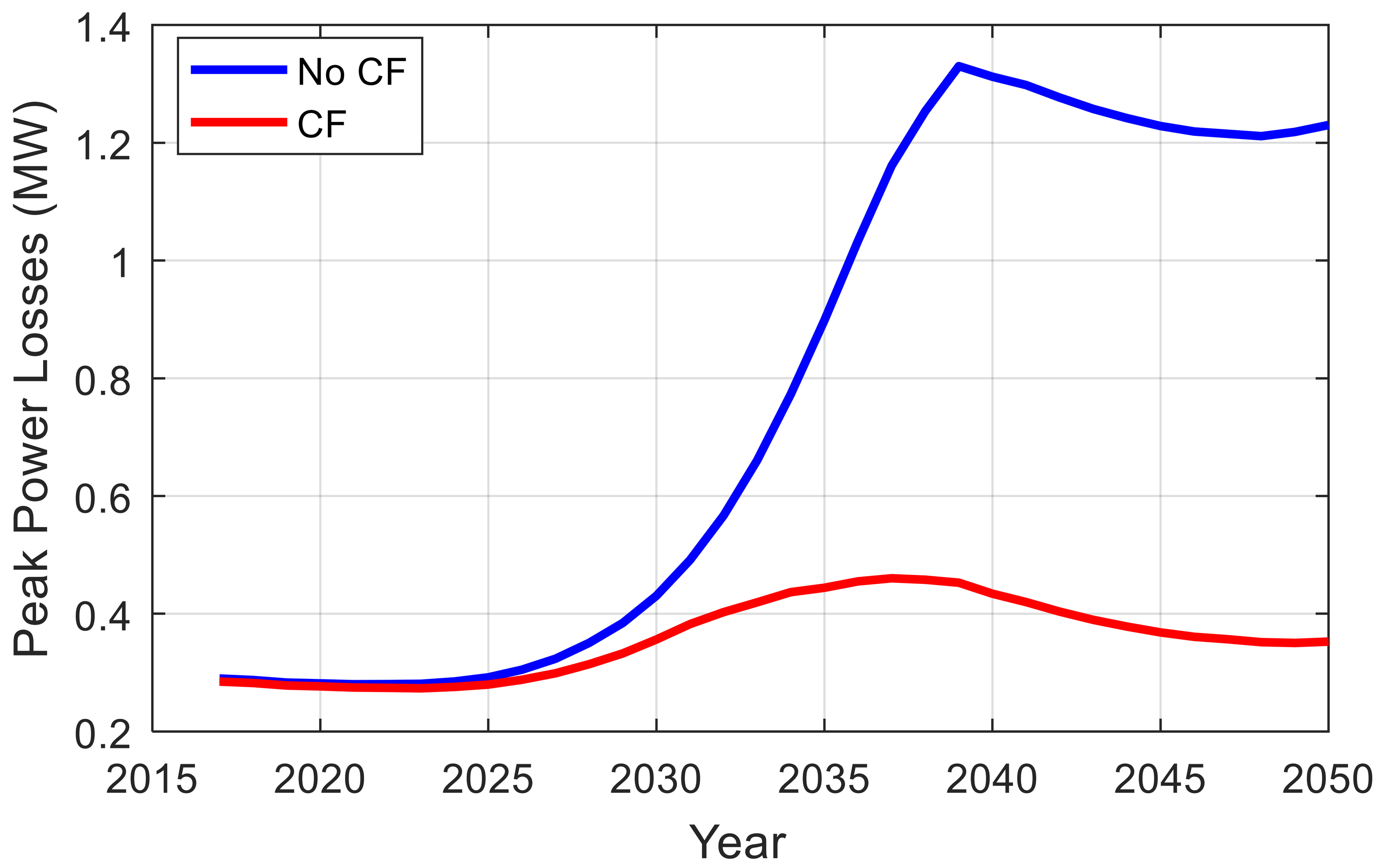
Impact of Future Network Scenarios – Detailed Results



