

Sensitivity of Triple Product Asymmetries in $D^+ \rightarrow K_S^0 K^+ \pi^- \pi^+$ Decay at LHCb

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Contents

1	Introduction	1
2	Observables and datasets	1
3	MVA	2
4	Simultaneous fit	7
5	Conclusion	9
6	Acknowledgement	9

1 Introduction

CP violation of charm decays has never been observed yet. This time we try to apply triple-product asymmetries to the signal decay $D^+ \rightarrow K_S^0 K^+ \pi^- \pi^+$ as a complementary way for searching it. The aim of this project is to calculate sensitivity of certain observables from the likelihood and extrapolate it to full LHC Run2 for LHCb (The LHCb detector is described in References 1 and 2).

2 Observables and datasets

1. Observables

There are four particles in the final state of the decay $D^+ \rightarrow K_S^0 K^+ \pi^- \pi^+$. The momentum of K^+ , π^- and π^+ are independent and can be used to build the T-odd

observable

$$C_T = \vec{p}_{k^+} \cdot \vec{p}_{\pi^+} \times \vec{p}_{\pi^-}.$$

Asymmetries and CP violating observable are defined as

$$A_T = \frac{N(D^+, C_T > 0) - N(D^+, C_T < 0)}{N(D^+, C_T > 0) + N(D^+, C_T < 0)},$$

$$\bar{A}_T = \frac{N(D^-, -\bar{C}_T > 0) - N(D^-, -\bar{C}_T < 0)}{N(D^-, -\bar{C}_T > 0) + N(D^-, -\bar{C}_T < 0)},$$

$$a_{CP} = \frac{1}{2}(A_T - \bar{A}_T).$$

Due to other effects, A_T and $\bar{A}_T$ can be nonzero, but when taking the difference between them, these effects cancel. So a_{CP} is a true measure of CP violation.

2. Dataset

The datasets include separate samples for K_S^0 decaying in the Vertex detector (LL) or after (DD). Both DD and LL include events of two decay channel samples:

(a) $D^+ \rightarrow K_S^0 \pi^+ \pi^- \pi^+$

Control sample. No CP violation is expected in this channel. We use it as an input source for TMVA to search the best Boosted Decision Tree (BDT) constraint to suppress background on the signal sample.

(b) $D^+ \rightarrow K_S^0 K^+ \pi^- \pi^+$

Signal sample. There is possibly CP violation in this channel.

