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# Braking torque estimation through machine learning algorithms

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**Abstract.** MotoGP class motorcycles rely on carbon braking system to cope with their incredible acceleration capability and high speed. Hence, assessing the torque generated by the front discs is a key to improve the vehicle performance. As direct measurement of the braking torque is not allowed during races, its value may be estimated through a physical model, using as inputs the brake fluid pressure (monitored on board), the braking system geometry and the friction coefficient ($\mu$). However, the results obtained with this method are highly limited by the knowledge of the instantaneous friction coefficient between the disc rotor and the pads. Since the value of $\mu$ is a highly nonlinear function of many variables (namely temperature, pressure and angular velocity of the disc), an analytical model appears impractical to establish. This work aims to implement an innovative algorithm, based on machine learning, for determining $\mu$ from the signals regularly available in races, to enable accurate breaking torque computation. The proposed method consists of two main tools. An *artificial neural network* (ANN) is developed to approximate the unknown function that relates the input variables to $\mu$, while a *Kalman filter* (KF) is implemented to estimate the real temperature distribution on the disc surface that constitutes one of the most important ANN inputs. The proposed algorithm has been successfully validated with real data collected from extensive tests in racetracks, with a special sensor setup.

## Introduction

This research activity is carried out in collaboration with Ducati Corse (a division of Ducati Motor Holding S.p.A., Bologna, Italy) and investigates new methods for estimating the braking torque generated by carbon brakes mounted on MotoGP class motorcycles.

Currently, the company is able to estimate the braking torque delivered by the front brakes through an analytical model of the braking system. Given the pressure in the hydraulic circuit (available from telemetry) and the braking system geometry, such model calculates the braking torque assuming a constant value for the friction coefficient, $\mu$. The selected value for $\mu$ has been defined on the basis of the company database and experience to fit a large portion of the breaking maneuvers performed in the racetracks of the MotoGP championship. However, measuring the braking torque during some specific racetrack tests revealed significant discrepancies between the real and the predicted values. Every time the operating conditions of the brake differed from the most common values, the constant friction coefficient approach turned out to be inaccurate for the calculation of the torque provided by the front brakes. Determining experimentally the instantaneous value of $\mu$ through measurements performed on a test rig is too expensive and time consuming. Indeed this approach implies that for every new brake configuration or variant developed all the possible operating conditions must be covered. Therefore, the research is aimed at achieving a more accurate calculation of the braking torque on the front wheel by estimating the instantaneous $\mu$ through a machine learning (ML) algorithm.

An essential requirement for accurately estimating the friction coefficient is reliably assessing the thermal dynamics of the system. Originally, the monitoring of the brake temperature was performed directly through the sensor present on board. However, it soon became clear that, besides being quite noisy, a single spot acquisition was not representative of the whole temperature

distribution along the disc. Therefore, a two-dimensional (2D) finite element (FE) model of the disc is implemented along with a Kalman filter (KF) to predict with higher accuracy and reliability the temperature distribution on the disc-pads contact patch [1, 2]

The second part of the study focuses on the definition of a ML-based approach suitable for the disc-pad friction coefficient prediction. Some works investigated ML algorithms to estimate the friction coefficient of steel disc in test rig experiments [3]. To the Authors' best knowledge, no studies can be found concerning carbon brakes in real operating condition**.** A preliminary investigation [4] permitted to identify Artificial Neural Networks (ANN) and Decision Trees as the most promising algorithms. In particular, they could provide similar accuracy, with decision trees appearing faster, but also more prone to overfitting. In this paper, both algorithms are further investigated for possibly enhancing their performance. A new ANN is trained using the k-fold cross validation method [5] and with new inputs that improve its prediction capabilities. In addition, a new decision tree is developed by using the Minimal Cost-Complexity Pruning technique, which is an effective way to optimize the algorithm hyperparameters, to reduce overfitting issues.

