

1 **Light-jet mis-tag efficiency calibration with the ATLAS Experi-**  
2 **ment**

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**Summary.** — In the ATLAS Experiment, an important source of systematic uncertainty for many physics analyses, especially in the top quark sector and in searches for high mass resonances, is constituted by those light jets, originated by up, down and strange quarks, and gluons, which can be wrongly identified as  $b$ -jets. It is therefore crucial to determine the rate and the efficiency of mis-identification of light jets with heavy flavour jets. The light jet efficiency calibration is challenged by the high rejection factors of the state-of-art  $b$ -tagging algorithms. It is therefore difficult to find a filtered sample of events pure enough in light jets following  $b$ -tagging selections. This problem is particularly challenging due to the excellent performances in  $b$ -jet identification of the modern algorithms widely used in ATLAS, based on deep neural networks (DL1r, DL1d) and graph neural networks (GN2). A possible solution for the low statistics issue after the  $b$ -tagging selection is the so-called “negative tag” method, which consists in enriching the  $Z$ + jets data sample artificially via the inversion of the sign of the impact parameter of the tracks associated to the jets. In this contribution, the algorithm and the strategies adopted in the light jet calibration in ATLAS are presented, with particular focus on the calibration with  $Z$ + jets events. The most recent ATLAS results obtained for LHC Run-2 and Run-3 are finally discusses.

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7 **1. – Calibration**

8 Many analyses in ATLAS [1], such as measurements or searches involving top quarks  
9 or Higgs bosons, rely on the identification of jets containing  $b$ -hadrons ( $b$ -jets) with high  
10 tagging efficiency and low mis-tagging efficiency for jets containing  $c$ -hadrons ( $c$ -jets) or  
11 containing neither  $b$ - nor  $c$ -hadrons (light-flavour jets). The relatively long lifetime and  
12 high mass of  $b$ -hadrons together with the large track multiplicity of their decay products  
13 is exploited by  $b$ -tagging algorithms to identify  $b$ -jets. The  $b$ -tagging algorithms are  
14 trained using Monte Carlo (MC) simulated events and therefore need to be calibrated

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15 in order to correct for efficiency differences between data and simulation that may arise  
 16 from an imperfect description of the data, e.g. in the parton shower and fragmentation  
 17 modelling or in the detector and response simulation.

18 ATLAS analyses use selection requirements defining a lower bound on the tagger  
 19 discriminant to select  $b$ -jets with a certain efficiency. Four of these so-called single-cut  
 20 operating points (OPs) are defined, corresponding to  $b$ -jet selection efficiencies of 85%,  
 21 77%, 70% and 60%. The OPs are evaluated in a sample of  $b$ -jets from simulated  $t\bar{t}$  events.

22 The efficiency of identifying a  $b$ -jet ( $\epsilon^b$ ) and the mis-tagging efficiencies ( $\epsilon^c$  and  $\epsilon^{\text{light}}$ ),  
 23 which are the probabilities that other jets are wrongly identified by the  $b$ -tagging algo-  
 24 rithms as  $b$ -jets, are measured in data and compared with the predictions of the simula-  
 25 tion. These tagging and mis-tagging efficiencies are defined as:

$$(1) \quad \epsilon^f = \frac{N_{\text{pass}}^f}{N_{\text{all}}^f}$$

26 where  $f \in \{b, c, \text{light}\}$ ,  $N_{\text{pass}}^f$  is the number of jets of flavour  $f$  selected by the  $b$ -tagging  
 27 algorithm and  $N_{\text{all}}^f$  is the number of all jets of flavour  $f$  in the data set. The flavour  
 28 tagging efficiency in data ( $\epsilon_{\text{data}}^f$ ) can be compared with the efficiency in MC simulation  
 29 ( $\epsilon_{\text{MC}}^f$ ) and a calibration factor, also called the *scale factor* (SF), is defined as:

$$(2) \quad SF^f = \frac{\epsilon_{\text{data}}^f}{\epsilon_{\text{MC}}^f}$$

30 The calibration factors correct the efficiencies and mis-tagging efficiencies in simu-  
 31 lation to better reproduce performance obtained in data and are applied to all physics  
 32 analyses in ATLAS that use  $b$ -tagging. The  $b$ -jet efficiency ( $\epsilon^b$ ) is calibrated using the  
 33 method described in Ref. [2], where the SFs <sup>$b$</sup>  are extracted from a sample of events con-  
 34 taining top-quark pairs decaying into a final state with two charged leptons and two  
 35  $b$ -jets. The  $c$ -jet mis-tagging efficiency ( $\epsilon^c$ ) is calibrated via the method described in  
 36 Ref. [3], where the SFs <sup>$c$</sup>  are extracted from events containing top-quark pairs decaying  
 37 into a final state with exactly one charged lepton and several jets. The events are recon-  
 38 structed using a kinematic likelihood technique and include a hadronically decaying  $W$   
 39 boson, whose decay products are rich in  $c$ -jets.

