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

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Abstract

The advancement of Machine-learning (ML) methods such as Gaussian Process Regressions (GPR) have enabled the development and use of Reduced Order Models for complex automotive dynamic systems, as alternatives to conventional parametric methods or multi-dimensional look-up tables. GPR provides a mathematical framework for probabilistic representation of complex non-linear system. This paper 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.

1 Introduction

A P2 hybrid electric vehicle (HEV) bridges the transition from a conventional vehicle with an internal combustion engine to a full battery Electric Vehicle (EV). A disconnect clutch is a critical component in HEV, which couples or decouples the engine from the motor to enable a transition between EV and HEV modes. Moreover, the disconnect clutch may be used as an engine cranking device by diverting motor torque before the engine starts firing and producing sustainable torque [11].

The disconnect clutch, also referred as wet clutch, is a wet friction device lubricated with transmission fluid [5, 7]. As shown in Figure 1 a), a wet clutch transfers torque through viscous shear force under hydrodynamic lubrication. When pressure is applied to the clutch, the fluid film is squeezed resulting in the friction and separator plates developing mechanical contacts. In this phase torque transfer is via both mechanical contact and viscous shear. When the clutch is fully locked it enters boundary lubrication and transfers torque through mechanical friction only. In EV mode, the clutch is open and carries no torque. During EV-HEV transition, for engine cranking, the disconnect clutch is engaged by increasing the pressure on the hydraulic actuator piston. An example with normalized pressure and torque values is depicted in Figure 1 b). As the clutch pressure is raised from point A to B, the engine torque increases nonlinearly. After engine ignition at B, the pressure is reduced to point C. A clear hysteresis loop is observed describing the state transition A-B-C. With such dynamics, conventional

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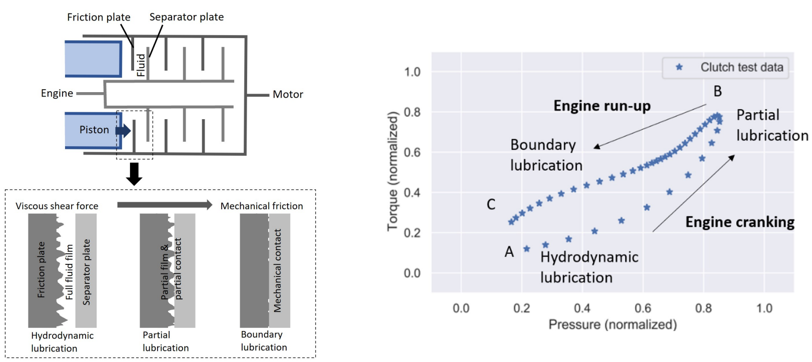
parametric regression methods may fail to represent such nonlinearity. Therefore, ML methods such as Gaussian Process Regression (GPR) could be employed to learn and predict clutch behavior.



a) Disconnect clutch torque transfer processes and frictional interface conditions

b) Anatomy of disconnect clutch transfer function

Figure 1: Introduction of web clutch behavior

The contributions of this paper are:

1. To the best of our knowledge this is the first implementation of GPR based wet clutch model in an automotive application.

2. The paper discusses deployment under limited computation and memory resources

3. Data sampling strategies are discussed for in-vehicle GPR model training and managing adverse impacts of biased data.

2 Design of GPR based disconnect clutch transfer function

Empirical models have been widely utilized in automotive control to represent system behavior [6, 1]. They also find used in design analysis, diagnosis and prediction. An empirical model may be represented by a complex multi-dimensional lookup table [4], however, it often becomes too large to store all the data to cover the full range of operating conditions. For in-vehicle applications, each table entry may be updated one at a time based on new data sets. However, in the absence of a functional structure, it can be difficult to maintain the coherency between table entries in multi-dimensional space [4].

Alternatively, a multivariate parametric regression may be conducted with empirical data to build a Reduced Order Model. The model parameters may be updated using a recursive least square method or Kalman filtering as new data becomes available. However, such parametric models are inherently limited by the mathematical structure of the base function. In many applications, it is difficult to find an adaptable parametric function that accurately predicts transient system behavior due to inherent nonlinearity's, especially in a multi-dimensional space.

