

We show our gratitude to Anonymous Referee #2 for his constructive comments. We have revised the manuscript accordingly. Please find our point-to-point responses below.

Response to Anonymous Referee #2's comments

To my understanding, this manuscript proposes a neural network method to fill for missing/invalid values in particle size distributions (PSDs) measured in situ, based on correct values measured at other size bins and on knowledge of meteorological parameters. They train a number of neural networks in which one out of 23 bins in the considered size distributions is considered missing, and is predicted based on meteorological parameters and/or on the other 22 size bins.

The study seems to show that, if PSD values are known at 22 size bins, meteorological data do not add much information for the prediction of the missing value. This finding does not sound particularly surprising to me, as I would expect PSDs to be relatively smooth, and knowing their values at 22 size bins should indeed provide a good deal of information about its value at some neighbouring bins.

MAIN COMMENTS

- While the technical work of setting up and training the neural networks looks correct as far as I can see, the main problems I see with this paper are the following:

- 1) The first problem is that I had to carefully peruse the manuscript several times before understanding what the main goal exactly was. This means that the Authors should be more upfront in describing the goals of the study and its setup in the introduction. In particular, looking at the Introduction from Line 146 onwards, I had the impression that the scope was much broader than just interpolating a PSD at some missing values. Maybe also the title can be made more informative: instead of reading "Neural network modelling ... on other particle sections, etc." it may be something like "Replacement of missing values in in situ measured particle size distributions by means of neural networks". This would give the reader a more immediate idea of what they are going to find in this paper.

Response: We understand that it might be a bit misleading to put 'neural network modelling' as the title. Considering the suggestion by the referee, we change the title as 'Data imputation in in situ measured particle size distributions by means of neural networks'. Although the concept of the paper is the replacement of negative data from raw values of particle sizer instruments, the operational applicability is wider than that because the proposed neural network method can serve as a supplement to better the current built-in algorithm of in situ particle sizer instruments. To emphasise this significant goal, we cut the unnecessary parts in the introduction and reiterate this ultimate goal throughout the manuscript.

- 2) The second problem is that I am not entirely sure what the scientific significance of this study is. Training a neural network to fill in a single value in a PSD based on knowledge of other 22 values looks like a rather standard technical exercise to me. I am not sure if it makes sense to write a scientific paper about this, but since I am not part of the in situ measurement community I may not be the most appropriate person to comment on this. In general, when you use a NN to fill for missing values in the PSD you are basically developing a functional relationship between the PSD value at the missing bin and its values at other bins, and it is quite obvious that this relationship will work well or less well depending on how the real PSD actually behaves. I am not sure what general conclusions can be drawn from the analysis presented in section 4, except for the one – widely expected in my opinion – that knowing already the PSD at almost all size bins helps a lot in predicting the missing value, compared to only knowing some meteorological information.

Response: In the field of in situ aerosol measurement, we have identified the problem that the built-in algorithm in instruments could be sometimes ill-configured and generate meaningless numbers, such as negative values especially when the actual number concentration is low. Currently, while some experts use the built-in inversion algorithm, some develop their own inversion methods. However, the tailor-made inversion algorithms have their drawbacks. Therefore, the use of built-in inversion in aid of neural networks could be a good alternative. Considering the other suggestion the referee gave, we compare this FFNN method with other simpler methods and it apparently demonstrates a better performance in terms of accuracy and reliability even though all those simpler methods also only use PSD for interpolation.

- To have a clearer idea of the added value of using a NN to replace a missing size bin in a PSD, it would be interesting to see how the NN method performs compared to a simpler approaches such as linear interpolation.

Response: Thank you for the suggestion. We agree that comparing the feed-forward neural network (FFNN) methods with other simpler approaches would be a good added value to this paper. For this, we compute the unconditional mean (UM), linear interpolation (LinI), logarithmic interpolation (LogI), next neighbour interpolation (nNI), previous neighbour interpolation (pNI) and conditional mean by regression of meteorological parameters and other particle size number concentrations as inputs (CM–met and CM–PSD, respectively). The comparison of R^2 and NRMSE is presented as Table 3 and Table 4. We also summarise the results as texts to the manuscript in Section 4.1. FFNN models outperform all the univariate methods and FFNN–PSD also shows better accuracy than CM–PSD.