HV Case Study Network



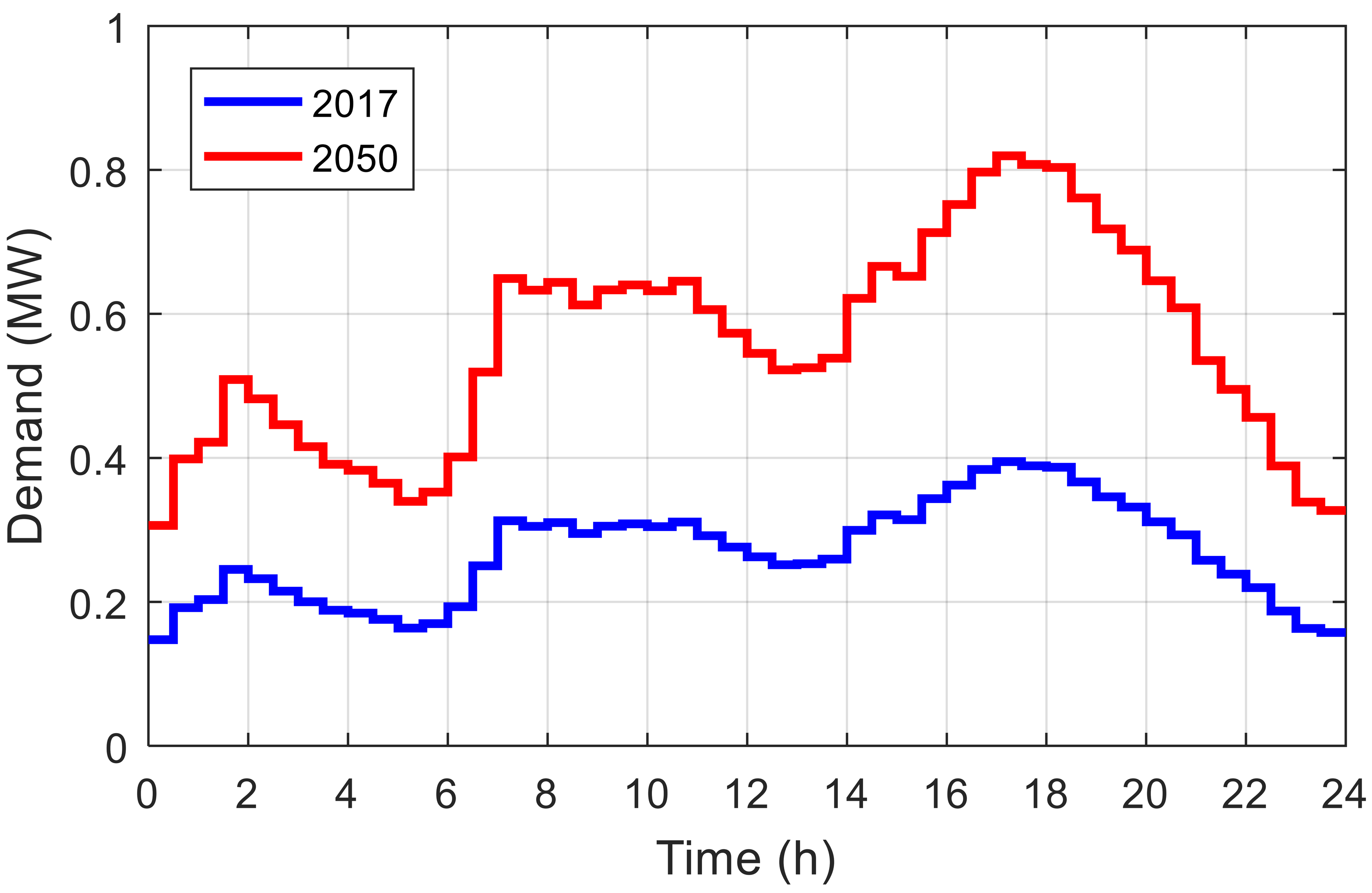
Hourly Variation of Losses.



Power Losses Calculated at Peak Demand with and without Customer Flexibility (CF) from 2017 to 2050.

FUTURE LOAD SCENARIO DATA

The future load scenario datasets for this study are obtained from NPg's Element Energy Load Growth forecasting model, which takes outputs from National Grid's Future Energy Scenarios (NGSO FES 2018): 'Two degrees' and interprets how they are distributed across NPg's substation. The load profile of a representative load point – in 2017 and 2050 – is shown below as an illustrative example.



CONCLUSION

Distribution network losses present a significant cost to network customers. Future networks, with higher utilisation and increased peak demand, could have higher losses than those experienced today. It is therefore vital that DSOs understand how and where these losses occur, how they will evolve with changing demand and increased use of low carbon technology, and where and when it is appropriate to take actions to reduce losses. This paper provides initial investigation into how demand growth and customer flexibility will affect losses, and proposes a broader methodology for further investigation, with the ultimate goal of enabling accurate load estimation without the need for computationally intensive studies.

