

Off-Shell Higgs Production Measurement in the $H \rightarrow ZZ^{(*)} \rightarrow 4\ell$ and $H \rightarrow ZZ^{(*)} \rightarrow 2\ell 2\nu$ Decay Channels with ATLAS Run 3 Data using Neural Simulation-Based Inference

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Measurements of the production of off-shell Higgs Bosons at the Large Hadron collider are most notably of interest due to its role in studying constraints on the Higgs boson decay width.

Two Higgs decay channels are investigated in this study. The $H \rightarrow ZZ^{(*)} \rightarrow 4\ell$ final state and the $H \rightarrow ZZ^{(*)} \rightarrow 2\ell 2\nu$ final state.

The dominant background is in both cases the irreducible contribution from $q\bar{q} \rightarrow ZZ$ production.

In both channels the $g\bar{g} \rightarrow H^* \rightarrow ZZ$ signal interferes substantially with the $g\bar{g} \rightarrow ZZ$ continuum background, so it cannot be measured independently of it.

The probability density of an event with observables x therefore features a non-linear contribution with regards to the signal strength μ from this interference contribution,

$$p(x|\mu) = \frac{1}{\nu(\mu)} [\mu \cdot \nu_S \cdot p_S(x) + \sqrt{\mu} \cdot \nu_I \cdot p_I(x) + \nu_B \cdot p_B(x) + \nu_{NI} \cdot p_{NI}(x)], \quad (1)$$

where ν_i are the corresponding yields of the contributing processes. The signal strength is then measured by performing a data fit on the corresponding negative log likelihood of this probability density.

The traditional approach compresses the high-dimensional event information into a single summary variable, such as the transverse mass m_T^{ZZ} in the $2\ell 2\nu$ case, and extracts the signal strength μ by performing a Poisson-based data-fit on the bin contents,

$$L(\mu, \theta) = \prod_{\text{bins}} \text{Poisson}(N_{\text{obs}} | N_{\text{exp}}(\mu, \theta)) \quad (2)$$

. A scan of the test statistic $t(\mu) = -\log L(\mu) + \log L(\hat{\mu})$, where $\hat{\mu}$ is the best fit value of the signal strength, is then used to probe the parameter of interest.

However, it can be shown that in the presence of non-linear contributions from interference effects, no single observable is optimally sensitive over the full global scale of μ . As such, a single histogram observable will not provide optimal sensitivity for all values of μ in the test statistic scan.

An alternative approach to address this issue is motivated by the Neyman-Pearson lemma: the ratio of probability densities is the optimal observable for distinguishing

two hypotheses. The probability density estimation problem is therefore reformulated as a probability density *ratio* estimation problem with respect to an arbitrarily chosen reference distribution $p_{\text{ref}}(x)$. The likelihood then splits into a Poisson-based total event count term and an event-by-event shape term consisting of the probability density ratio for each given event,

$$L(x|\mu) = \text{Pois}(N_{\text{obs}} | N_{\text{exp}}(\mu)) \prod_i^N \frac{p(x_i|\mu)}{p_{\text{ref}}(x_i)}, \quad (3)$$

For this approach to be feasible it is necessary to efficiently produce accurate estimations of the probability density ratios for each individual event. A Neural Network classifier trained on Monte Carlo samples to separate events drawn from the (simulated) probability density distributions $p_i(x)$ of each template process i from events drawn from $p_{\text{ref}}(x)$ approximates

$$\hat{s} \approx \frac{p_i(x)}{p_i(x) + p_{\text{ref}}(x)} \implies \frac{p_i(x)}{p_{\text{ref}}(x)} = \frac{\hat{s}}{1 - \hat{s}}, \quad (4)$$

which is commonly referred to as the "likelihood ratio trick". For this assumption to hold, however, it is a necessary requirement that the relative yields v_i and v_{ref} of the probability densities are identical in the training dataset used to fit the Neural Network parameters. This approach to use a Neural Network trained on simulated samples to directly estimate probability density ratios is generally referred to as Neural Simulation-Based Inference (NSBI).

Previous studies using data from the second data-taking at the ATLAS detector of the Large Hadron collider ($\sqrt{s} = 13$ TeV, $L \approx 140 \text{ fb}^{-1}$) showed noteworthy improvements in sensitivity in the $H \rightarrow ZZ^{(*)} \rightarrow 4\ell$ channel when using the NSBI-based approach compared to a more traditional histogram-based approach.

With the now concluded third data-taking run of the ATLAS experiment ($\sqrt{s} = 13.6$ TeV, $L > 350 \text{ fb}^{-1}$), a new off-shell production measurement will again be performed, which is the central point of this study.

To iterate on the Run 2 results, the NSBI method will be extended to also be applied in the $H \rightarrow ZZ^{(*)} \rightarrow 2\ell 2\nu$ decay channel to perform a combined, fully NSBI-based, result of the $H \rightarrow ZZ^{(*)} \rightarrow 4\ell$ and $H \rightarrow ZZ^{(*)} \rightarrow 2\ell 2\nu$. As no NSBI-based measurement has hitherto been performed in the $H \rightarrow ZZ^{(*)} \rightarrow 2\ell 2\nu$ channel, the potential for improvements compared to the traditional histogram based approach are still unclear.

Additionally, avenues for improvements to the NSBI procedure to potentially increase its efficiency will also be investigated over the course of this study.