Dear editor,

We like to express our appreciation to the reviewers for their comments. We are resubmitting the revised version of the paper number PIP–21–281. We have studied the comments of the reviewer carefully, and have changed the text according to the comments they have listed. Below we refer to each of the reviewer's comments.

Response to Reviewer #1

Comment 1. *A solar cell with BSF is chosen as the basis of the work, claiming that "BSF is one of the popular designs used for industrial mass production...", but this is no longer the case, BSF solar cells are present in the market due to old manufacturing lines that are still operative, but the standard now is PERC technology. If the training of the network is based on SCAPS simulations, why was not trained with a PERC structure? At least, some hint on how results would be with a PERC structure should be given. (By the way, the BSF in this work is made with B-doping, which is also a minoritary approach at the industrial level, where BSF is of Aluminium).*

Reply: The text was revised.

Comment 2. *As far as I understand, the simulation with SCAPS could be improved: emitter and BSF are uniform and this is not the case in reality. There is no mention to the metallization, are there no contacts? There should be, and they will influence the carrier transport and also the surface recombination velocities in the metal-semiconductor interface, among others.*

Reply: The text was revised.

Comment 3. *Why a voltage sweep restricted to 0.45 V? This is rather low when compared to the voltages at the maximum power point of BSF solar cells... Wouldn't it influence in the extraction of the ideality factor values?*

Reply: The text was revised.

Comment 4. *I am not sure that I interpret well the results in table 5. In the text the authors state that "the results even exceed expectations". But what I see is that the predictions fail in general, largely for the trained dataset cases, but also for the full dataset. There is some discussion on why $DNN_{FeFeB-Fe}$ performs worse than DNN_{FeFeB} and that is Ok... but DNN_{FeFeB} also fails in many cases, isn't it? (temperatures higher than 300K for the higher Fe content, 100% or more error for the training dataset...).*

Reply: The text was revised.

Comment 5. *In the jargon, we do not talk of surface resistance, but sheet resistance. Also, it is the first time that I read the "anti-recombination isotype barrier" for a high-low junction or a BSF.*

Reply: The text was revised.

Comment 6. *It is mentioned in the paper that there is Suplementary Material, but I have not had the opportunity to read it.*

Reply: The text was revised.

Comment 7. *On the other hand, the paper needs a thorough revision of English, preferably by a native or bilingual speaker. English is not my mother tongue, but I think that there are many expressions that are not correct, and make the reading difficult. From the abstract ("The low-cost and express...", "an ideality factor values"...) to the conclusions ("not numerous input parameters can be multiplied and transformed to the picture and apply a vision model..."(?), and a lot in between: "both for microelectronics, logic technologies and solar cells", "the various semiconductor barrier structures", "practical using", "Fours", "SFB", "in our further calculation", "simulated with using", "in comparing with", "more narrow", etc. etc.*

Reply: The text was revised.

Response to Reviewer #2

Comment 1. *2 Simulation details*

It is assumed that all SRH recombination in the device come from iron impurities and the associated deep level defects. It seems necessary to discuss its validity, and it could be interesting to put it against the fact that Al-BSF devices based on Czochralski silicon wafers are considered. More generally, if another type of defects is present in the solar cell, also inducing SRH recombination, is it possible to estimate to what extend are the DNNs trained here still accurate ?

Reply: The text was revised.

Comment 2. *When Fe-FeB and Fe cases are presented, it could be clearer to provide very few more explanations on both types of defects, and the important fact that iron-boron pairs can be temporarily dissociated, providing the Fe case, through the heat treatment or high illumination already mentioned.*

Reply: The text was revised.

Comment 3. *3 Deep neural network models*

*It is clear how the main training dataset is created, and how the 4 * 9 * 11 * 19 = 7524 IV curves are generated. However, the definition of the test datasets and the values for temperature, base thickness, iron concentration and doping level are not clear for each T-varied, d-varied, etc. test set.*

Reply: The text was revised.

Comment 4. *For instance, in the case of the T-varied test set, it is mentioned that the same base thickness, iron concentration and doping level values are used as in training dataset. However, 4 * 9 * 19 = 684 and the amount of 894 IVs can't be explained by multiplying with any number of temperature values. In Supplementary Material, the associated summary table do neither explain this value 894. More generally these tables are difficult to interpret. It is possible that the subset of 144 values for T-varied test has been duplicated.*

Reply: The text was revised.

Comment 5. *4 Results and discussion*

On figures 4, 5, 6 and 7, very interesting results are presented, and analyses of the dependence of estimation error with temperature, boron or iron densities and base thickness are well done. However, it seems that the same error statistics of results obtained on test datasets (instead of training dataset) would more directly assess the quality of predictions by the DNNs. For instance, the Fe-varied dataset has been identified to be the closest to "real demand" or results obtained with the all-varied dataset would also be most probably very useful. Such results could be showed in Supplementary Material, in the same form as figures 4, 5, 6 and 7.

Reply: The text was revised.