## 40 2. – Light-jet mis-tag efficiency calibration: the “negative tag” method

41 The mis-tagging efficiency for light jets,  $\epsilon^{\text{light}}$ , is difficult to calibrate because after  
 42 applying a  $b$ -tagging requirement, the resulting sample of jets is strongly dominated by  
 43  $b$ -jets. Thus, the fraction of light-flavour jets passing a loose selection on the  $b$ -tagging  
 44 score is too low to estimate  $\epsilon_{\text{data}}^{\text{light}}$ . In order to extract an unbiased and precise scale factor  
 45 for light jets, SF<sup>light</sup>, a sample enriched in mis-tagged light-flavour jets is required.

46 One of the strategies widely adopted by the ATLAS Collaboration is the so called  
 47 “negative tag” method [4, 5]. It consists in calibrating data via a modified version of the  
 48 recommended  $b$ -tagging algorithms (DL1d [6], GN2 [7]) mentioned above, that achieves  
 49 lower  $\epsilon^b$  to  $\epsilon^{\text{light}}$  light ratios without changing  $\epsilon^{\text{light}}$  significantly. This strategy is based  
 50 on some assumptions related to the tracks assigned to a certain jet. In general, tracks  
 51 matched to  $b$ -jets have relatively large and positively signed impact parameters (IPs)

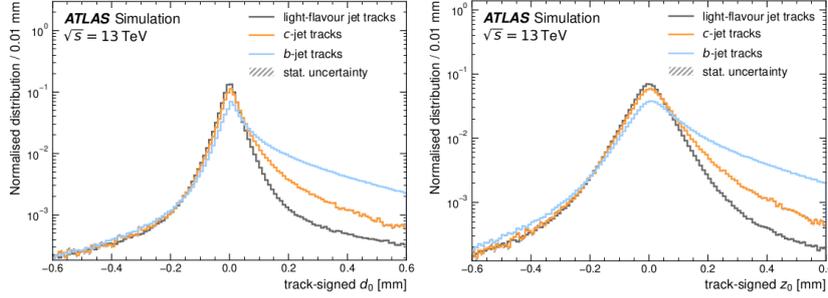


Fig. 1. – Signed transverse impact parameter  $d_0$  (left) and signed longitudinal impact parameter  $z_0$  (right) distributions for tracks matched to  $b$ -jets,  $c$ -jets and light-flavour jets in simulated  $t\bar{t}$  events. The selected tracks are matched to particle-flow jets with  $p_T > 20$  GeV and  $|\eta| < 2.5$ , and pass the jet-vertex tagger selection. The distributions are normalised to unity. Statistical uncertainties are also shown. Plots are taken from [8].

52 due to the long lifetime of the  $b$ -hadrons and the presence of displaced decay vertices.  
 53 In contrast, tracks matched to light-flavour jets typically have IP values consistent with  
 54 zero within the IP resolution such that a more symmetric IP distribution <sup>(1)</sup> is expected.  
 55 The expected IP distributions of the tracks associated with  $b$ -jets,  $c$ -jets or light-flavour  
 56 jets are shown in Fig. 1.

57 The negative tag method assumes that the probability for a light flavour jet to be mis-  
 58 tagged remains almost the same when inverting the IP signs of all tracks and displaced  
 59 vertices. This is based on the assumption that light flavour jets are misidentified as  $b$ -jets  
 60 mainly due to resolution effects in the track reconstruction, which result in tracks with  
 61 positive IPs inside the jet. Given the symmetric IP distributions, the fractions of tracks  
 62 and vertices from tracks with positive IPs remain stable after inverting the IP signs of  
 63 all tracks and vertices. The presence of the positive tail in the IP distribution challenges  
 64 this assumption and its impact is taken into account by a dedicated “extrapolation  
 65 uncertainty”.

66 Therefore, the adoption of this method allows to enrich artificially the fraction of light  
 67 jets in the considered data sample via inverting the sign of the impact parameter of the  
 68 tracks associated with the jets. It can be finally applied to both DL1d and GN2 taggers,  
 69 which namely become DL1dFlip and GN2Flip, for the mainstream calibration provided  
 70 by the ATLAS Flavour Tagging group in  $Z+$  jets events, as well as for alternative cali-  
 71 brations in di-jet events.