## Materials and Methods

The first stage of the research is aimed at implementing the FE model in Matlab, which will constitute the physical model used by the Bayesian filter for the posterior optimal temperature estimation. To assess the performance of the proposed approach, racetrack tests were performed by installing on the motorcycles a multi-spot sensor able to measure the disc temperature in four different radial positions (Fig. 1). Such sensor (not allowed during races) was employed for calibration and validation of the algorithm. Indeed, the final goal is achieving an accurate estimate of the temperature distribution based on the onboard (single-spot) sensor measurements.

As for the machine learning algorithms, the true friction coefficient values that represent the target for each input vector in the training dataset were obtained by performing specific track tests in which the motorcycle front wheel was equipped with a wheel torque transducer. Given the measured torque and the corresponding value of hydraulic pressure it is possible to calculate the friction coefficient values (i.e., to generate the ground truth for the network training dataset) by inverting the analytical model of the brake mentioned previously.

Once the temperature distribution is correctly estimated, it can be processed by the machine learning algorithm that outputs the actual value of the friction coefficient. Then, the latter information is fed into the original analytical model of the brake that is expected to compute the braking torque with enhanced accuracy.

*Analytical model of the brake*. Knowing the current value of the friction coefficient, the pressure in the hydraulic circuit measured by the sensor and the brake disc/caliper geometry, the model outputs the braking torque on the front wheel $T_{bf}$, by using the following expression:

$$T_{bf} = 2 \cdot \mu \cdot F_n \cdot R_{eff} \cdot K_\mu \tag{1}$$

where $\mu$ is the friction coefficient; $R_{eff}$ is the effective radial distance at which the tangential force ($F_t = \mu \cdot F_n$) is applied; the parameter $K_\mu$ is a scaling factor, which is a rational function of $\mu$ related to the specific caliper geometry (its exact expression cannot be provided due to non-disclosure agreements – NDA); the factor 2 is related to the presence of two brake discs (with two distinct calipers) on the front wheel; finally $F_n$ represents the normal force applied by the pads on the disc, calculated as

$$F_n = A_p \cdot p, \tag{2}$$

where $A_p$ is the total cross section of the four pistons and $p$ is the pressure of the brake fluid.

It is worth noting that training ML tools to directly estimate the value of the braking torque (instead of $\mu$) is not deemed convenient. Indeed, calculating the braking torque through the analytical model (Eq. 1) permits to assess the effects of different design parameters of the braking system without the need of re-training the algorithm. In fact, MotoGP teams are allowed to choose different brake discs and pads according to the characteristics of each track. With the proposed approach, a different setup can be addressed simply by adjusting the parameters of the physical model (in particular the effective radius and the amplification coefficient $K_\mu$).

*2D FE model and KF*. Measuring the disc temperature using the infrared sensor available on board is not robust enough to allow the machine learning algorithms to catch the correct temperature dependency of the friction coefficient. In fact, this kind of sensor detects the disc temperature at a fixed radial distance in the disc-pads contact patch, disregarding the temperature gradient and the overall thermal behavior of the disc. From the measurements performed with the multi-spot sensor (Fig. 1) it turned out that the heat generated by the friction with the pads is not always distributed uniformly along the contact patch. Conversely, the pads wear and the pressure distribution inside the caliper can induce local temperature peaks on the disc and very high temperature gradient that cannot be recorded by the single-spot sensor.