GPR is a non-parametric probabilistic regression model that leverages kernel functions to represent system response. GPR models also provide estimates of prediction uncertainty. However, as is the case for all ML algorithms, the success of a GPR model for a specific application depends on the selection of input features and kernel functions. In addition, for in-vehicle applications, it is critical to design a GPR model for on-board deployment subject to compute and memory resource constraints. In the following, we discuss the processes for feature selection, kernel selection and data sampling to specifically manage the trade-off between underfitting and overfitting for an in-vehicle wet clutch transfer function development.

2.1 Feature selection

Feature selection is a process to identify a subset of input variables that are most relevant for predicting the target variables [2]. It reduces the dimensionality of a model, improves training efficiency and reduces risk of overfitting especially for small data sets. There are different categories of feature selection methods: filter, wrapper, and embedded methods [3].

In this study, both filter and wrapper methods are employed to select features for GPR modeling.

1. Filter method to remove highly correlated features: Pearson correlation algorithm is used to explore the pairwise correlation between features. If the correlation coefficient is larger than 0.9, only one of the features is selected for ML modeling to avoid redundant inputs.

2. Wrapper method to identify feature importance: Forward feature selection with Bayesian Ridge regression, where accuracy and generalizability are compared.

2.2 Kernel selection

There are several pre-defined kernels that are commonly used for GPR modeling, such as white noise, radial basis function and Matern. A kernel function can be a single pre-defined kernel, a combination of pre-defined kernels, or a new user defined function. A valid kernel function should result in a positive definite kernel matrix, so that the kernel matrix is invertible.[8]

This study first evaluates commonly used kernels individually. Then, based on each kernel's capability, various combinations of these kernels are evaluated to select the best combination for highest model prediction accuracy and lowest latency.

2.3 Data sampling strategy

Wet clutch behavior will change during drive cycles due to environmental factors such as operating temperature or changes over a vehicle useful life due to clutch material wear. It is therefore desirable that the GPR model can learn the current clutch behavior on current data without excess reliance on historic information. In this case, model evolution history may be archived for tracking purposes. To ensure that the GPR model is applicable for real-time in-vehicle adaptation, a fast and efficient updating/retraining strategy should be designed. For example for a sample size of 'n', the compute load of a GPR model grows cubically $O(n^3)$ and requires quadratic $O(n^2)$ storage for training. Since in-vehicle compute resources are limited, a suitable training window size and data sampling strategy should be designed to select the minimal, unbiased training data set for in-vehicle GPR model adaptation/update.

To do that, first, the training window size is identified for in-vehicle application by evaluating its impact on trained model accuracy and uncertainty. Then, training data size is determined based on model performance and hardware constraints. Lastly, a sampling strategy based on predefined feature bin is designed to uniformly sample and update new data for training over the designed operating range. Figure 2 a) and b) show examples of sampling data from wet clutch engagement events based on predefined pressure and pressure-temperature bins respectively.

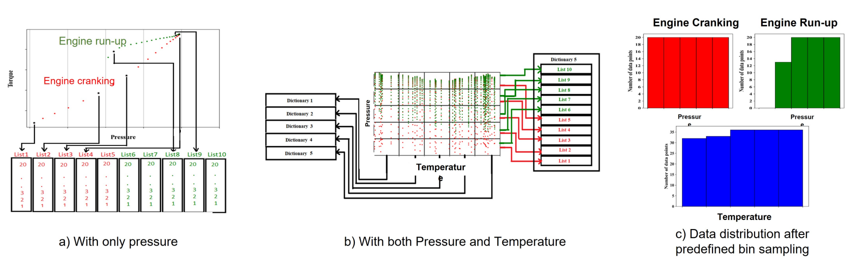


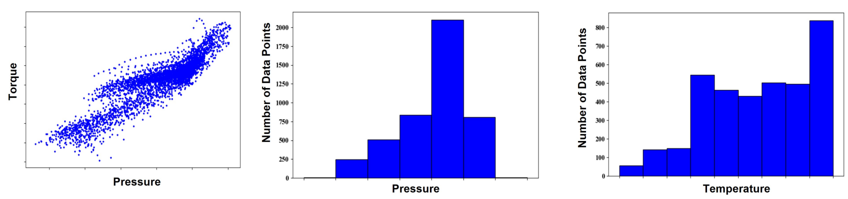
Figure 2: Predefined bin sampling strategy