3 MVA

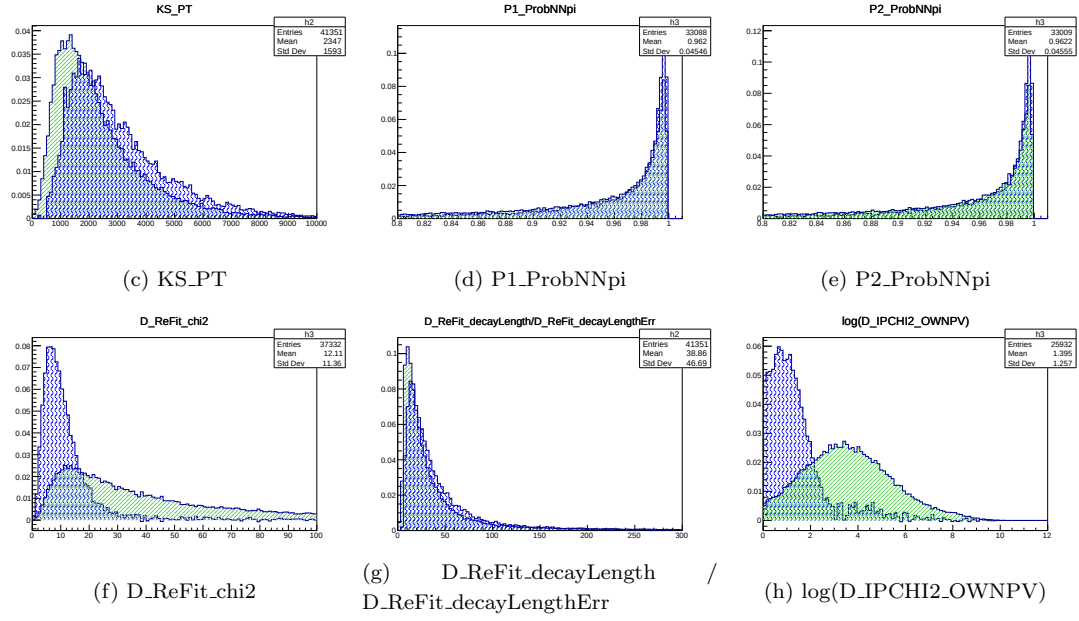
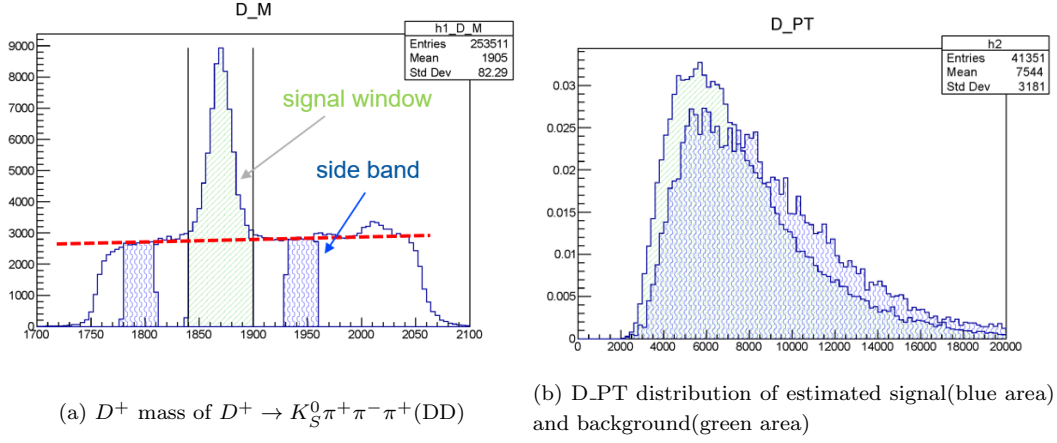
Suppress background using Multivariate Data Analysis with ROOT (TMVA).

1. Choice of Input Variables

If distributions of a variable are different between signal and background, then the variable is potential to be used to distinguish between signal and background. A simple and robust way to choose BDT training variables is background subtraction.

We define the signal window to be the $\pm 30\text{MeV}$ range symmetric around the expected D^+ mass and a lower sideband and an upper sideband, each 30 MeV wide, symmetrically spaced with respect to the center of the nominal signal region. The signal windows and sidebands are shown in Figure 1(a).

Figure 1: Background subtraction on small sample of $D^+ \rightarrow K_S^0 \pi^+ \pi^- \pi^+$ (DD)

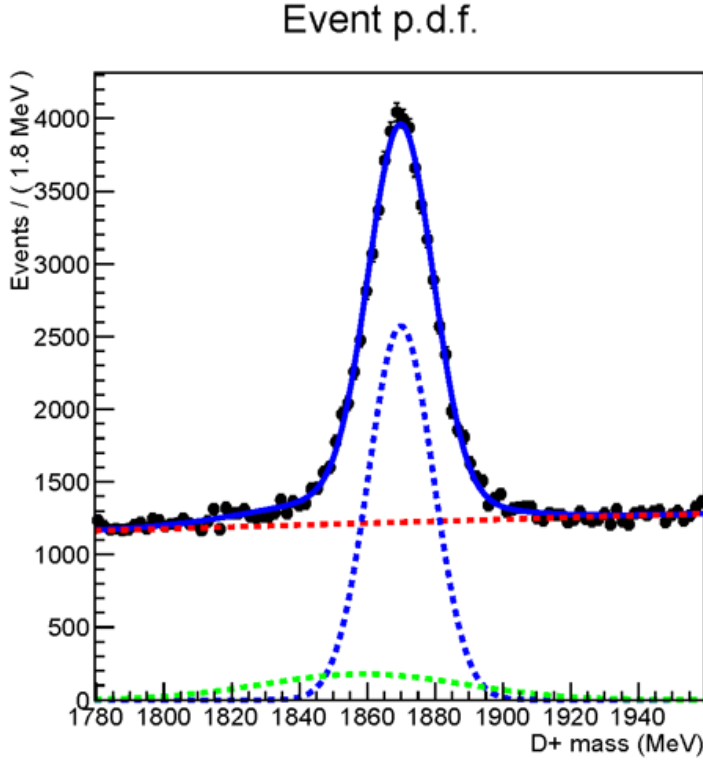


After the background subtraction, we choose transverse momentum of the D meson, transverse momentum of the Kaon, probability that the second particle is a pion, probability that the third particle is a pion, chi-square of fit in D^+ vertex, ratio of decay length to its uncertainty in D^+ meson vertex, and logarithm of D meson IP w.r.t. the PV as the variables and expressions used in TMVA.