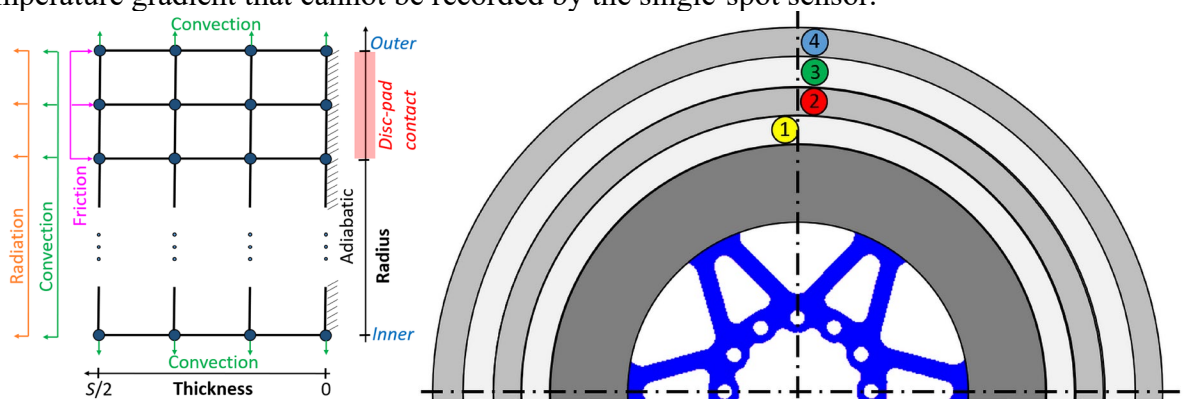


*Fig. 1: Schematic of 2D FE model (left – l) and multi-spot sensor setup (right – r).*

Building a thermal model of the carbon disc allows to take into account the whole temperature distribution on the disc hence giving a more robust information to the ML algorithms. The temperature on the disc evolves according to the energy transferred by convection, conduction, radiation and friction with the pads. In the 2D FE model implemented, temperature is a function of the radius, the thickness and time. As shown in Fig.1, thanks to the disc symmetry, only half of its thickness can be simulated, by imposing an adiabatic boundary condition in the median plane. Conversely, the opposite boundary represents the lateral surface of the disc in contact with the brake pad, hence being affected by convection, radiation and friction. The remaining two boundaries represent the frontal and internal surface of the disc in which only convection is simulated, for sake of simplicity.

Since, during the race, the actual temperature of the disc may drift away from the simulated results due to many external factors (e.g., the presence of slip stream or pads wearing), running the FE model alone can not grant reliable results. Therefore, a KF is developed to make up for the approximation error introduced by the physical model. At each time step, the filter updates the theoretical prediction performed by the thermal model with the empirical information coming from the single spot sensor and outputs the a posteriori temperature estimation.

*Artificial Intelligence Algorithms*. To preserve the ability to generalize to non-training data, hence avoiding overfitting, it is common practice to divide the dataset into training, validation and testing sets. However, partitioning the available data into three sets drastically reduces the number of samples which can be used for learning the model. Moreover, the results obtained depend on the particular choice for the three sets. To solve this problem the cross-validation (CV) procedure

is implemented. The CV approach consists in splitting the training set into $k$ smaller sets and iteratively training the ML model using the data belonging to $k$-1 folds while the remaining part of the data is kept for validation. The performance of the algorithm is computed by averaging the values obtained for each fold. This approach can be computationally expensive, but it allows to assess the performance of any ML algorithm across the whole dataset without wasting data. As for the implemented algorithms, both the ANN and the decision tree were trained using CV technique dividing the dataset into 10 equally populated folds.

The decision tree was pruned using Minimal Cost-Complexity Pruning technique (MCCP). MCCP involves the selective removal of certain leaves of a tree to optimize its hyperparameters (namely the maximum number of leaves, the minimum number of samples per leaf and the depth of the tree). This process is parametrized by the complexity parameter, $\alpha$, that indicates a particular tree dimension. How $\alpha$ is calculated is beyond the scope of this work, but more information on the MCCP can be found at [6]. The more leaf nodes a tree has, the higher its complexity becomes and the lower the value of $\alpha$. A null $\alpha$ corresponds to the full-size tree that is grown until the sum of the squared residual for each leaf is minimized (high overfitting). By increasing the value of $\alpha$ the weakest link of the original tree is pruned and a new optimal subtree is generated. This process is repeated until only one leaf is left, leading to a set of optimal subtrees (Fig. 2). For each of the ten folds the MCCP algorithm trains all these trees and tests them on the data kept for validation. As $\alpha$ increases the error on the training set grows because the less leaf nodes the tree contains (lower complexity) the less possibilities for fitting the training data. However, it can be observed that limiting the complexity of the tree may increase the accuracy on the validation set because the overfitting is reduced, and the algorithm generalizes better to unseen data. On the other hand, for high values of $\alpha$ the tree becomes too simple and the error on the validation set starts increasing again (Fig. 2). MCCP aims at selecting the simplest tree that gives the best average performance across the whole dataset.