- While it is fair to say that a NN predicting PSD solely based on meteorological inputs constitutes indeed a predictive model (you can try to predict the PSD anytime and anywhere you have the needed meteorological input), I am not sure the same holds for the NN that also uses measurements of the PSD itself. I mean, if you are not measuring the PSD I guess you cannot operate such NN. Therefore, I would say that the NN using PSD values as input is not a “model to estimate the PSD” but just a “NN to interpolate missing values in the PSD”. Can you please elaborate on the impact that using PSD values as input has on the operational applicability of your NN?

Response: This is very important that you have pointed out the operational applicability of the proposed neural network models (FFNN). We understand that this proposed method uses the measurements of the PSD itself and it is apparently an imputation method instead of a predictive model. However, we believe that, due to the shortcomings of the built-in algorithm in particle sizer instruments, this FFNN method can improve the algorithm and generate meaningful numbers when measuring the particle size distribution. For this, we further elaborate the significant impacts on the operational applicability of the FFNN methods that use PSD as inputs. Besides, to avoid confusion, we replace the word ‘models’ with ‘methods’ throughout the manuscript.

OTHER COMMENTS

- P1, L18, “which are able to deposit...”. What is the subject of this sentence?

Response: The sentence is now revised as ‘... fractionated size distribution, in which particles of different diameters are able to deposit ...’

- P1, L21, “invert” -> “solve”

Response: Revised accordingly.

- P2, L47. I guess D_p is the particle diameter. You should state this explicitly in the text.

Response: 'D_p' is the particle diameter in this manuscript. This explanations are now stated several times in the current version. And it is now revised as 'D_p' as suggested by another referee.

- P3, L109 and L118. What are these "kernel functions", and what does it mean that they are "not optimally configured"?

Response: The kernel functions describe the probability of particles of a certain size being measured at a certain flow rate. Thus the measured concentration in a size bin is the sum of the actual concentrations multiplied by the kernel functions. For example in Gaussian inversion method, the width and height of the kernel functions were chosen so that they resemble the difference between the measured activation curves, taking the detection efficiency into account (Lehtipalo et al., 2014). They can be 'not optimally configured' in case of a change in measured activation curves or a drop in detection efficiency. A short sentence is added to the introduction paragraph to explain this in detail.

- P3, L112, and P5, L184. It looks to me like the acronym CPC has not been defined anywhere.

Response: The acronym CPC represents Condensation Particle Counter and the definition is now included in the text.

- P4, L146, "objectives" -> "objective"

Response: Revised accordingly.

- P5, L182 and L185. I think the acronym DMA is also not defined anywhere in the paper.

Response: The acronym DMA represents Differential Mobility Analyzer and the definition is now included in the text.

- P6, L211. I guess you mean "linearly interpolated in time" here

Response: Revised accordingly.

- Section 2.3. Please summarize the inputs you used in your NNs (which and how many), preferably in a table. This information is hard to find in the paper as it is now, and should be readily available to the reader.

Response: Part of the information (the inputs of the three approaches of neural network methods) was shown in Figure 1. Considering the suggestion, we update the figure by mentioning the number of layers and number of neurons we test when developing the neural network methods.

- P6, L226. What do you mean by "generate a signal or remain silent"? Are you using a binary threshold activation function? Later on you say that you are using a sigmoid.

Response: We use sigmoid as the activation function. To avoid confusion, we remove 'generate a signal or remain silent'. Thank you for the bringing this up.

- P10, several instances. What do you mean by "mutual size distribution"? "mutual" between what?

Response: 'Mutual' here meant mutual relationship between the size sections in the aerosol population. To avoid confusion, we remove some of them and insert the above explanation in Section 4.1.

- P11, L384, I guess "which leads to a lower predictably" contains some typo. What do you actually mean?

Response: The correct word sentence is 'which leads to a lower predictability', which is now corrected in the paragraph.

- P12, L455, by “trivial” do you mean “negligible”?

Response: Thank you for suggesting a better word in this sentence. This is now corrected accordingly.

- P13, L466, “ill-configured” -> “misconfiguration” ?

Response: Thank you for suggesting a better word in this sentence. This is now corrected accordingly.