2. $sPlot$

Before the train we should first extract s-weight to use in TMVA for $D^+ \rightarrow K_S^0 \pi^+ \pi^- \pi^+$. The fit result is shown below. The P.D.F. contains two gaussians (blue and green dashed curves) for signal and a cubic polynomial (red dashed curve) for describing background.

Figure 2: $sPlot$ fit result for $D^+ \rightarrow K_S^0 \pi^+ \pi^- \pi^+$



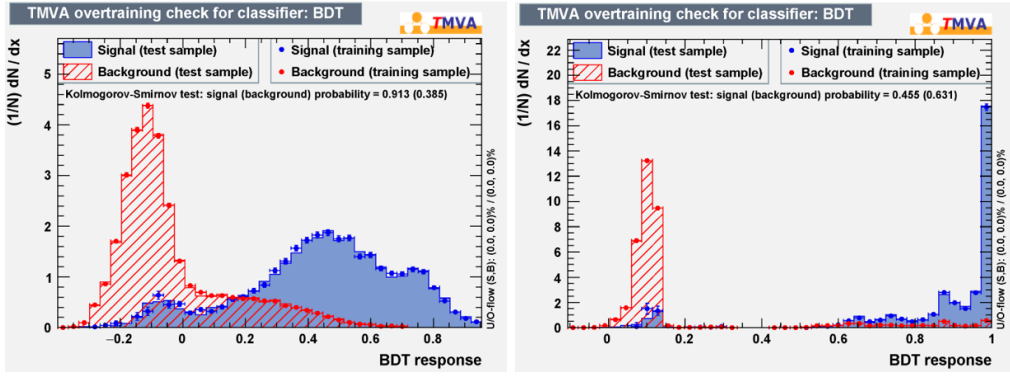
3. Train with selected variables and expressions

Considering the overtrain, we should adjust the parameters of BDT method to reduce overtrain as much as possible. The Kolmogorov-Smirnov (K-S) test outputs from the TMVA are usually interpreted as being a signal of good non-overtrained

performance if they are close to one, and on the other hand being a signal of overtraining they are very close to zero. Below is the parameter values and K-S test results of DD and LL for $D^+ \rightarrow K_S^0 \pi^+ \pi^- \pi^+$.

Sample category	NTrees	MaxDepth	nCuts
DD	150	2	20
LL	50	2	10

Figure 3: TMVA overtraining check for classification



(a) Overtraining Check for DD

(b) Overtraining Check for LL

- Find the best BDT constraint and suppress the background

The calculation of BDT response for $D^+ \rightarrow K_S^0 \pi^+ \pi^- \pi^+$ is based on the result of TMVA training. Then we normalize the signal yield and background yield to $D^+ \rightarrow K_S^0 K^+ \pi^- \pi^+$ to calculate the corresponding significance with BDT constraint. The significance is defined as

$$S = \frac{N_s}{\sqrt{N_s + N_b}},$$

where N_s is the signal yield of signal sample and N_b is the background yield. Since the control sample and signal sample of same decay branch have different signal and background yield, we should not simply apply the significance value from the former to the latter. Let $N_{sgn}^c(-\infty)$ be the signal yield of the control sample without BDT constraint, $N_{sgn}^c(x)$ be the one with constraint (BDT response $> x$). Let $N_{sgn}^s(-\infty)$ be the signal yield of signal sample without BDT constraint. Then the signal yield of signal sample with BDT constraint should be

$$N_s \equiv N_{sgn}^s(x) = N_{sgn}^c(x) \times \frac{N_{sgn}^s(-\infty)}{N_{sgn}^c(-\infty)}$$