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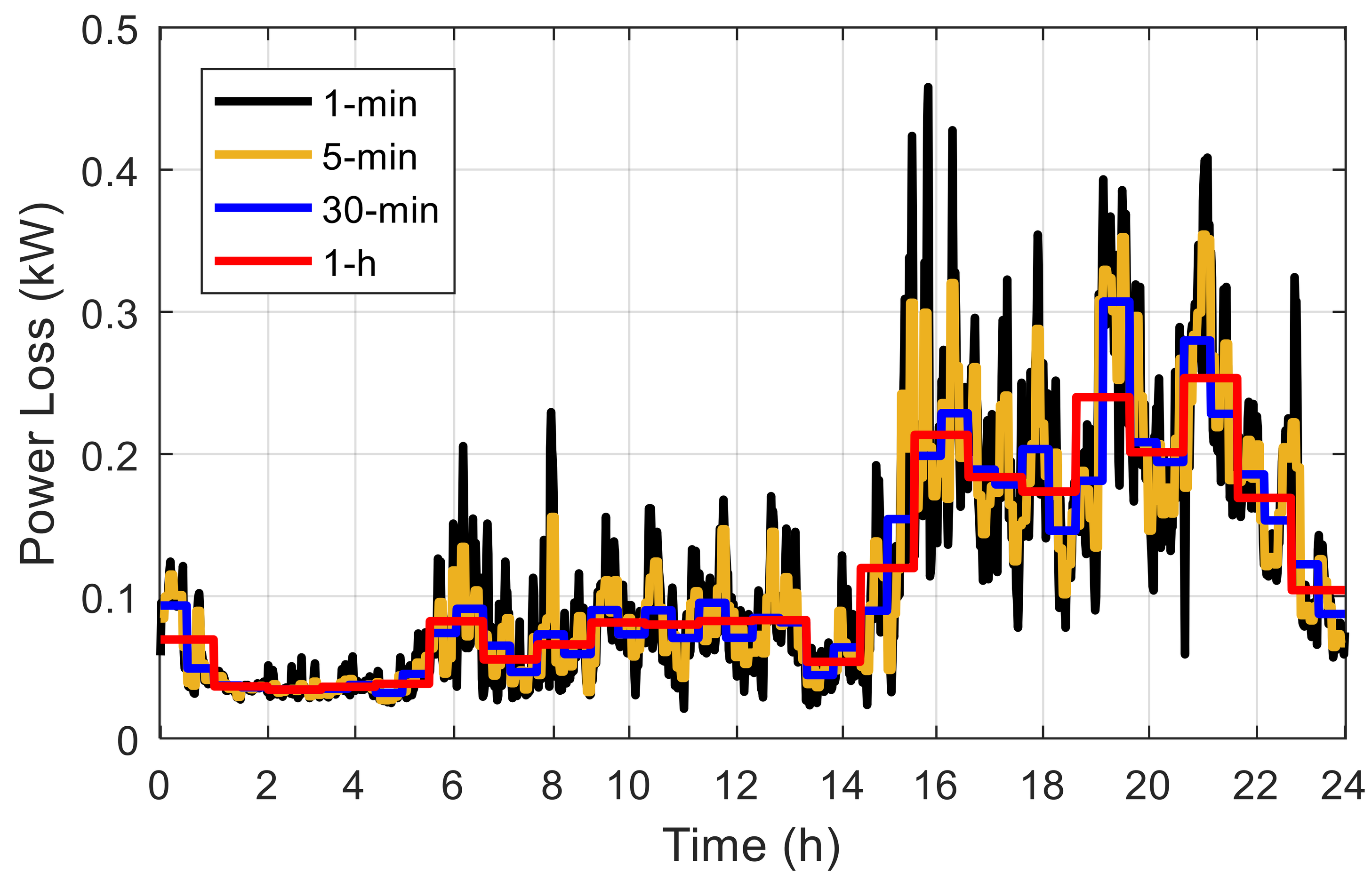
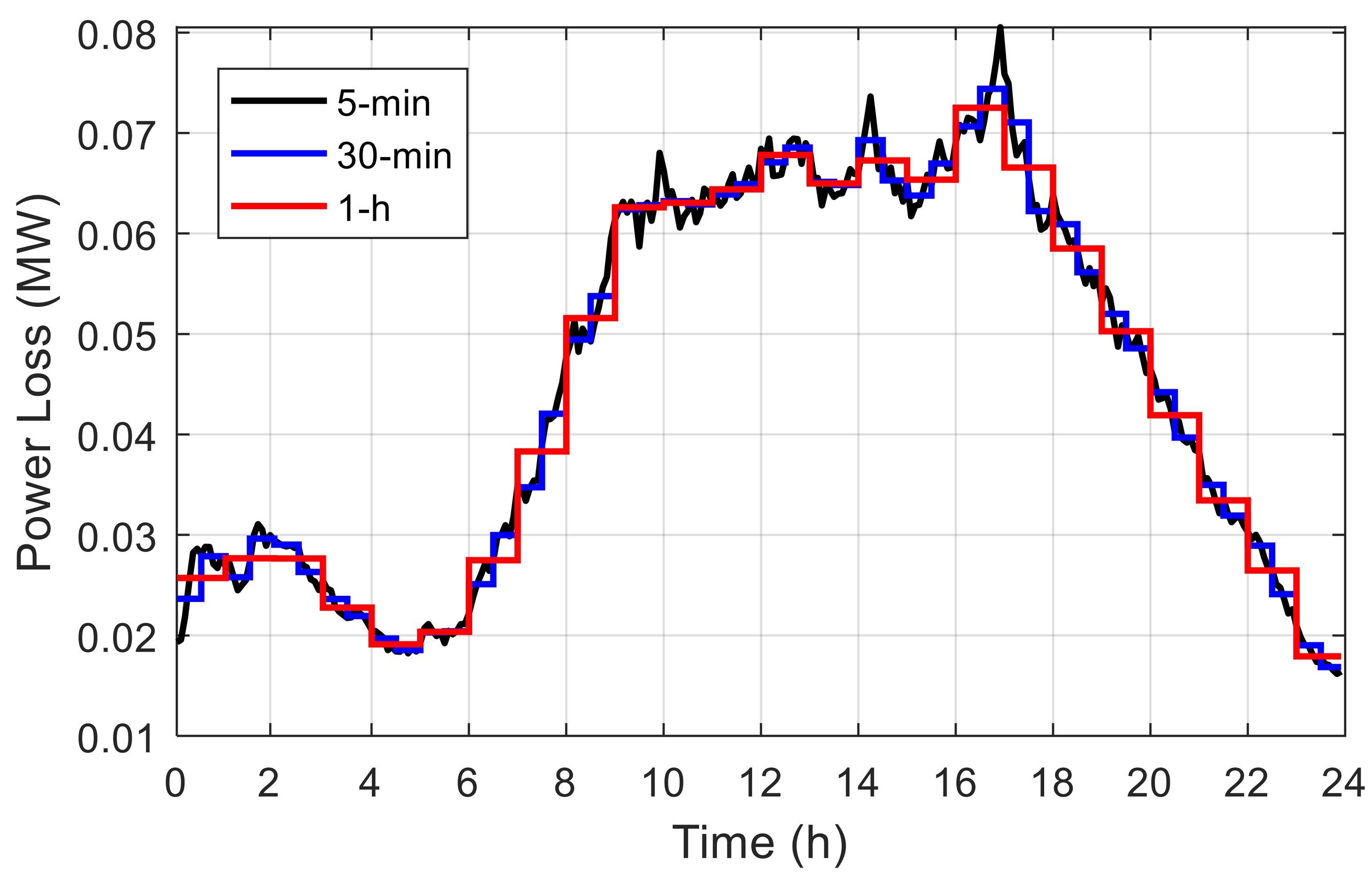
Impact of Data Resolution – Detailed Results





The estimated active power losses in an LV (left) and HV (right) network at different data resolutions

Time Resolution	Energy Losses (kWh)	Error (%)
1-min	2.54	–
5-min	2.51	1.06
30-min	2.47	2.63
1-h	2.46	3.18

Time Resolution	Energy Losses (MWh)	Error (%)
5-min	276.86	–
30-min	276.69	0.06
1-h	276.47	0.14

Energy loss estimation errors in an LV (left) and HV (right) network at different data resolutions

Conclusions

The project studied the effect of loading sampling rate on loss evaluation using 1-min, 5-min, 30-min, and 1-h time steps. Two networks – an HV rural and an LV urban – were considered in the analysis, and the results indicated that the most significant factor that impacts losses (in terms of time resolution) is the variability of the feeder loading, which is related to the load diversity. The error in energy losses was approximately 0.1% and 3% in HV and LV, respectively; load diversity is much higher in HV because of the number customers supplied at this voltage level compared to LV. Increasing the sampling rate leads to greater underestimation of energy losses because of the resulting smoother profile.

