1. Division Tracking Number: DOE-137-NLR-24051-24

2. Date Prepared: 04/05/2024 Proposal Due Date: 04/25/2024

3. Work Proposal Title: MC Calibration

4. Estimated Period of Performance in number of months: 60

5. Organization issuing the Solicitation, and Solicitation Number. **A copy of the solicitation must be attached to this request.** (Example: Golden Field Office, Number DE-PS36-06-GO96018, or DARPA, BAA-09-69)

Department of Energy, DE-FOA-0003176-000001

6. How did you hear about this funding opportunity? (Mark with an X)

Newsletter  Program Manager  Sponsor Website

Industry Partner  Sponsor Announcement  Other

7. Argonne PI: Walter Hopkins High-Energy Physics

(Name) (PI Division)

8. Division Director   
 Approval: Rikutaro Yoshida \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

(Name) (Signature) (Date)

9. What unique capability does Argonne have to perform this work, such that this work is not in competition with the private sector?

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| The proposal is for fundamental science research conducted within the ATLAS collaboration at CERN and thus will not compete with the private sector in any way. The private sector doesn't currently perform fundamental particle physics research within ATLAS. The Argonne ATLAS group has been part of the ATLAS collaboration for many years. The established collaboratiton within ATLAS and the Argonne Leadership Computing Facility offers unique capabilities that greatly aid the success of the proposal.  The scope of work does not compete with the private sector. |

10. Complete columns B – F as appropriate, or add additional columns

|  | Lead Proposer | Team Member A | Team Member B | Team Member C | Total Amount Requested |
| --- | --- | --- | --- | --- | --- |
| Enter name of business, laboratory, university, etc. | UChicago Argonne, LLC DBA Argonne National Laboratory |  |  |  |  |
| Proposed total share of award in $ | $ | $ | $ | $ | $2,750,000 |
|  |  |  |  |  |  |
| Cost sharing if applicable |  |  |  |  |  |

11. Proposal Description: (Approach, anticipated benefits, Argonne’s work scope and role of each team member. Approximately 2-3 paragraphs total, use extra page as necessary). You are encouraged to attach the full proposal if available.

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| Machine learning (ML) has increasingly become a critical tool in High-Energy Physics (HEP), offering significant advancements in various tasks such as simulating calorimeter showers, identifying particles such photons and electrons, and distinguishing between signal and background processes. The application of ML in HEP is accompanied by certain challenges that need careful consideration. One such challenge is the alignment of input variable distributions between Monte Carlo (MC) simulations and experimental data. Differences between MC simulations and recorded data can introduce additional uncertainties into ML predictions, affecting the overall systematic uncertainties in physics measurements. Additionally, ML algorithms may be sensitive to experimental systematic uncertainties which are typically assessed by varying underlying experimental parameters (e.g., the energy resolution of a subdetector). Furthermore, ML models can sometimes create unintended correlations between their outputs (such as estimated energy or particle classifications) and other variables critical for calibrations or background estimations.  Recently proposed ML approaches such as adversarial~\cite{louppe2017learning} and distance correlation (DisCo) techniques have shown promise in various applications such as reducing uncertainties in a long-lived particle search and decorrelating jet substructure variables from jet mass.  These approaches are part of a group of methods that aim to improve the "domain adaptation'' of ML algorithms, i.e., the ability of an ML model trained with one set of data to be robust enough to be applied to data that expected to be different from the training data. Domain adaptation techniques have the potential to be more broadly applied when developing ML models to estimate physics object properties, to identify physics objects, to reduce the sensitivity data-MC discrepancies, and to changes in the underlying parameters of simulations. Thus, domain adaptation approaches could be used to reduce the total uncertainties of physics results within HEP.  This proposal presents the development of a framework to deploy domain adaptation techniques to minimize uncertainties when using machine-learning-based physics object identification and property estimation by ensuring that ML models are robust against experimental systematic uncertainties. The framework has broad applications but will first be used to maximize object identification (ID) efficiencies and property estimation precision by making use of all available information that would otherwise be left unused due to mismodelling and calibration concerns. |

12. Argonne’s level of effort is within that which is allowed under the solicitation: \_\_\_\_\_\_\_

(TCP initial)

13. Manager, Sponsored Research Office  
      

(Name) (Signature) (Date)

\* **If selected for award, the full approved SPP proposal and New Proposal Information Questionnaire will require DOE approval prior to receipt of funds from the sponsor.**