Figure 4: Significance vs BDT constraint

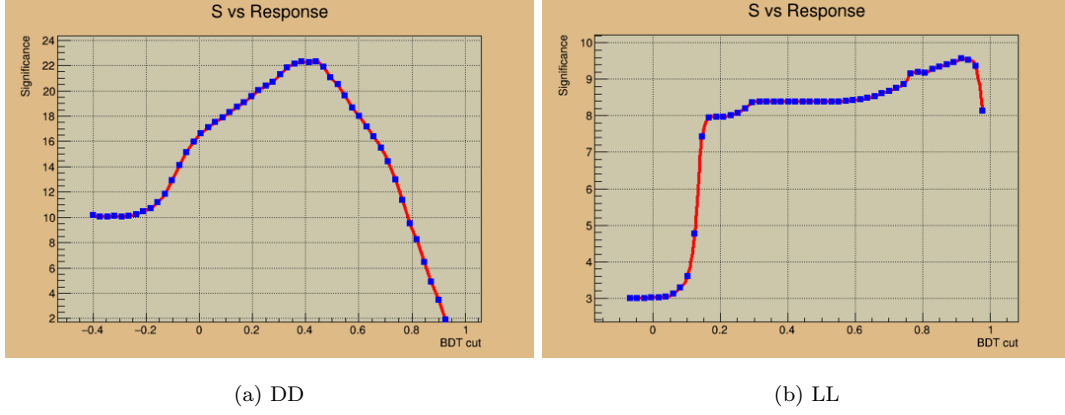
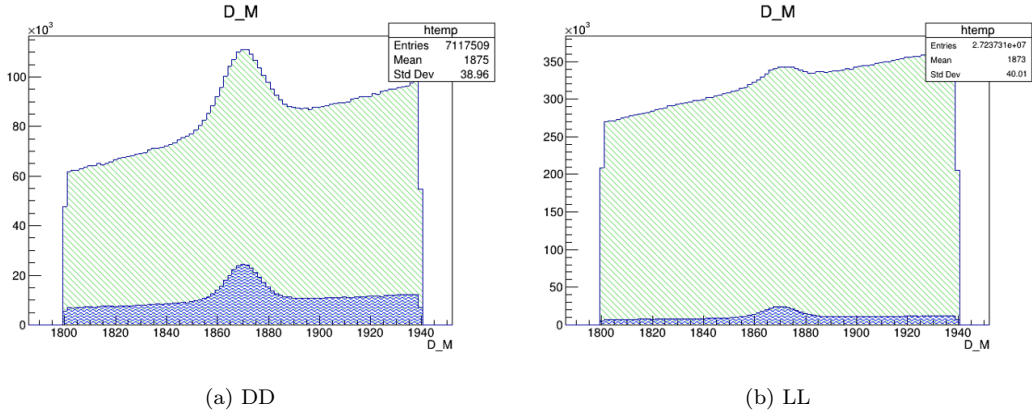


Figure 5: $D^\pm$ mass spectrum. Blue area $\rightarrow$ with BDT constraint. Green area $\rightarrow$ before BDT constraint