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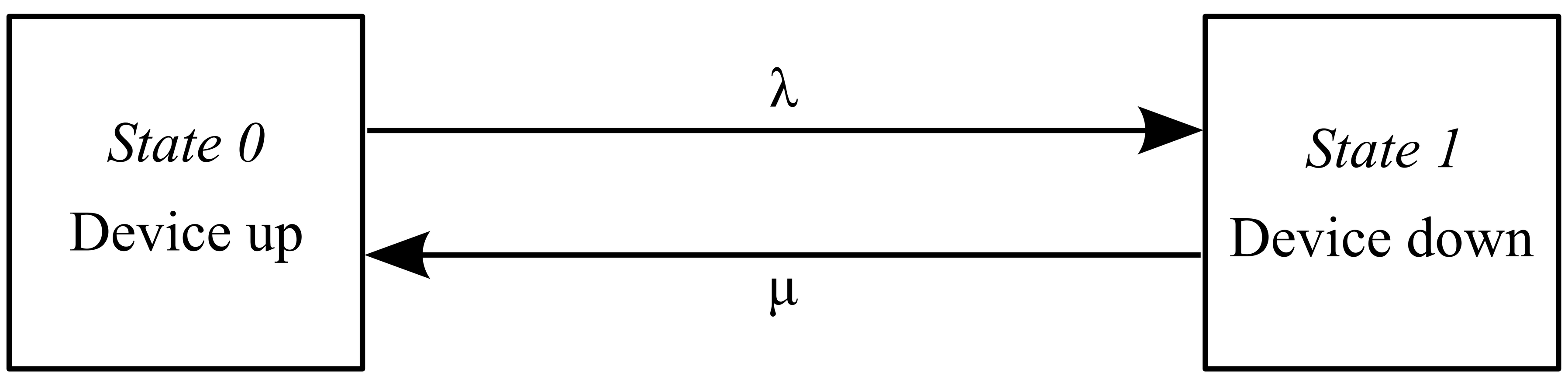