3 Use case study

To demonstrate the proposed framework, wet clutch engagement events data is collected from a test vehicle in a controlled environment. All model accuracy is evaluated with Root Mean Square Error (RMSE). Initial data contains actuator pressure from in-vehicle sensor and clutch torque from an alternate source, referred to as the Virtual Torque Sensor (VTS) [12]. With this data, we first compared ML methods[9] (Appendix A) and found they outperformed traditional parametric regression approaches and GPR performed the best in terms of accuracy and generalizability relative to Support Vector Regression and Random Forest.

Next, data from test drives (> 30mins) is collected. The data set includes actuator pressure, accelerator pedal position, and transmission fluid temperature. Clutch torque is available from the VTS as discussed above. From this data, it is found that pressure is the most important feature, followed by temperature, and pedal position is the weakest [10] (Appendix B). Additionally, various combinations of kernels were examined (Appendix C). It is shown that RBF/Mattern+White achieved best model accuracy and generalizability but with high compute cost. DotProduct had a slightly lower accuracy but with much reduced training time. Finally, it is determined that a training window size covering 20 clutch events (each clutch event includes about 50 data points) is adequate (Appendix D).

For assessment of model implementation in a vehicle , we use the RBF+white kernel, and a reduced training data size of 200 samples (randomly selected from 20 clutch events). Training data is updated whenever new clutch events are available and the GPR model is updated when the predicted torque deviates from the ground truth (VTS).



a): Wet clutch transfer function (124 clutch events) b): Pressure distribution c): Temperature distribution

Figure 3: Wet clutch data and its pressure, temperature distribution

We also tested with engine cold-start (starting after 6 hours of vehicle parked state). Data is collected over 124 clutch events. It is seen in Figure 3 that pressure and temperature are not uniformly distributed for this condition. In order to avoid bias in training data, 5 predefined bins, covering the entire operating range are designed for both pressure and temperature. When updating training dataset, with a new clutch event, 10 data points are randomly selected, and assigned to one of the predefined bins while removing old data from that bin (first in first out). This allows maintaining a uniform distribution over the training data set.

Table 1: GPR model performance comparison with different training data sampling strategies (all values are averaged, and normalized

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

Table 1 compares model performance with/without the sampling strategy. It is clear that sampling training data based on both pressure and temperature provides the best performance in terms of model accuracy and generalizability for the in-vehicle wet clutch application.

4 Conclusion and future work

This paper discussed the development of a real-time deployable accurate, robust and low latency GPR model of a wet clutch transfer function critical for hybrid electric vehicles. We provide discussions on managing 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 discussed. Vehicle data is collected from real world driving to demonstrate benefits of the proposed framework. As future work, we will extend the predefined bin sampling strategy with Bayesian optimal experimentation as an active and efficient data sampling strategy.

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A Comparison of ML approaches for wet clutch transfer function development

Clutch engagement data are obtained from multiple engine restart events in a test vehicle. The data set consists of 756 pairs of torque and pressure values. Data is split with 75% for training and 25% for testing the predictive performance of the trained model. For model building, the scikit-learn package is used in the Python 3.6 environment.

First, the univariate linear regression (LR) is evaluated as a baseline model with only pressure as an input. Next, by recognizing the relationship between the hysteresis loop and pressure derivative in time domain, the multivariate linear regression (MLR) with both pressure and the first derivative of pressure as inputs is introduced to improve the linear model accuracy. Finally, three non-parametric ML methods - GPR, SVR, and RF are employed. As shown in Table 2, among those three methods, GPR has the best generalization based on the RMSE from training (regression/machine learning) and testing (prediction) results.

