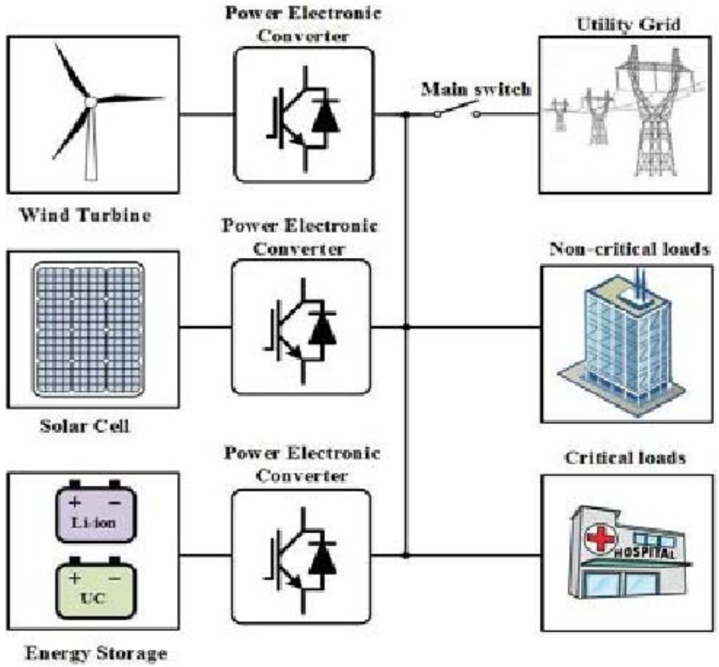
Thermal Estimation of Power Electronic Converters

ECE 592 Final Project by Zack Miller, John McDonald and Elijah Bouma-Sims

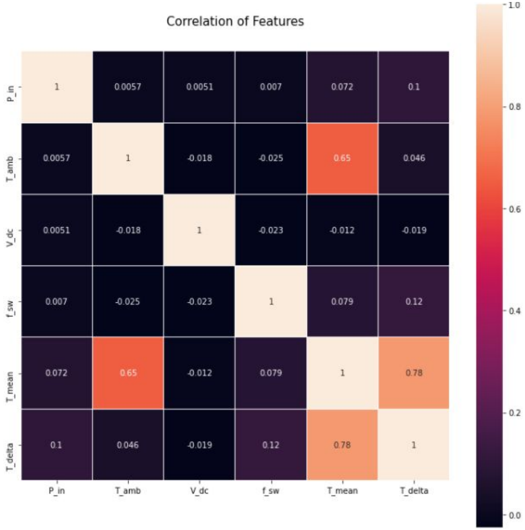
Background and Motivating Problem

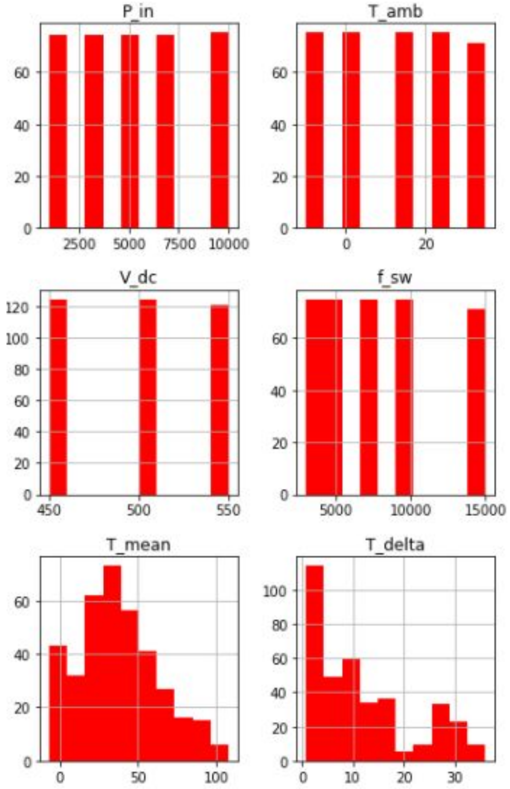
- **Power Electronic Converters** (PECs) are an integral part of the power grid
    - Also a large source of downtime/associated cost
    - Reliability of switching components is often dependent on thermal stress.
- **Goal**: Efficiently estimate mean/delta junction temperature of a PEC system using machine learning to create device control algorithms which maximize reliability.
- Extend prior work by looking at more models and comparing computational complexity and accuracy.
- Test on real data with Rainflow analysis



