

Gaussian Process Regression for In-vehicle Disconnect Clutch Transfer Function Development



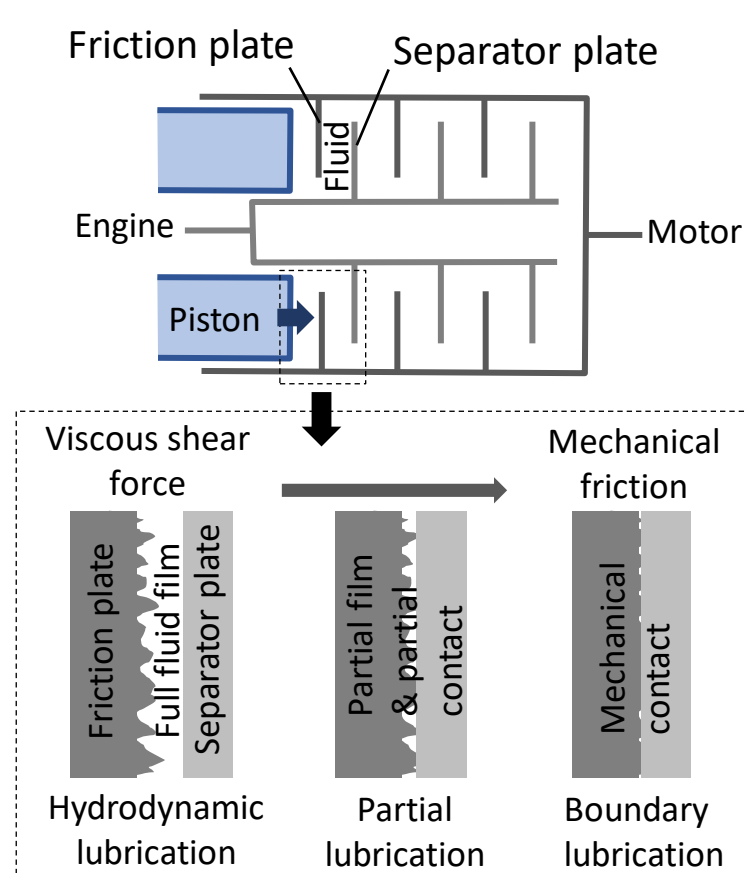
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Introduction

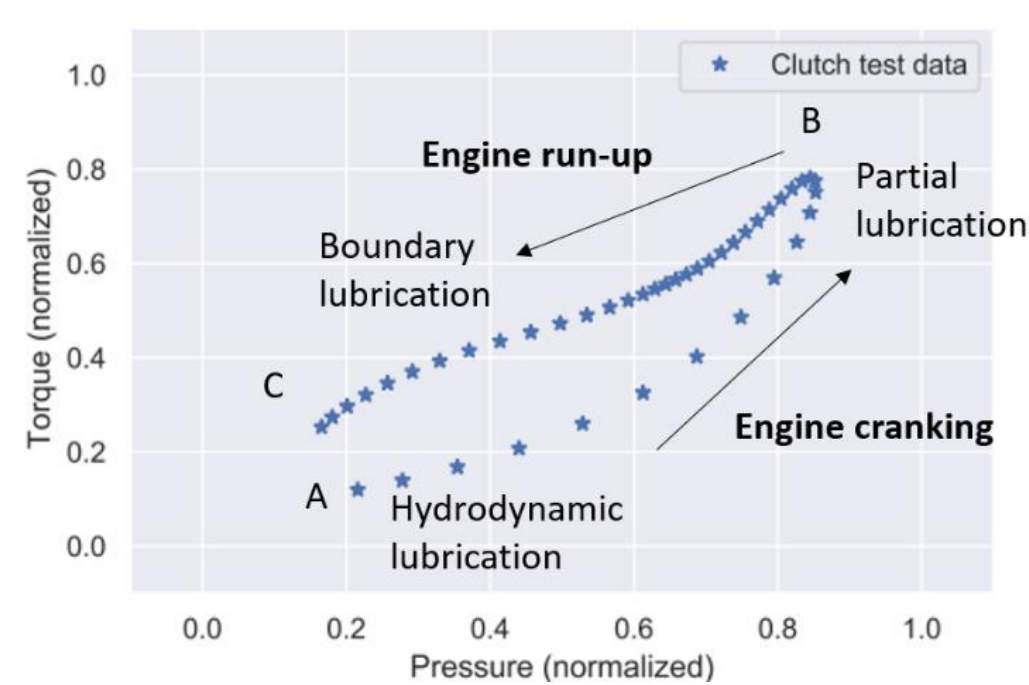
- The advancement of Machine-learning (ML) methods such as Gaussian Process Regressions (GPR) have enabled the development and the use of Reduced Order Models for complex automotive dynamic systems.
- This work discusses the use of GPR to characterize nonlinear dynamic behavior of an engine disconnect clutch used in a P2 hybrid propulsion architecture for efficient in-vehicle deployment, under computational and memory resources constraints.