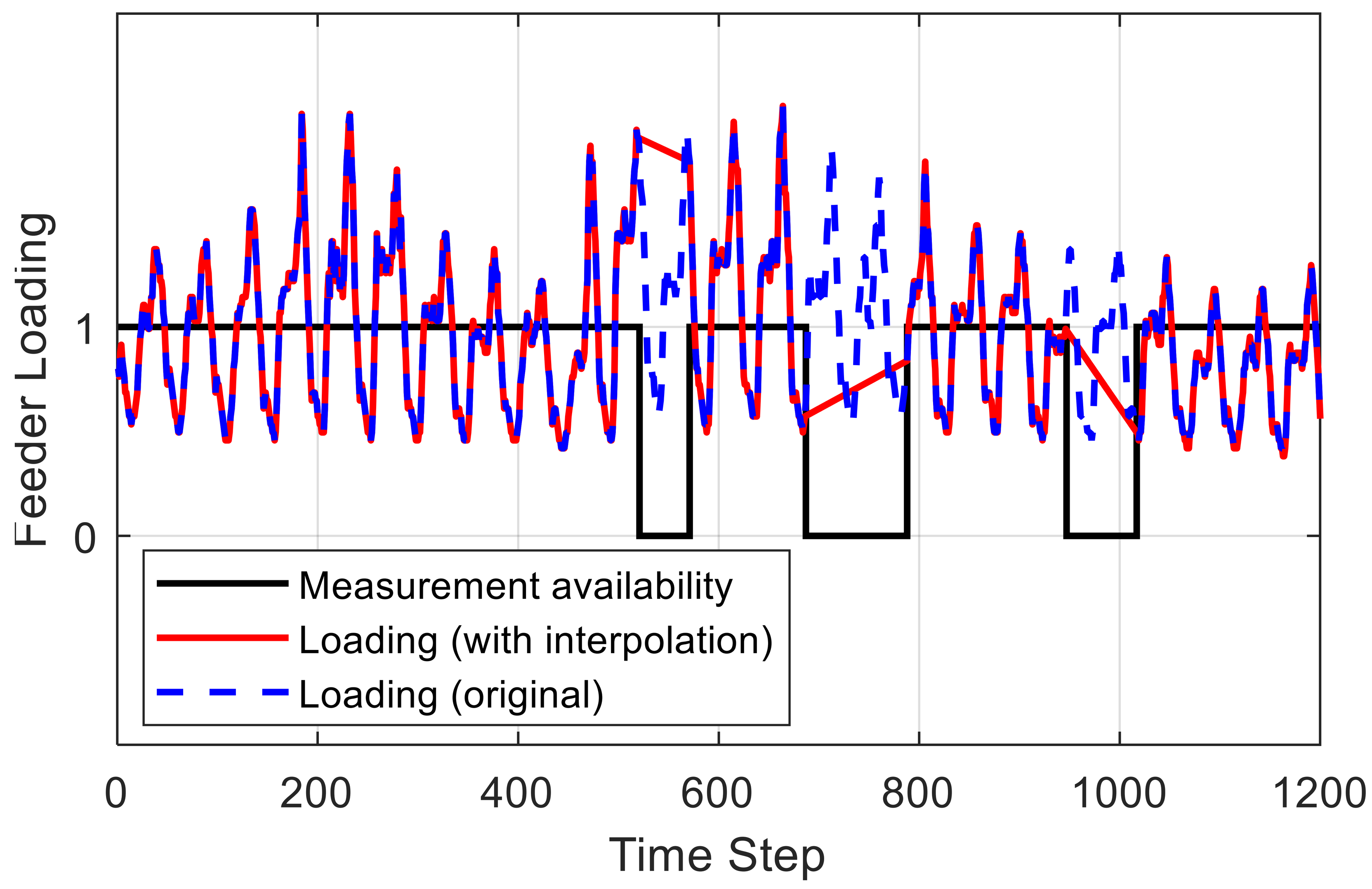
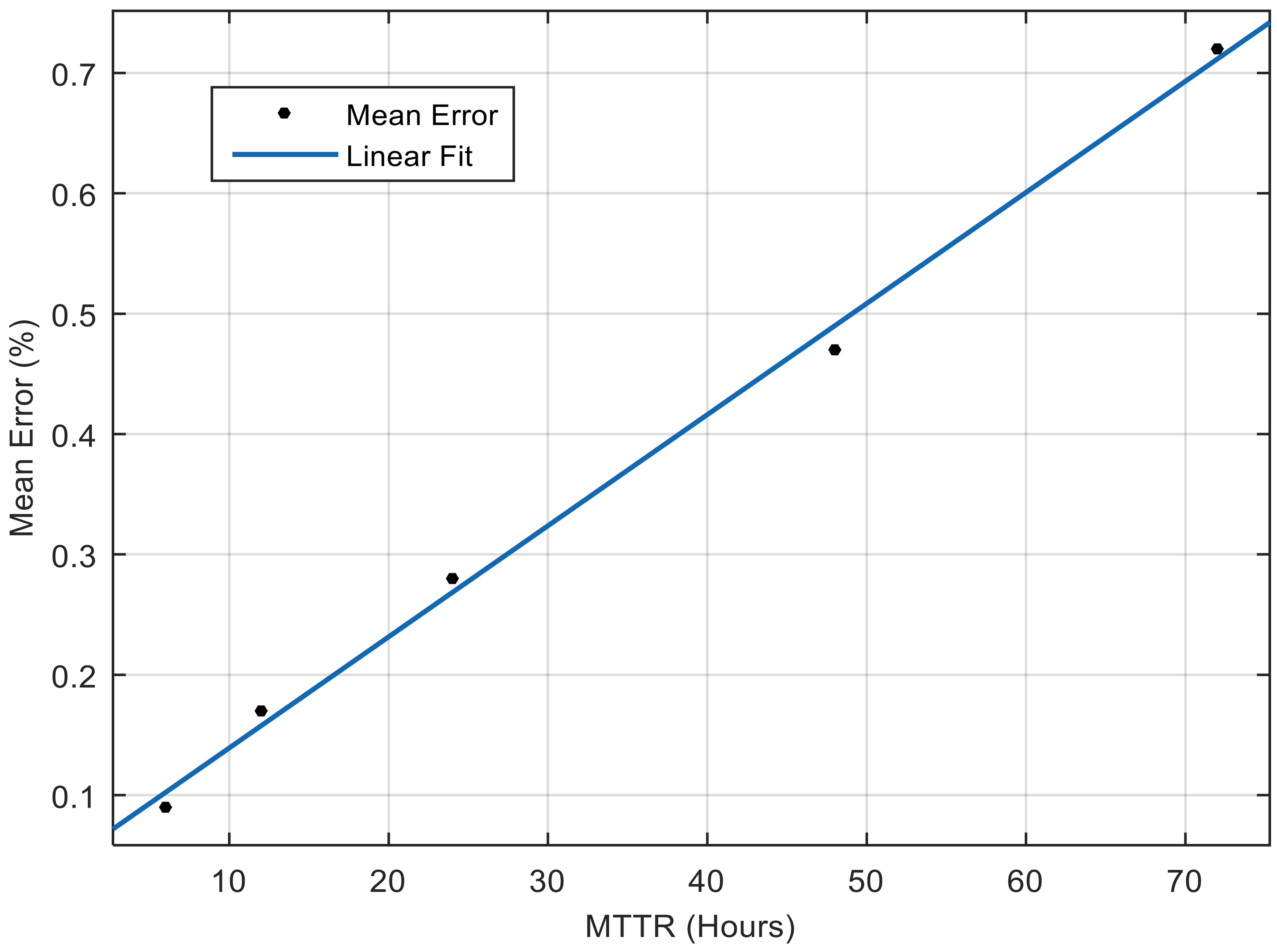
Impact of Missing Data– Detailed Results