### 72 3. – Preliminary results on Run-2 and Run-3 data

73 The calibration of the light-jet mis-tagging efficiency is performed independently in jet  
 74  $p_T$  intervals in order to account for the  $p_T$  dependence of  $\epsilon^{\text{light}}$ . A simultaneous binned fit  
 75 to the distribution of the mass of the secondary vertex,  $m_{SV}$ , in each pseudo-continuous

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<sup>(1)</sup> The tracks matched to light-flavour jets have a slight bias towards positive-sign values due to the presence of some long-lived particles (e.g.  $K_S$  or  $\Lambda$ ), as shown in Fig. 1. The contribution from the mis-modelling of long-lived particles is expected to be negligible relative to the mis-modelling of the  $d_0$  and  $z_0$  resolutions [4].

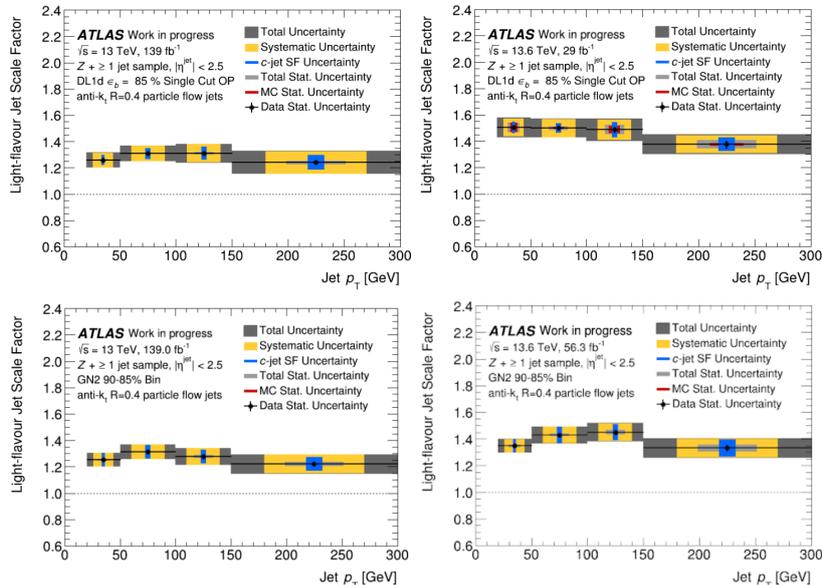


Fig. 2. – SFs to calibrate the  $\epsilon^{\text{light}}$  of the pseudo-continuous OPs for the DL1d (first row) and GN2 tagger (second row) on the full set of Run-2 data (left) and a  $56.3 \text{ fb}^{-1}$  sample (top right) and a  $29 \text{ fb}^{-1}$  sample (bottom right) of Run-3 data collected by the ATLAS detector. The size of the uncertainty bands in the direction of the jet  $p_T$  axis is arbitrary and corresponds to the choice of the calibration intervals in  $p_T$ .

76 interval of the  $\epsilon_{\text{data}}^b$  and  $\epsilon_{\text{data}}^{\text{light}}$  in the  $b$ -tagging discriminant is performed in order to  
 77 simultaneously determine  $\epsilon_{\text{data}}^b$  and  $\epsilon_{\text{data}}^c$  discriminant intervals. The sensitivity of the fit  
 78 does not allow the SFs of all three jet flavours to be derived simultaneously. Therefore,  
 79  $\epsilon_{\text{data}}^c$  is constrained to the MC predictions and  $\text{SF}^c$  is fixed to unity within an uncertainty  
 80 of 30%, as suggested by studies of the  $c$ -jet mis-tagging efficiency calibration [3].

81 For a given interval of jet  $p_T$ , the expected number of jets for a defined discriminant  
 82 interval  $i$  is given by:

$$(3) \quad N_i(m_{\text{SV}}) = N_{i,\text{MC}} \cdot C \cdot \sum_{f=\text{light},c,b} F^f \cdot \text{SF}_i^f \cdot \epsilon_{i,\text{MC}}^f \cdot P_i^f(m_{\text{SV}})$$