Describe the Data

	P_in	T_amb	V_dc	f_sw	T_mean	T_delta
0	10000.0	-10	450	3000	-5.928024	0.805927
1	1000.0	-10	450	3000	-1.246890	3.386914
2	3000.0	-10	450	3000	6.240659	7.289350
3	5000.0	-10	450	3000	16.497414	12.719379
4	7000.0	-10	450	3000	38.390845	24.692551





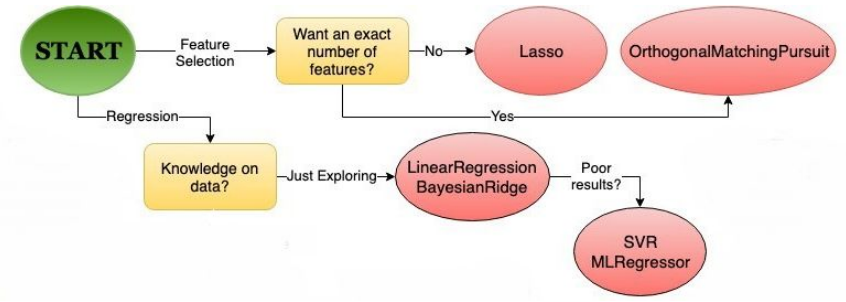
Predicting T_mean & T_delta

- Mean junction temperature
- Change in junction temperature

We observe:

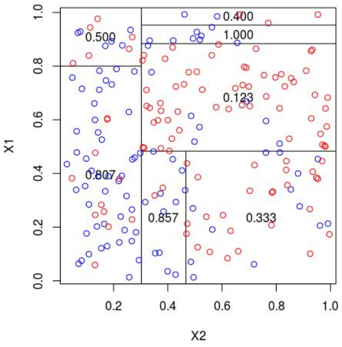
- Monotonic data
- Small amount of data
- More observations than predictors
- Shape: `(371, 6)`
- Discrete predictors, continuous resp.

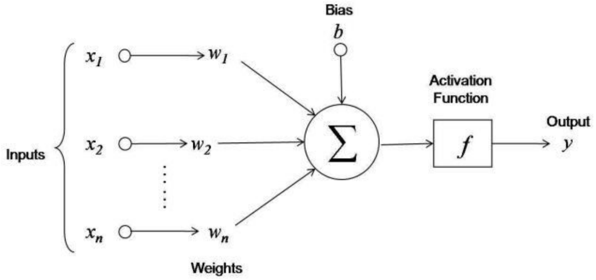
Methods of Analysis



Choosing model based on data set
Feature selection / dimension reduction not necessary
Just exploring data set

- Linear regression
- Bayesian Ridge
- SVM (better performance?)
- Decision tree
- Artificial Neural Network

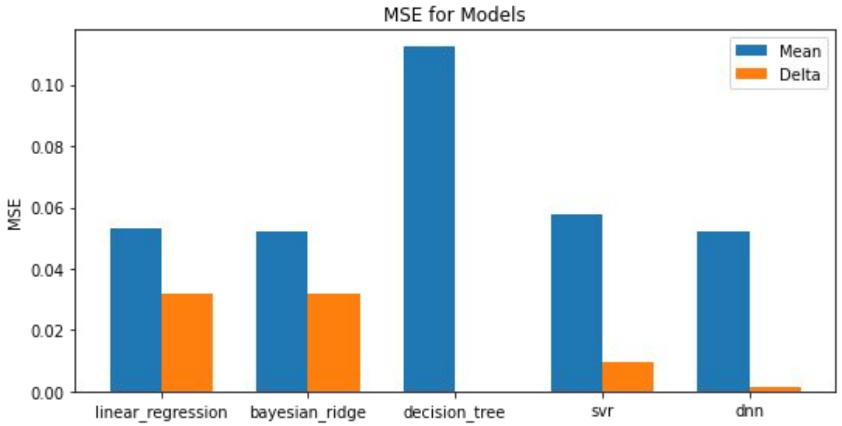




Referenced images:
https://gdcoder.com/decision-tree-regressor-explained-in-depth/
https://towardsdatascience.com/choosing-a-scikit-learn-linear-regression-algorithm-dd96b4
https://medium.com/@rajatgupta310198/getting-started-with-neural-network-for-regression-and-tensorflow-58ad3bd75223

