DINo: Deep learning Intelligence for Nuclear reactions

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Abstract In radiation therapy, precise dose calculations are crucial for treatment plan improvement, relying on advanced algorithms based on Monte Carlo simulations. Persistent discrepancies between experimental data and hadronic models in particle therapy highlight the need for improved accuracy. This study introduces DINo (Deep learning Intelligence for Nuclear reactions), a deep learning algorithm designed to explore solutions for these challenges. DINo uses partial proton nuclear reactions cross-sections to extrapolate total cross-sections, mitigating limitations in existing models. Focused on protons, with an extensive representation in the TENDL nuclear data library, DINo, as a dense neural network, learns from TENDL's 2019 model values, effectively predicting total cross-sections for unexplored initial energies. Preliminary results tend to indicate DINo's superior predictive capabilities compared to the TENDL model, promising enhanced precision in nuclear reaction data and refined dose calculations for particle therapy.

1 Introduction

Dose calculations in radiation therapy heavily rely on advanced algorithms incorporating both physical and biological processes, based on data provided by Monte Carlo simulations. However, discrepancies persist between experimental data and hadronic models, particularly in nuclear reactions in particle therapy, leading to potential inaccuracies in dose calculations. Therefore, the implementation of measured data into existing codes is challenging but essential [6]. This abstract proposes the development of a deep learning algorithm called DINo (Deep learning Intelligence for Nuclear reactions) that proposes to leverage partial proton nuclear reactions cross-sections to extrapolate total cross-sections data, mitigating the data limitations within current models.

2 Materials and Methods

The TENDL nuclear data library [1], based on TALYS theoretical code, includes the state of the art in nuclear reaction models, taking into account all major reaction mechanisms encountered in light particle-induced nuclear reactions. The library encompasses a great amount of proton data, leading to the choice of protons as the focal point for this study. Figure 1 illustrates the cross-sections for incident protons on a ^{12}C target, given by the TENDL library, focusing on the comparison between the TENDL model results with experimental data from EXFOR [7] for the p(^{12}C,X)^{11}C reaction alongside with the total cross-section.

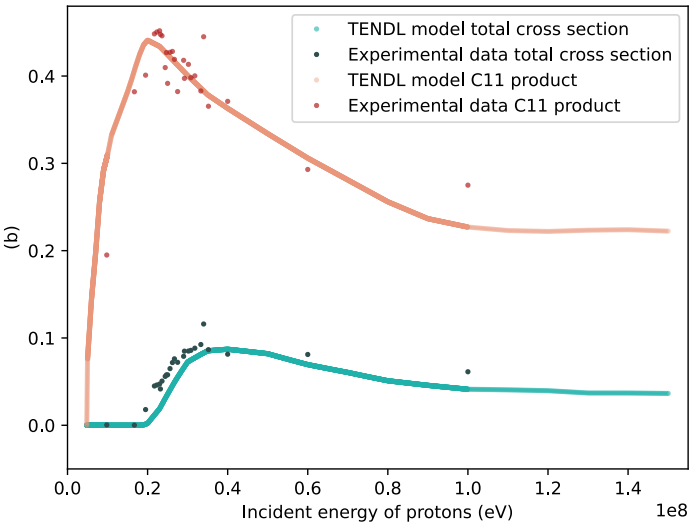

Figure 1: ^{11}C product cross-sections and total cross-section for incident protons on a ^{12}C target – TENDL model results compared to experimental data (data error in the order of 2% not visible on the plot).

The $\chi^2 = \sum \frac{(predicted-expected)^2}{expected}$ value for the comparison between TENDL model and experimental data for total cross-section is 4.5±1.0.

Introduced as a dense neural network (DNN), the DINo algorithm learn from the TENDL 2019 model values, focusing on charge changing cross-section of ^{11}C as a function of proton projectile initial energy, alongside with their corresponding total cross-section. DINo aims at predicting total cross-sections for initial energies not covered by current experimental data. On figure 3 is shown a simplified scheme of the algorithm global structure.

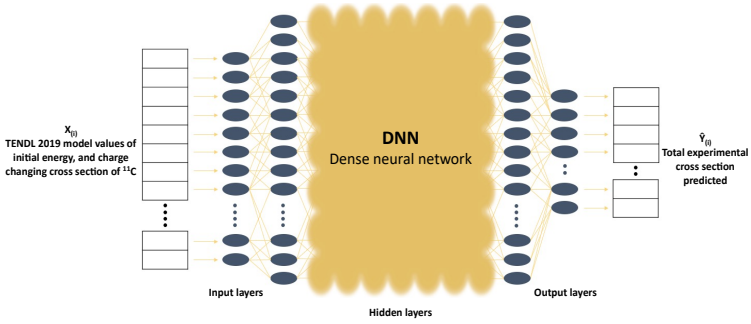

Figure 3: DINo simplified structure

During the algorithm learning phase, 70% of the TENDL model values of ^{11}C charge-changing cross-sections, alongside with their corresponding initial energy, serve as input data. Simultaneously, the total cross-section values, linked to the respective initial energies, are designated as output. To evaluate the algorithm's proficiency, 30% of the TENDL model values are reserved for testing at each epoch. Following 60 epochs, the algorithm is ready for application to experimental data.
During the algorithm testing phase on data, it receives experimental values for ^{11}C charge-changing cross-sections with associated initial energy, enabling it to predict the corresponding experimental values for total cross-sections at those specific initial energies.