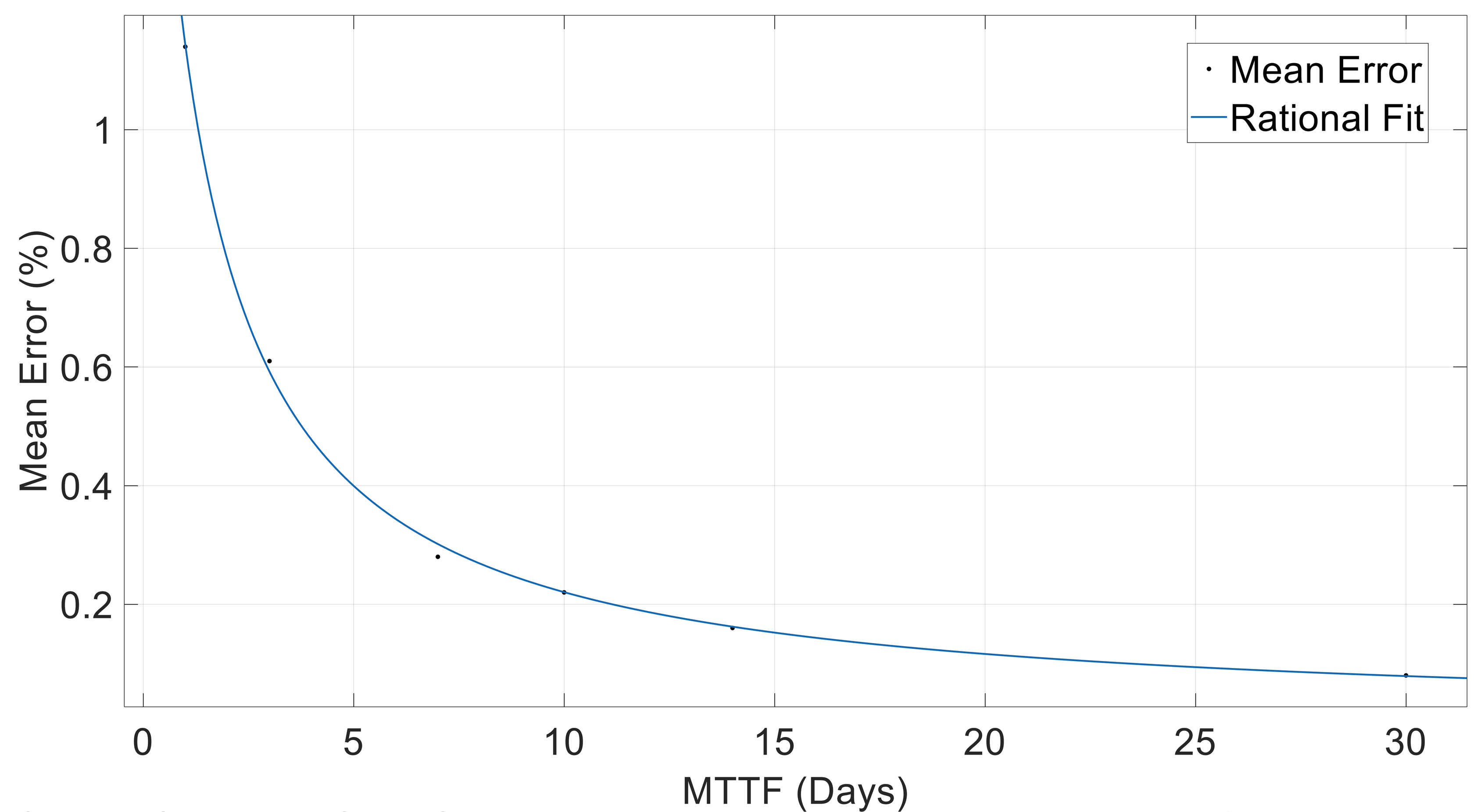
Measuring device state space diagram (λ and μ represent the failure and repair rates, respectively).