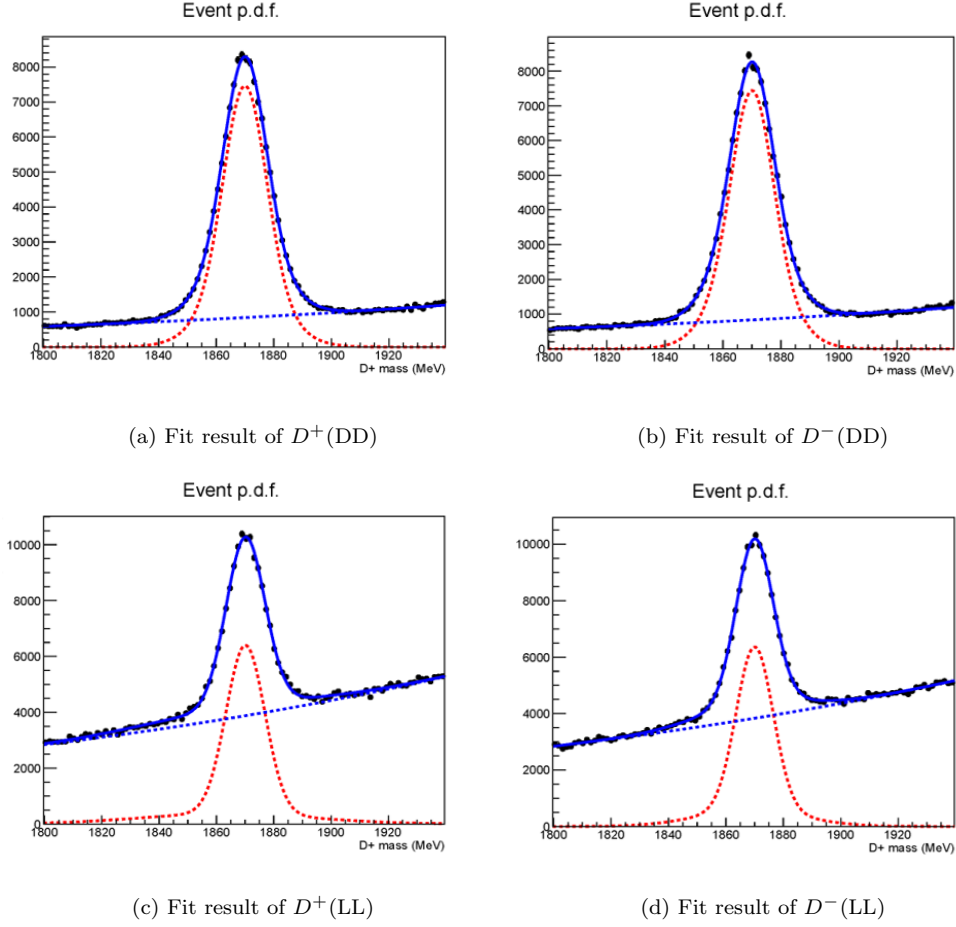


When BDT response > 0.43 , the significance reaches the maximum value for DD. While for LL, it is 0.90 (See Figure 3 and 4). Figure 4 shows the performance of the BDT cut in suppressing background.

5. Fit mass spectrum and get parameter values

The next step is applying the BDT constraint to the $D^+ \rightarrow K_S^0 K^+ \pi^- \pi^+$ sample (DD and LL). Before that, we should fit D^+/D^- 's mass spectrum for DD/LL to get 4 models ($D_{(DD)}^+$, $D_{(DD)}^-$, $D_{(LL)}^+$ and $D_{(LL)}^-$) with parameters. (See Figure 6)