3 Results

Figure 4 presents predicted experimental total cross-sections values by DINo alongside TENDL model values and actual experimental data.

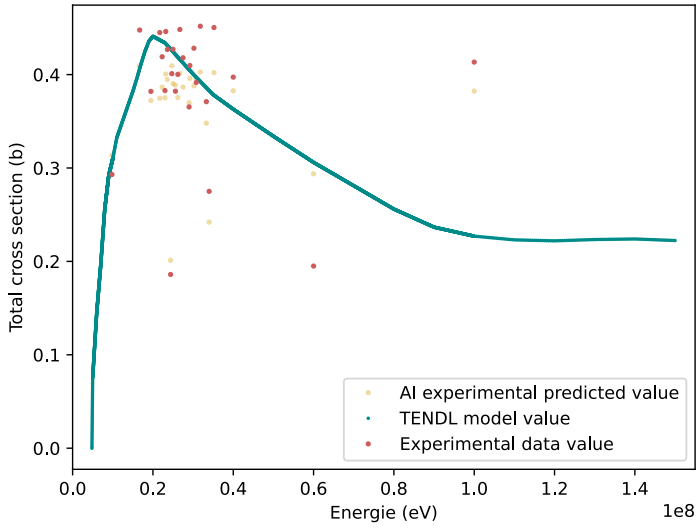

Figure 4: Total cross-section for incident protons on a ^{12}C target as a function of incident energy: TENDL model results and DINo prediction compared to experimental data (data error in the order of 2% not visible on the plot).

The comparison in Figure 5 highlights the efficacy of DINo predictions in relation to both TENDL model results and experimental data. The χ^2 values demonstrate a superior compatibility between the experimental data and the DINo algorithm predictions compared to the TENDL model.

Indeed, the χ^2 between the experimental data and the TENDL model is, like said in previous section, 4.5 ± 1.0 when the χ^2 between the experimental data and the DINo algorithm prediction is 2.9 ± 0.6.

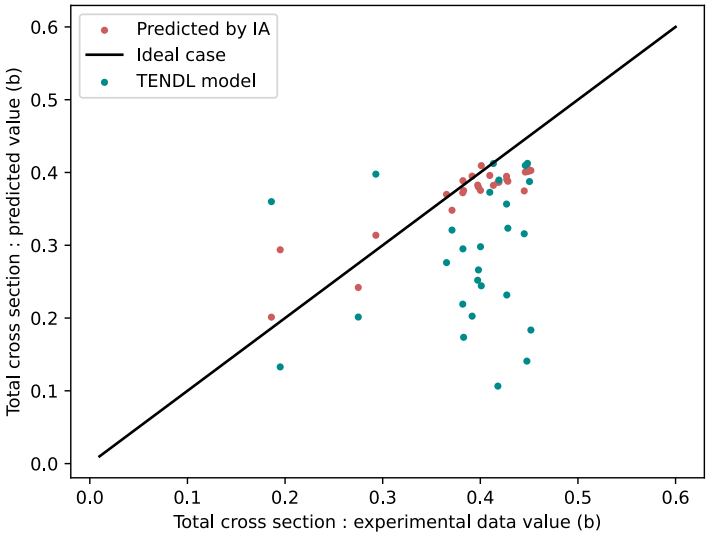

Figure 5: ^{11}C product cross-sections and total cross-section for incident protons on a ^{12}C target: TENDL model results and DINo prediction compared to experimental data (data error in the order of 2% not visible on the plot).

4 Discussion

In this study, the deep learning algorithm DINo exhibits enhanced predictive capabilities for total cross-sections compared to the TENDL model. Even in the worst case scenario, DINo's prediction align with TENDL's performance. Indeed, the χ^2 of 3.5 is reached as the best TENDL's performance and the worst DINo's performance. In optimal situations, DINo outperforms the TENDL model by a factor 2.4.

5 Conclusion

These findings underscore the potential of the deep learning approach in improving the accuracy of predicting nuclear reaction data, in order to to enhance the precision of dose calculations in particle therapy.

To establish the efficacy and reliability of the proposed algorithm in predicting missing experimental data, further investigations on additional charge-changing cross-sections and different target materials are needed. This study lays the foundation for future research aimed at expanding the scope and applicability of the deep learning algorithm in the realm of nuclear reactions.

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