Table 2: Comparison of regression methods

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

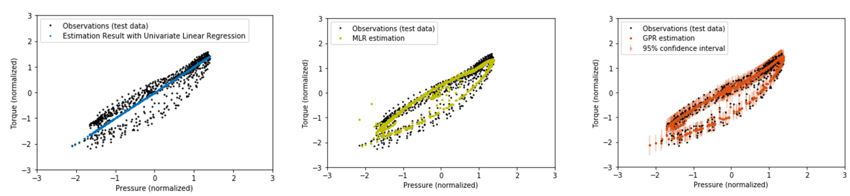
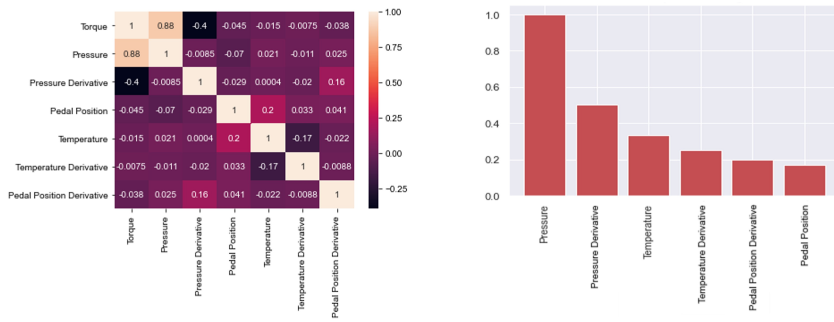


Figure 4: Comparison of wet clutch transfer function built by different ML methods

B Feature selection

Feature selection reduces the dimensionality of a model and improves training efficiency and reduces overfitting risks especially when data size is small. There are different categories of feature selection methods: filter, wrapper, and embedded methods. Filter methods select features based on statistical measures such as variation, missing ratio, correlation to other features as well as target variables. It is noted that the correlation is subjective and can be determined by algorithms such as Pearson Correlation, Chi Square, Mutual Information, and Linear Discriminant Analysis. Wrapper methods select features based on the performance of ML model during training. A feature may be added or removed based on the performance of the ML model under consideration. This procedure is usually time-consuming. Typical algorithms include forward feature selection, backward feature elimination, and recursive feature elimination. Embedded methods employ ML algorithms that have their own built-in feature selection function such as Lasso, Ridge, Tree based algorithms and Shapley Additive exPlanations (SHAP) [3]. This paper leverages both filter and wrapper methods to select input features for the GPR model.

1. Filter method: Pearson correlation algorithm is used to explore the pairwise correlation between features. For correlation coefficient larger than 0.9, only one of the feature pair is selected for ML modeling to avoid redundant inputs.



a) Correlation matrix b) Feature importance ranking

Figure 5: Feature selection for GPR wet clutch transfer function

2. Wrapper method: Forward feature selection with Bayesian Ridge regression, where accuracy and generalizability are compared.

Figure 5 a) shows the correlation coefficients between pairs of input features, as well as the correlation coefficient between each feature and the target variable, namely clutch torque. Because none of the input features are strongly correlated (correlation coefficient < 0.9), all features may be considered.

Figure 5 b) presents the feature importance ranking based on a recursive method with Bayesian Ridge regression. Overall, pressure is the most important information, followed by temperature. Accelerator pedal position shows the weakest correlation with clutch torque.

C Performance comparison of GPR kernels for wet clutch transfer function

A large amount of vehicle data is collected for a P2 hybrid electric vehicle from mixed city-highway driving. The data includes disconnect clutch torque from Virtual Torque System (VTS) [12], clutch actuator pressure, accelerator pedal position and transmission fluid temperature at a sample rate of 10 msec. To evaluate the model performance, data is split into training set (80%) and testing set (20%). Model accuracy is represented by RMSE, which is also dimensionless.

The vehicle data are characterized by nonlinear behavior with the presence of measurement noise. As shown in Table 3, Constant kernel and White kernel are not capable of capturing nonlinear shapes with a relatively high RMSE value for both training and testing data. On the other hand, RBF, Matern and Rational Quad tend to fit training data too well with almost zero RMSE value in training. However, they also learn random fluctuations or noises as patterns that might not be generalizable with new data. This is why their RMSE values in testing are much higher than in training. Therefore, adding white noise can be advantageous in this case study. Comparing RBF, Matern and Rational Quad, their ability to capture the details in training data is similar. However, RBF and Matern consume much less time than Rational Quad in training.