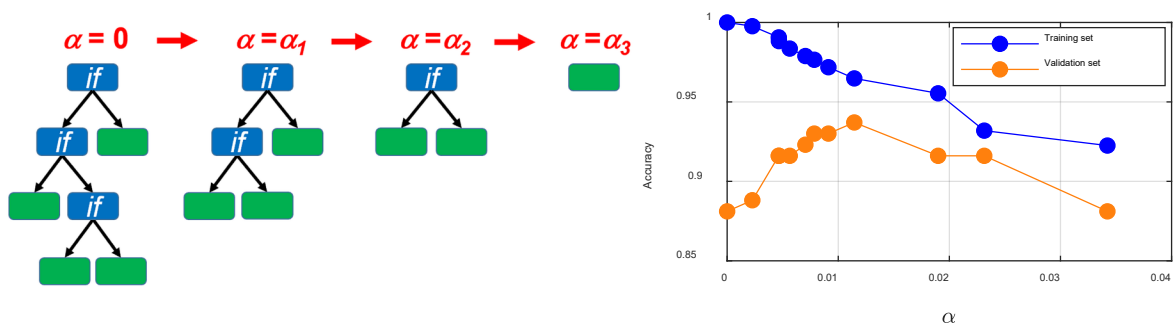


*Fig. 2: MCCP subtrees creation (l) and qualitative trend of tree accuracy with respect to α (r).*

As for the ANN, in [4] the most promising results were provided by a four-layered network with two hidden layers. The first layer consisted of the input signals, while both hidden layers had ten neurons (each one with the hyperbolic tangent as activation function). The same network architecture here considered, but new inputs are introduced, which help the algorithm to identify the actual friction coefficient. In addition to the pressure in the hydraulic circuit, the angular speed of the front wheel and the average disc temperature (calculated using the 2D-FE model and the KF) the ML algorithms were provided also with the temperature of the brake at the beginning of every braking maneuver, the duration of the braking maneuver and the difference between the average disc temperature and the temperature measured by the infrared sensor mounted on board ($\Delta T$).

The latter is introduced to take into account how a non-uniform power distribution in the disc affects the friction coefficient value. Figure 3 shows two braking maneuvers with similar average temperature on the disc and almost identical fluid brake pressure. The one at the bottom shows a very high temperature gradient on the disc-pad contact region while the one at the top presents

almost uniform temperature distribution (the single-spot temperature measurement is equal to the average temperature on the disc estimated by the FE model). In the first scenario the region in which the sensor is located is contributing the most in the generation of the braking torque. Hence, due to the local temperature peak, the friction coefficient is drastically lower than the other case in which the local temperatures are cooler and uniform. This results in a significant discrepancy between the breaking torque measured experimentally (black line) and the values predicted by the constant friction coefficient approach (dashed). Since these breaking maneuvers present similar pressure values and the braking system geometry is the same (Eq. 1) the braking torque estimated by assuming a constant $\mu$ is very similar for both cases. However, in case of a local temperature peak, this prediction overestimates the measured torque by more than 20%.