Figure 6: 4 models with parameters

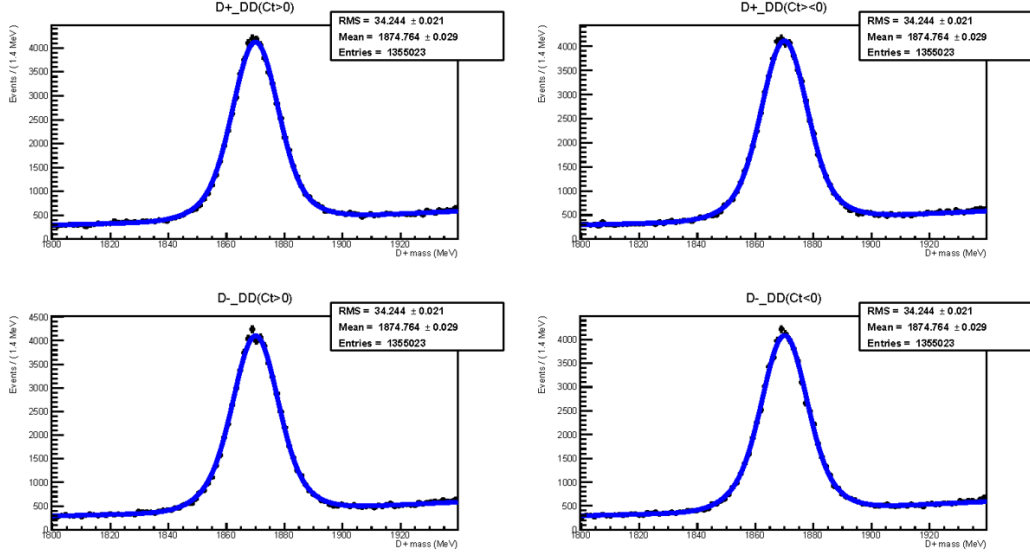


4 Simultaneous fit

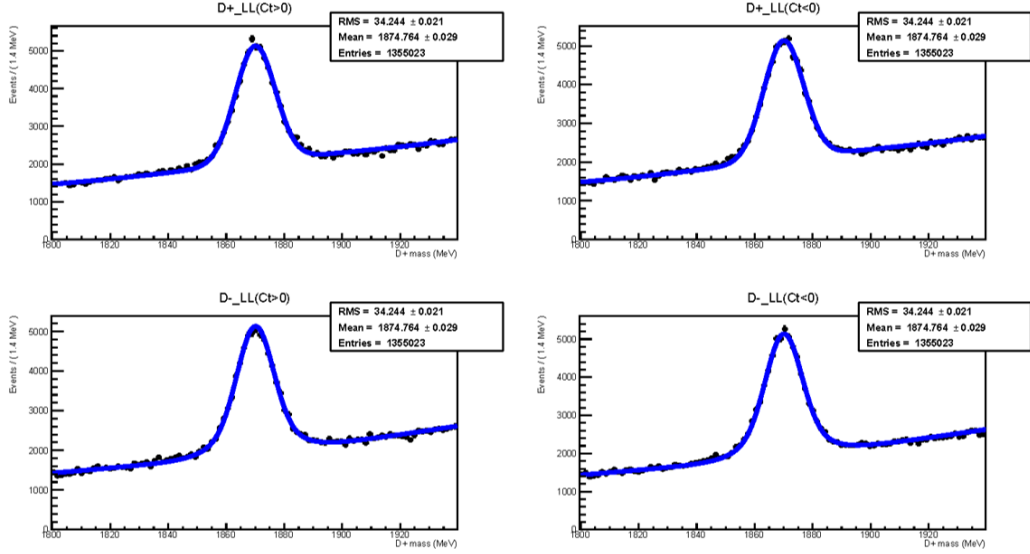
1. Fit models to subsamples

There are 4 models and 8 subsamples (2 subsamples ($C_T > 0$ and $C_T < 0$) for each model). A_T^{sig} , $\overline{A}_T^{sig}$ are in common among DD and LL. A_T^{bkg} , $\overline{A}_T^{bkg}$ have separate values for DD and LL. We fit the 8 P.D.F.s simultaneously to 8 subsamples to get the result (see Figure 7 and Table 1). A_T^{sig} , $\overline{A}_T^{sig}$ are set to be "blind" using blind analysis using class *RooUnblindPrecision* (See reference 4). Uncertainty of a_{CP} are derived from propagation of uncertainties of A_T^{sig} and $\overline{A}_T^{sig}$.

Figure 7: Fit result for 8 subsamples



(a) DD



(b) LL

2. Extrapolation

The integrated luminosity of our sample is $L=1.33 \text{ fb}^{-1}$. For LHC Run2, $L^f = 6 \text{ fb}^{-1}$

Table 1: Simultaneous fit result

Variable	Value	Uncertainty
signal yield (DD)	226757	± 546
signal yield (LL)	166245	± 578
background yield (DD)	168905	± 494
background yield (LL)	796116	± 1035
A_T	2.3×10^{-3}	2.5×10^{-3}
$\bar{A}_T$	-1.4×10^{-3}	2.5×10^{-3}
a_{CP}	1.8×10^{-3}	2.0×10^{-3}

Let N_S be the number of signal events in sample. Suppose $N_S \propto L$. For a large enough sample, the uncertainty is inversely proportional to the square root of sample size N.

$$\left. \begin{aligned} \frac{N_S}{N_S^f} &= \frac{L}{L^f} \\ \frac{\sigma_{a_{CP}}(N_S)}{\sigma_{a_{CP}}^f(N_S^f)} &= \sqrt{\frac{N_S^f}{N_S}} \end{aligned} \right\} \Rightarrow \sigma_{a_{CP}}^f(N_S^f) = \sigma_{a_{CP}}(N_S) \sqrt{\frac{L}{L^f}} = 2.0 \times 10^{-3} \times \sqrt{\frac{1.33}{6}} = 9.6 \times 10^{-4}$$

5 Conclusion

We use background subtraction as a simple and robust way to choose variables for MVA. Then a small control sample is used to train the classifier. BDT constraint proved to be an effective method to suppress background. We fit the signal samples with BDT constraint and extrapolate the uncertainty to the full LHC Run 2. This work is the first look into T-odd observables for the decay $D^+ \rightarrow K_S^0 K^+ \pi^- \pi^+$ at LHCb.

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