To further investigate RBF and Matern kernels for disconnect clutch model improvement, combination kernels are examined as listed in Table 3. Rational Quadratic kernel is excluded in the assessment. Only RBF and Matern kernels are evaluated with White kernel. As shown in the table, RBF and Matern kernels improve the model generalizability significantly when combined with White kernel, but also increase the amount of computational time. The addition of DotProduct kernel further degrades computation efficiency with no improvement in accuracy. Therefore, the final kernel candidates are reduced to two options:

1. DotProduct

2. RBF + White or Matern + White

The testing results are shown in Figure 6 for GPR model with DotProduct kernel and Matern+White kernel, respectively. The first option provides better model accuracy but requires more training time. The second option is faster in training, but less accurate in prediction as characterized by the larger spread in the figure.

Table 3: GPR kernel comparison

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**

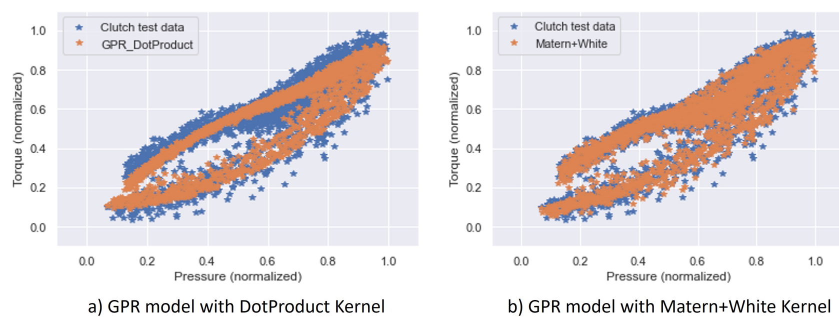


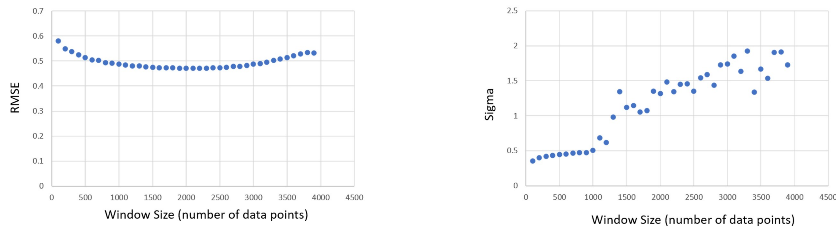
Figure 6: Comparison of wet clutch transfer function built with different kernels

D Training window size selection

Training window size needs to be determined to ensure that GPR model learns the current clutch behavior on current data without excess reliance on irrelevant historic information, while considering the hardware limitation for in-vehicle applications. In this study, a moving window strategy is examined with post-process vehicle data from drive sequences, the most appropriate data for regular updates to the GPR model with the Matern+White kernel. The evaluation criteria are the training accuracy of GPR model, which is represented by RMSE, and the average of uncertainty estimates captured by the standard deviation over the time window. It is noted that each disconnect clutch engagement events contains about 50 data points.

Window size experiments are conducted by varying window lengths between 100 to 4000 samples in 100 sample increments. After the GPR model is trained with data within the window, validation is conducted for every 2 disconnect clutch engagement events. Following this procedure, the average RMSE and standard deviation from the validation process is used to select the optimal window size for in-vehicle implementation.

Results from these experiments are shown in Figure 7. In a), the average RMSE initially decreases with increasing window size for training, then increases for window sizes greater than 2000 data points. b) shows the behavior of the averaged standard deviation over the window. The sigma value increases with window size and converges to about 0.5 at 1000 samples, following which the GPR uncertainty increases again while exhibiting a random behavior. This indicates that the clutch behavior is drifting over time. Therefore, based on RMSE and sigma, the window size of 1000 data sets is chosen for accurately tracking changing clutch behaviors.



a) GPR model accuracy VS training window size

b) GPR model uncertainty VS training window size

Figure 7: Training window size selection for in-vehicle GPR wet clutch transfer function development