Data Sampling Strategy

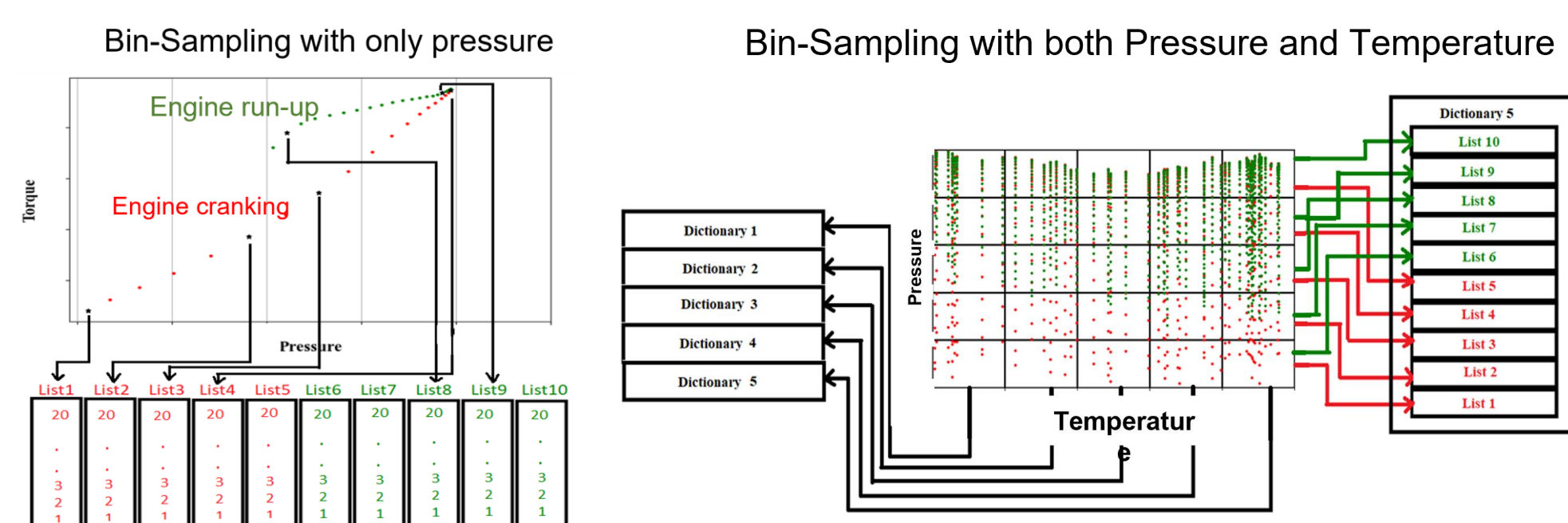
- Clutch behavior will change overtime due to environmental factors, material wear, etc.
- An efficient updating/retraining strategy should be designed for GPR model to enable its capability of real-time in-vehicle adaptation.
 - Design training window size to meet memory and computation requirement.
 - Design data sampling strategy to avoid data bias.



a) Disconnect clutch torque transfer processes and frictional interface conditions