83 where  $N_{i,\text{MC}}$  is the predicted flavour-inclusive event yield for each discriminant inter-  
 84 val;  $C$  is a global normalisation factor and  $F^f$  are the *jet-flavour fractions*;  $P_i^f(m_{\text{SV}})$  is  
 85 the probability density function of  $m_{\text{SV}}$  for jet flavour  $f$  in the  $i$ -th tagger discriminant  
 86 interval, taken from simulation. The  $P_i^f(m_{\text{SV}})$  is defined in such a way to integrate an  
 87 additional bin ( $m_{\text{SV}} < 0 \text{ GeV}$ ) representing the number of events where no secondary  
 88 vertex is found. The  $m_{\text{SV}}$  distribution has been obtained with tracks with nominal sign  
 89 as input to the secondary vertex finder algorithm. The  $C$ ,  $F^f$  and  $\text{SF}^{b,\text{light}}$  parameters  
 90 are allowed to float in the fit, while  $N_{i,\text{MC}}$  and  $\epsilon_{i,\text{MC}}^f$  are fixed to the predictions from  
 91 simulated events and  $\text{SF}^c$  is set to  $1.0 \pm 0.3$ .

92 Preliminary results on the Run-2 and Run-3 scale factors for the DL1d and GN2 taggers  
 93 are presented in Fig. 2 for the 85% and 90% OPs respectively.

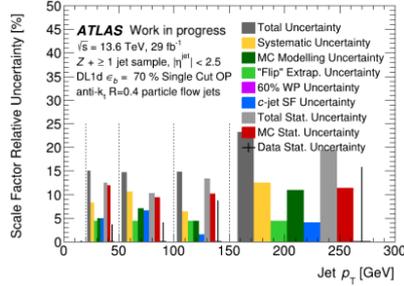


Fig. 3. – DL1d mis-tagging efficiency calibration uncertainties for light jets with a  $29 \text{ fb}^{-1}$  sample of Run-3 data from 2022. The breakdown of the different uncertainties is shown for the 70% OP.

94 The calibration SFs<sup>light</sup> of the DL1d and GN2 algorithms are presented. The 90%,  
 95 85%, 77% and 70% OPs have been successfully calibrated in data by using the negative  
 96 Tag method. However, it is not feasible to calibrate the 60% OP in data because of  
 97 insufficient statistics and the relatively large contamination by heavy-flavour jets.

98 The measurement of SF<sup>light</sup> is affected by four types of uncertainties, including those  
 99 due to experimental effects, the modelling of the  $b+$  jets and background processes, and  
 100 the limited number of events in data and simulation. For each source of uncertainty, one  
 101 parameter of the fit model is varied at a time, and the effect of this variation on SF<sup>light</sup>  
 102 is evaluated. The relative contribution of the various uncertainties is shown in Fig. 3 for  
 103 the DL1d tagger only, since those for GN2 tagger are still under validation at the time of  
 104 writing, and are listed below:

- 105 • Monte Carlo Modelling (dark green): modelling of fit template;
- 106 • “flip” extrapolation (light green): uncertainty to cover potential differences between  
 107 DL1(d)Flip and direct DL1(d) calibration;
- 108 • calibration of DL1(d)Flip for other jet flavours (blue): this includes contribution  
 109 of other jet flavours in selected sample, for instance the one by  $c$ -jets, which appears  
 110 to be subdominant;
- 111 • MC statistical uncertainty (red): it is related to the amount of simulated data  
 112 and gives subdominant contributions, except for high jet  $p_T$  and tight OPs (in  
 113 particular, 60%).

114 In addition to the systematic uncertainties listed above, a relative 50% uncertainty is  
 115 assigned by hand to the 60% OP, in order to keep track on the fact that the fit for that  
 116 OP is failing.

#### 117 4. – Conclusions

118 The light-flavour jet mis-tagging efficiency  $\epsilon^{\text{light}}$  of the DL1d  $b$ -tagging algorithm has  
 119 been measured with a  $139 \text{ fb}^{-1}$  sample of  $\sqrt{s} = 13 \text{ TeV}$  collision events recorded during  
 120 2015–2018 and a  $56.3 \text{ fb}^{-1}$  sample of  $\sqrt{s} = 13.6 \text{ TeV}$  collected during 2022 and 2023  
 121 by the ATLAS detector at the LHC. The measurement is based on an improved method  
 122 applied to a sample of  $Z$ +jets events. The negative tag method, based on the application

of an alternative  $b$ -tagging algorithm, designed to facilitate the measurement of the light-flavour jet mis-tagging efficiency, is used. Data-to-simulation scale factors for correcting  $\epsilon^{\text{light}}$  in simulation are measured in different jet transverse momentum intervals, ranging from 20 to 300 GeV, for four separate quantiles of the  $b$ -tagging discriminant. The total uncertainties range from 11% to around 25%, and the scale factors do not exhibit any strong dependence on jet transverse momentum.

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