Model Performance Comparison

- Decision tree lowest T_delta MSE. NN close second lowest
- Decision tree very poor for T_mean MSE, others perform similarly with bayesian ridge being best



Concerns:

- Potential overfitting

Computational Complexity

- Computational complexity for running the model is a particularly important consideration
    - We need control decisions to be made quickly; prediction complexity is key

Model	Training	Prediction
Linear Regression	O(p^2*n+p^3)	O(p)
Bayesian Ridge		O(p)
Decision Tree	O(n^2*p)	O(p)
SVM	O(n^2*p+n^3)	O(n_{sv}*p)
Neural Network	Varies	O(p*nl_1+$nl_1 nl_2$+...)

n the number of training sample

p the number of features

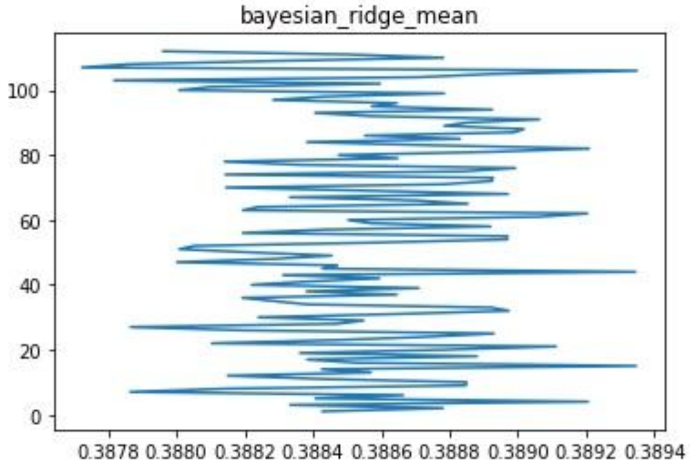
ntrees the number of trees (for methods based on various trees)

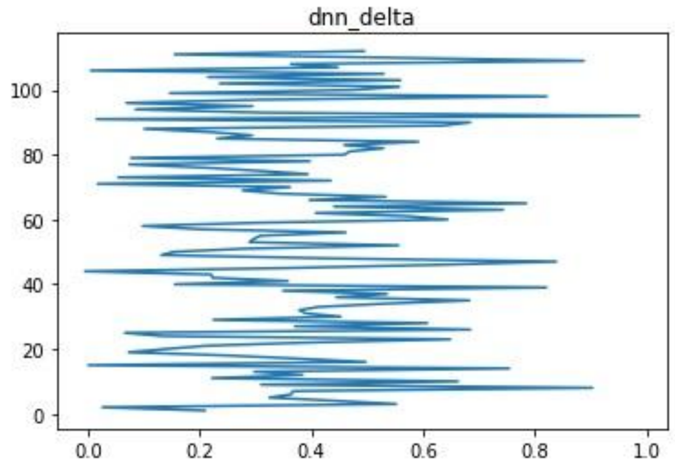
nsv, the number of support vectors

nli the number of neurons at layer i in a neural network

Rainflow Analysis

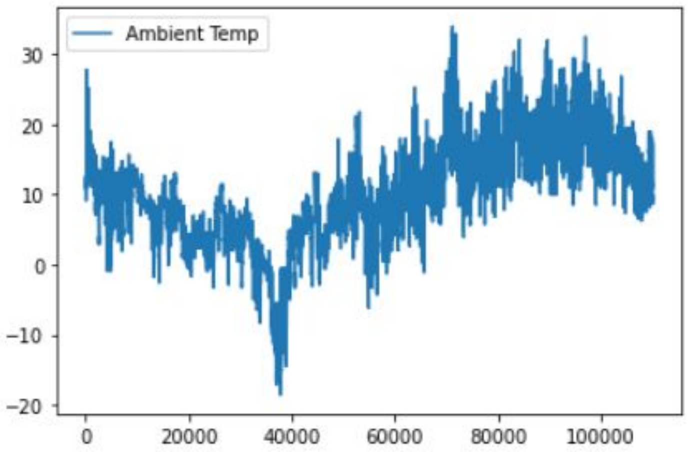
- Counting Algorithm that reduces a wide spectrum of data into equivalent cycle/half-cycles
- Enables a reasonable measure of fatigue or stress based on temperature variance
- Algorithm is initially applied to test data before mission profile data