b) Anatomy of disconnect clutch transfer function



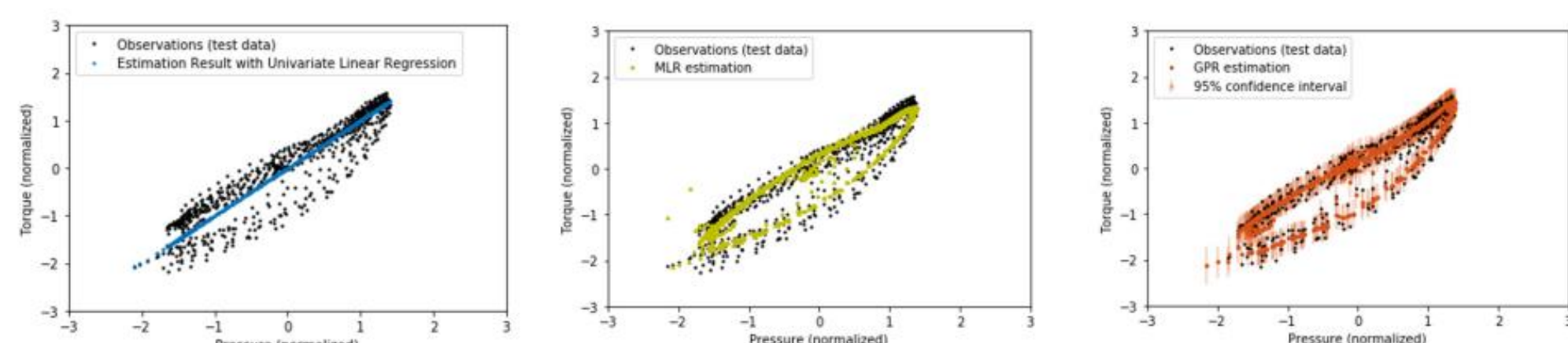
Contributions

- To the best of our knowledge this is the first implementation of GPR based wet clutch model in an automotive application.
- Discussed deployment under limited computation and memory resources for in-vehicle applications
- Data sampling strategies are discussed for in-vehicle GPR model training and managing adverse impacts of biased data.

Design of GPR based clutch transfer function

- Comparison of regression methods for wet clutch transfer function development

Model	Train time (s)	Train RMSE	Test RMSE
Univariate Linear Regression (LR)	0.90	14.67	13.08
Multivariate Linear Regression (MLR)	0.98	7.91	7.98
Gaussian Process Regression (GPR)	8.5	5.58	5.93
Support Vector Regression (SVR)	0.27	5.42	6.30
Random Forest (RF)	0.31	4.93	6.26



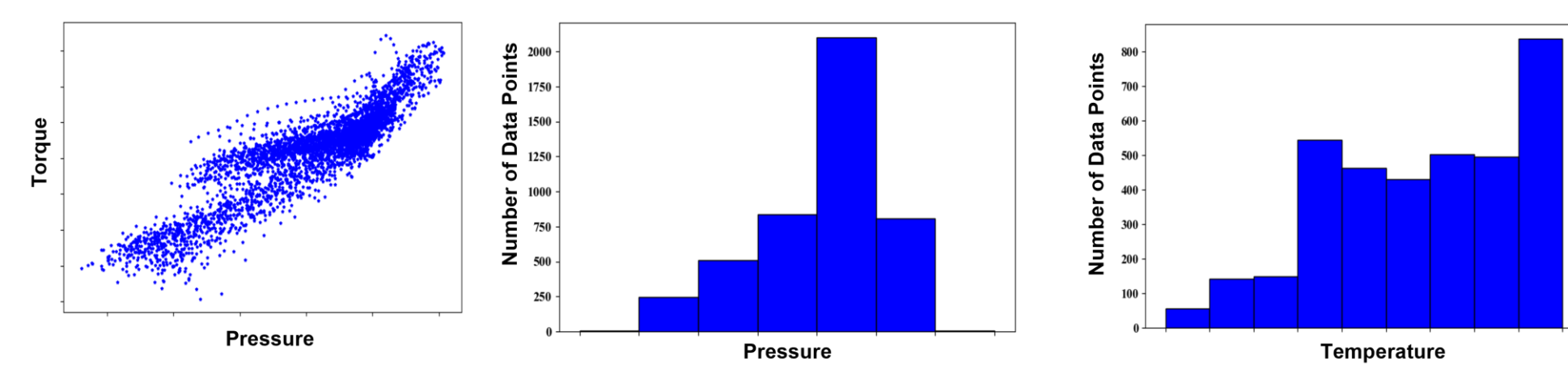
- Feature selection with filtering and wrapping methods