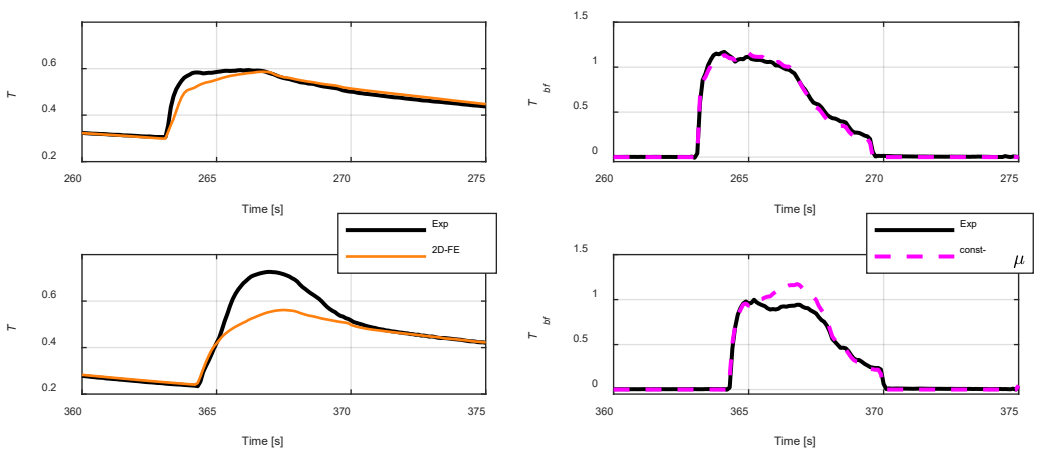


*Fig. 3: Effect of power distribution on torque estimation.*

**Main Results**

Table 1 compares the two tested ML algorithms. Their performance is expressed in terms of percent variation in the root mean square error ($\Delta\%_{RMSE}$) with respect to the constant-$\mu$ approach, and prediction speed (namely, computational time for predicting $10^4$ samples). The former is calculated averaging the values obtained for each fold. Even though the decision tree is one order of magnitude faster in making new prediction, the ANN is deemed the best solution for the friction coefficient recognition because it almost halves the RMSE obtained with constant $\mu$.

The implementation of the ANN as a preliminary stage for the torque calculation allows to enhance the results of the analytical model of the brake whenever the friction coefficient diverge significantly from the reference value, particularly in case of a very aggressive braking maneuver or a quite gentle one. For instance, Fig. 4 clearly shows that the proposed algorithm permits to significantly improve the accuracy of the braking torque prediction in case of hard braking (the same maneuver previously reported in Fig. 3, bottom, is considered).

Combining the thermal model of the brake and the new ANN allowed the creation of the colormap showed in Fig. 4, which provides a glimpse at the brake performance in many working conditions. The $X$ axis is related to a synthetic coefficient that takes into account the dependency of μ with respect to both pressure and angular velocity while the $Y$ axis is referred to the average disc temperature. Finally, the vertical axis and the color of the map indicate the values of $\mu$.

Table 1: performance of the tested approaches

| **Algorithm** | **$\Delta\%_{RMSE}$** | **Computational time [s]** |
|---|---|---|
| ANN [10;10] | – 42.7 % | 0.40 |
| MCCP Tree | – 17.1 % | 0.02 |

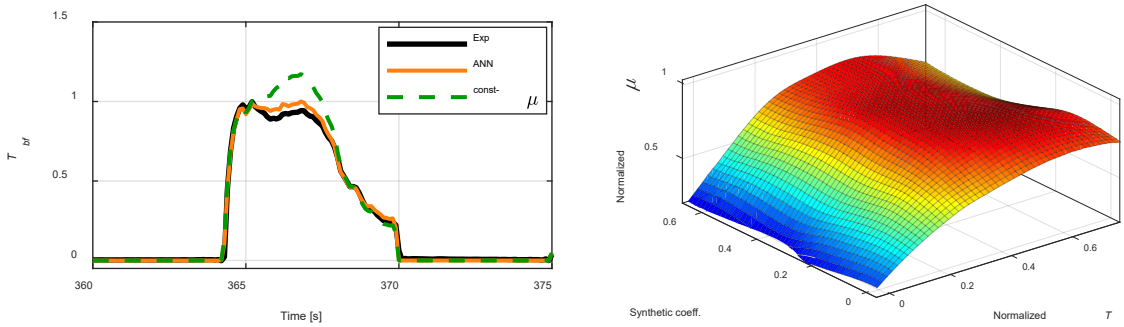


*Figure 4: braking torque estimation (l) and normalized μ colormap (r).*

## Conclusions

A novel method to estimate the friction coefficient of carbon brakes for racing motorcycles has been presented. It combines a thermal model of the brake, consisting of a Kalman filter and a two-dimensional finite element model, with an Artificial Neural Network. The proposed method has been validated with a large dataset collected from an experimental campaign conducted in many different racetracks. The developed algorithm permitted to map the friction coefficient over most of the operating conditions that may be experienced over a race.

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