Illustrative part of a simulation (25 days) carried out to investigate the effect of data unavailability on energy losses.



The relationship between MTTR and loss estimation error with a fixed MTTF of 1 week



The relationship between estimation error and MTTF with a fixed MTTR value of 1 day

Conclusions

The impact of data unavailability on estimation of energy losses was examined in this section and was found that the error is relatively low compared to the amount of missing data – 45 (equivalent full) days with no available data led to a maximum error of 1.5%. More missing data resulted in greater underestimation of energy losses and higher uncertainty as well. Finally, extended periods of missing values compared to more frequent (but shorter) unavailability periods (with the same ratio of available data) play a more important role in loss estimation in terms of uncertainty. The error estimation increased linearly with the duration of the periods of missing data (represented by a MTTR value), and had a rational ($\frac{1}{x}$ type) relationship with the spacing between periods of missing data, represented by the MTTF. The adjusted R^2 value for both of these relationships was greater than 0.99.

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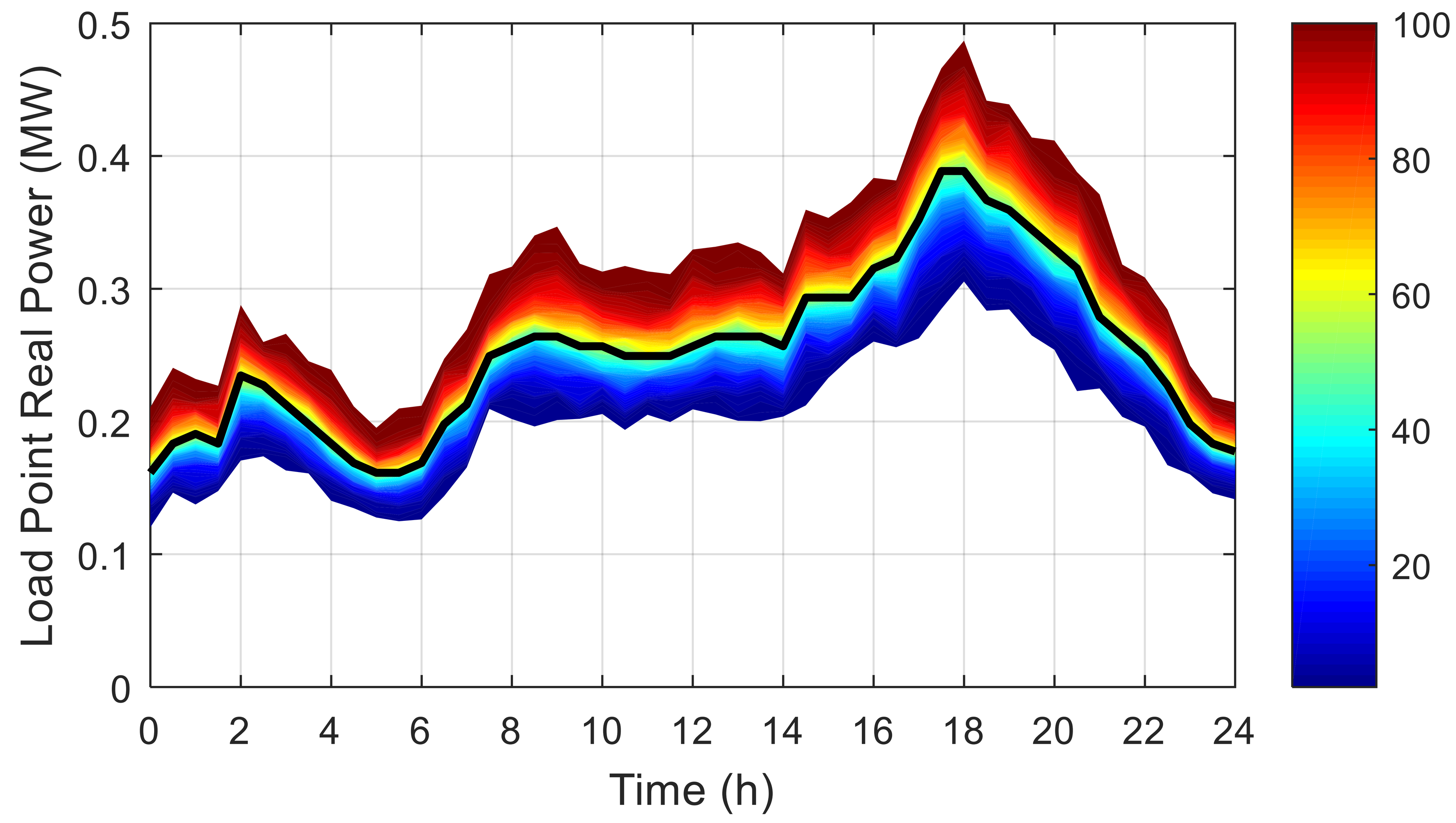
Impact of Measurement Uncertainty – Detailed Results

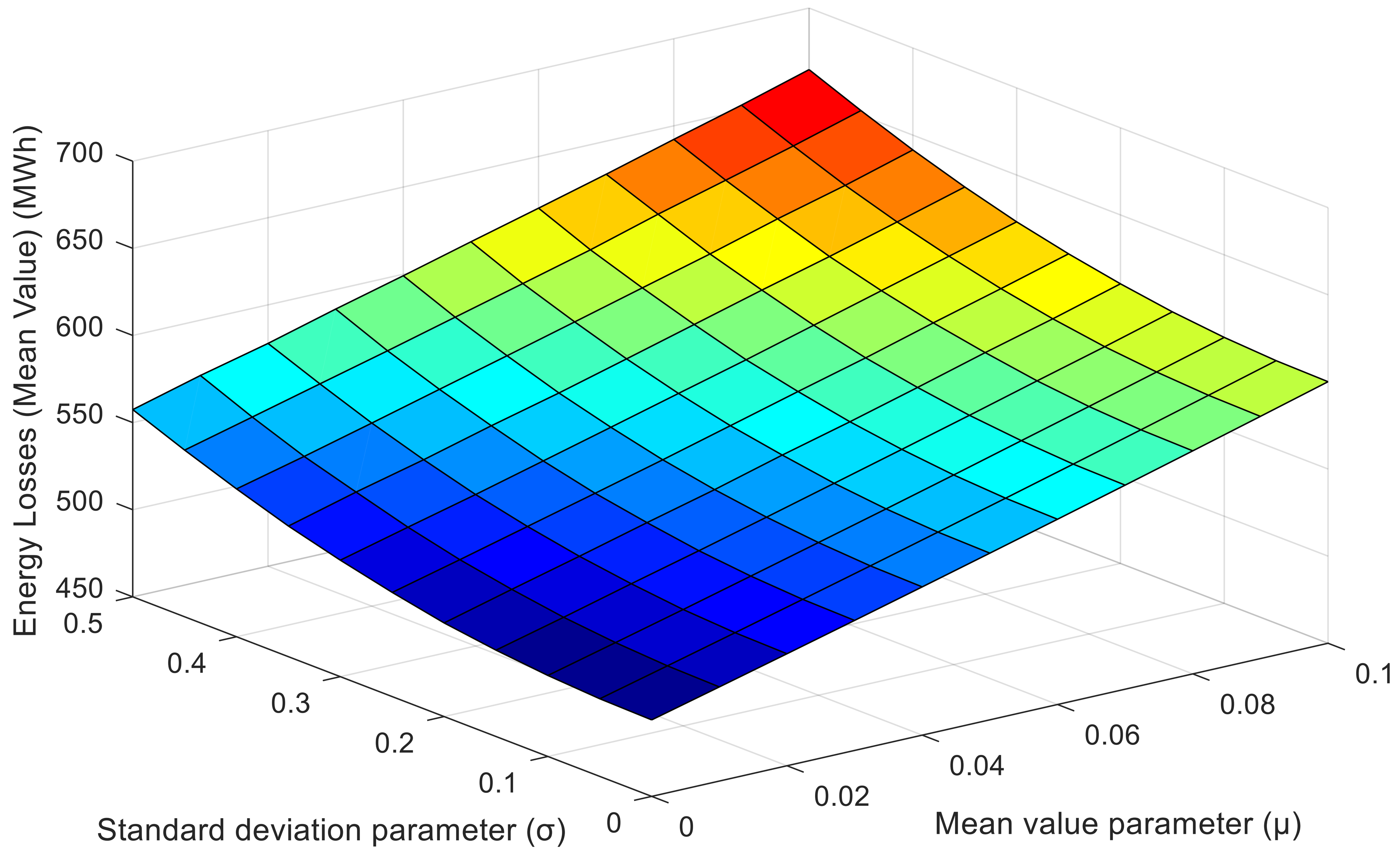
Load Uncertainty

Load uncertainty is analysed via Monte Carlo simulation; the real power of each load point is modified using normally distributed random numbers (r), which replicate the impact of random errors due to the standard deviation (σ) and systematic errors by adjusting their mean (μ).