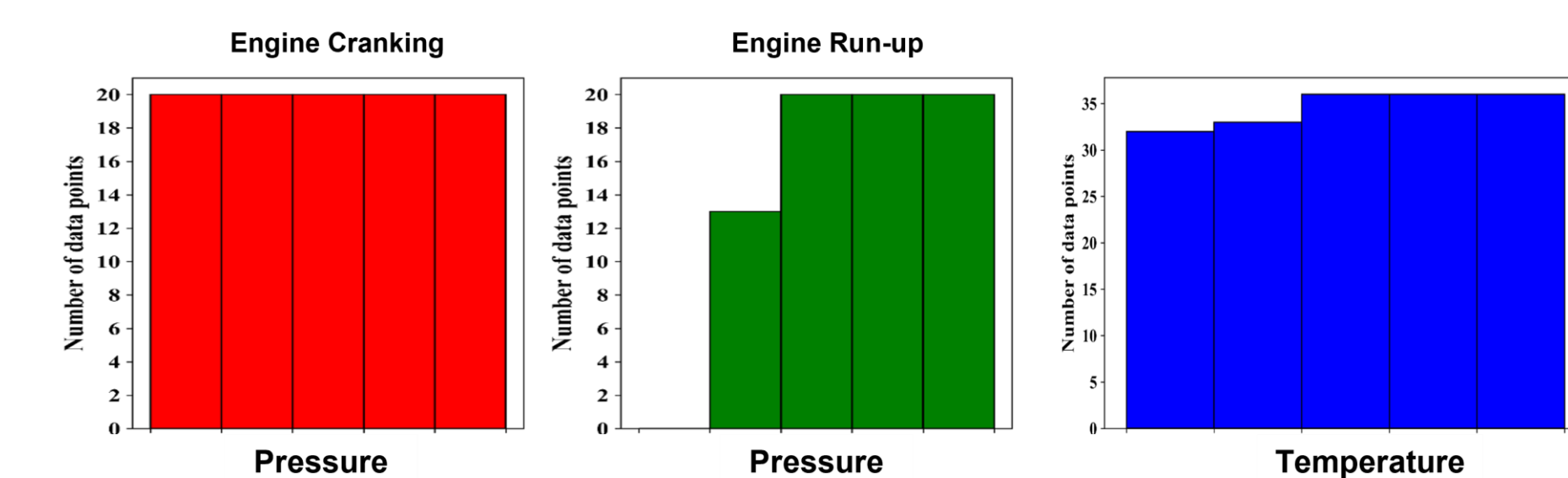
- Kernel selection

Model	Train time (s)	Train RMSE	Test RMSE
White	3.80	0.568	0.565
Constant	10.50	3.100	3.070
RBF	1.28	0.000	0.565
Matern	1.75	0.000	0.565
RationalQuadratic	30.90	0.000	0.052
DotProduct	1.17	0.058	0.057
RBF + White	10.9	0.0496	0.0500
Matern + White	11.3	0.0483	0.0495
RBF + White + DotProduct	44.0	0.0496	0.0500
Matern + White + DotProduct	48.8	0.0484	0.0495

Wet clutch data and its pressure, temperature distribution - before sampling



- After bin sampling with both pressure and temperature



- Model performance comparison with different data sampling strategy

Sampling Strategy	Train time (s)	Train RMSE	Test RMSE
Entire data (80%/20%)	65.36	0.0403	0.0415
Random sampling (200 over 20 clutch events)	0.03	0.0258	0.0596
With only pressure-bin sampling	0.03	0.0283	0.0522
With pressure-temperature-bin sampling	0.03	0.0316	0.0488

Conclusion

- Discussed the development of a real-time deployable accurate, robust and low latency GPR model for the wet clutch transfer function application in hybrid electric vehicles.
- To manage the trade-off between model performance, on-board computation and memory resources, feature selection, kernel selection, training window size and sample size, and sampling strategy are designed.
- Vehicle data is collected from real world driving to demonstrate benefits of the proposed framework.

Reference

- Y. Fujii, N. Kapas, and J. Tseng. Clutch Wet. Encyclopedia of Automotive Engineering, Wiley Sons, 2014
- Shui, H., Zhang, Y., Yang, H., Upadhyay, D. and Fujii, Y., 2021. Machine Learning Approach for Constructing Wet Clutch Torque Transfer Function. SAE WCX Digital Summit, 3(2021-01-0712).
- Shui, H., Zhang, Y., Yi, E., Bichkar, A., McCallum, J., Hopka, M., Upadhyay, D. and Fujii, Y., 2022. Optimization of Gaussian Process Regression Model for Characterization of In-Vehicle Wet Clutch Behavior (No. 2022-01-0222). SAE Technical Paper