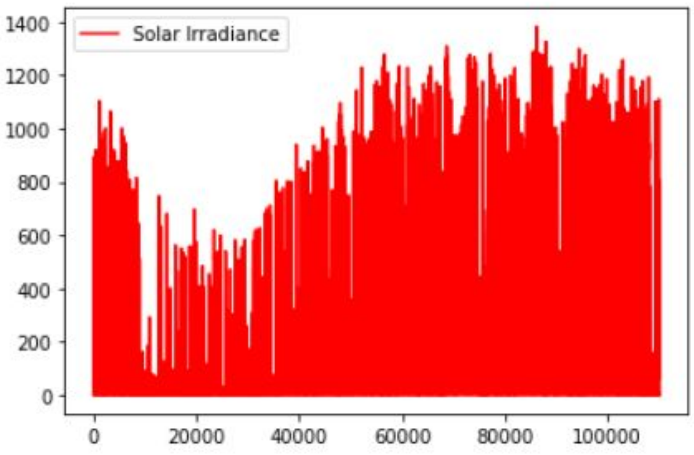




Mission Profile Data

- Mission Profile defines the operating conditions a renewable system (such as a PV Plant) might experience in a given year
- Weather data sampled in 5 minute intervals from Aalborg, Denmark was used to approximate the mean number of cycles estimated with Rainflow Analysis

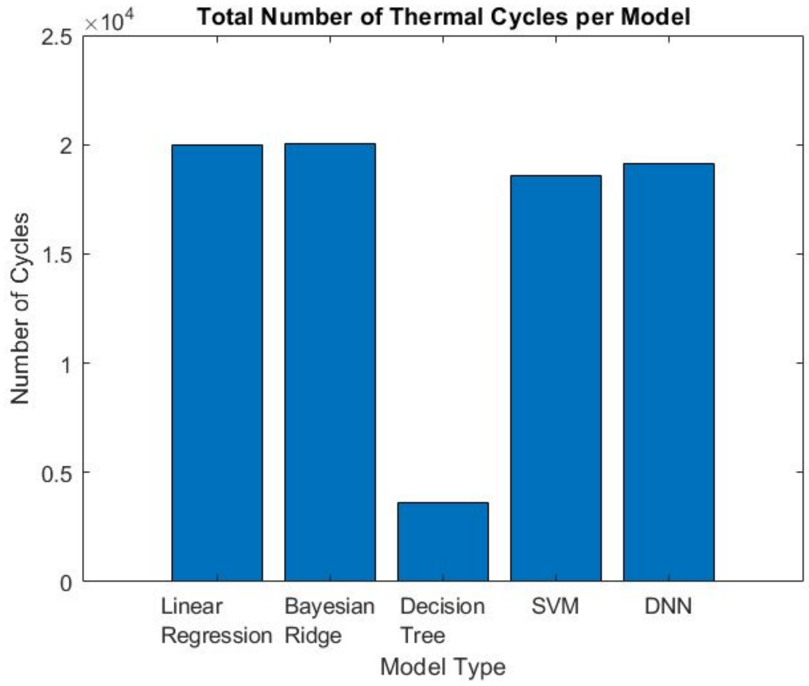




Thermal Cycling

- Analysis applied assuming fixed voltage and switching frequency
- Models performed roughly the same
- Decision Tree resulted in the worst performance

Linear Regression	19964.5
Bayesian Ridge	20041.5
Decision Tree	3639.0
SVM	18552.5
DNN	19156.5



References

[1]J . Zhang, “Power electronics in future electrical power grids,” in 2013 4th *IEEE International Symposium on Power Electronics for Distributed Generation Systems (PEDG)*, pp. 1–3, 2013

[2] H. Wang, M. Liserre, F. Blaabjerg, P. de Place Rimmen, J. B. Jacobsen, T. Kvisgaard, and J. Landkildehus, “Transitioning to physics-of-failure as a reliability driver in power electronics,” *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 2, no. 1, pp. 97–114, 2014.

[3] H. Lu, C. Bailey, and C. Yin, “Design for reliability of power electronics modules,” Microelectronics Reliability, vol. 49, no. 9, pp. 1250 – 1255, 2009. *20th European Symposium on the Reliability of Electron Devices*, Failure Physics and Analysis.

[4] T. Dragičević, P. Wheeler, and F. Blaabjerg, “Artificial intelligence aided automated design for reliability of power electronic systems,” *IEEE Transactions on Power Electronics*, vol. 34, no. 8, pp. 7161–7171, 2019