$$P_{i,k}(t) = D(t) \cdot a_k \cdot (1 + r_i(\mu, \sigma)$$



Demand quantiles of the load profile of a load point using μ = 0 and σ = 0.1; original load profile in black

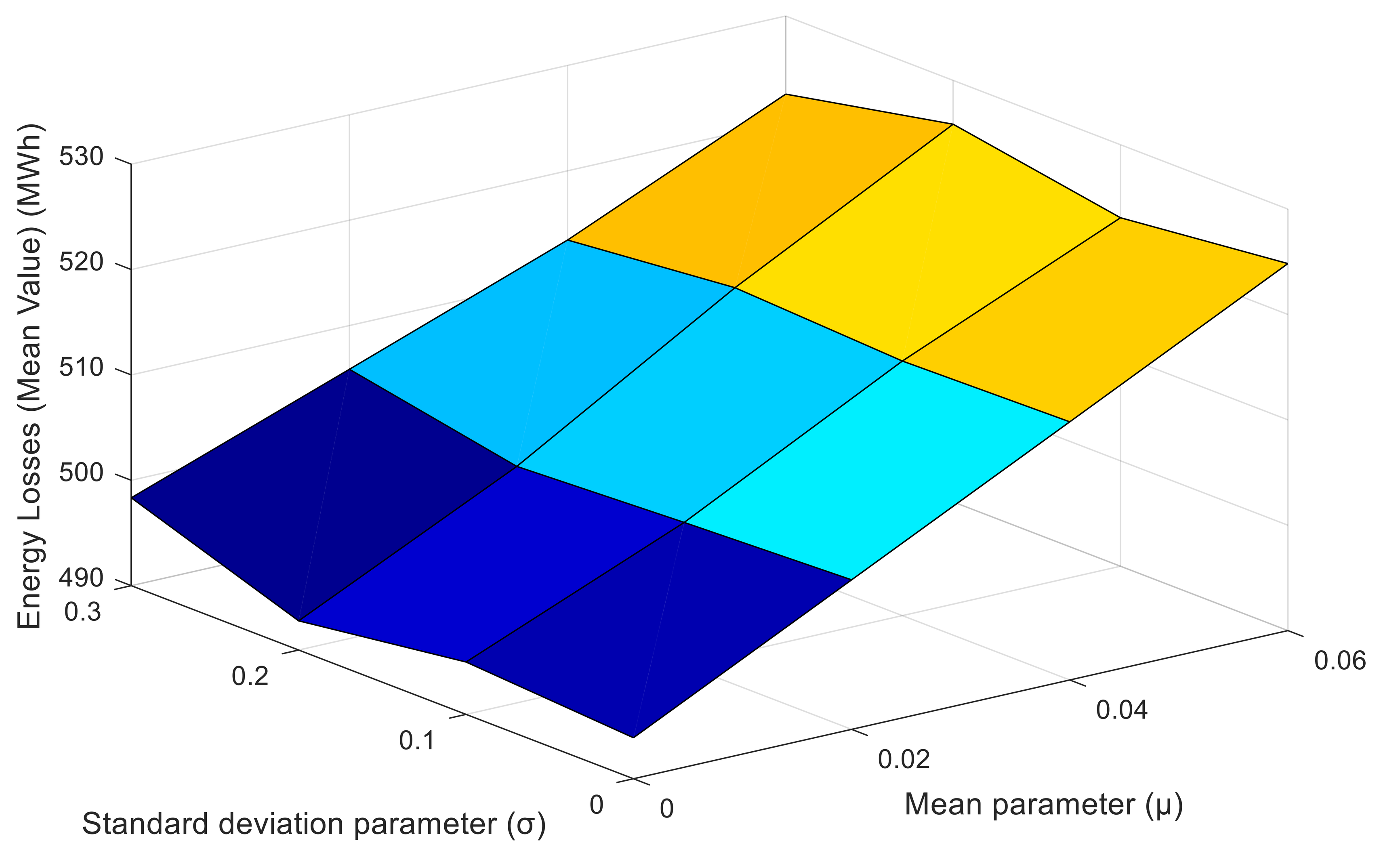


Surface plot of mean energy losses for different combinations of random and systematic errors; base case (μ = 0, σ = 0) energy losses = 493.89 MWh.

Network Uncertainty

The uncertainty of network parameters (resistances and reactances) were also analysed. The uncertainty is via the same method as the load uncertainty. $R_{i,j}$, $X_{i,j}$ are the resistance and reactance of branch j for simulation i, respectively; R_j, X_j are the original resistance and reactance of branch j, respectively; and $r_i(\mu,\sigma)$, $r'_i(\mu,\sigma)$ are the values of two normally distributed random numbers with mean μ and standard deviation σ, at simulation i.

$$R_{i,j} = R_j \cdot (1 + r_i(\mu, \sigma)),$$
$$X_{i,j} = X_j \cdot (1 + r'_i(\mu, \sigma))$$



Sensitivity analysis of network parameter uncertainty (random and systematic error) on the mean value of energy losses.

Conclusion

Uncertainty in demand observations leads to an underestimation of network losses in most cases; if there is a systematic error in the demand measurement, this has a more significant impact, though this could be more easily corrected through recalibration of the equipment. The error arising from a random error was less significant, but is also harder to eliminate.