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Interactive comment on "Dissolved oxygen prediction using a possibility-theory based fuzzy neural network" *by* U. T. Khan and C. Valeo

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RC 1: "The authors present the application of the Fuzzy Neural Network (originally proposed by Alvisi and Franchini, 2011) for the prediction of the dissolved oxygen concentration in a river. The topic is of interest and within the scope of the journal. The manuscript is well written and technically sound, even though some sections could be shortened. As properly pointed out by the authors in the conclusions, "the proposed model refines the exiting model by (i) using possibility theory based intervals to calibrate the neural network (rather than arbitrarily selecting confidence intervals), and (ii) using fuzzy number inputs rather than crisp inputs." Indeed, the first aspect represents a valuable, but rather limited, step forward with respect to the existing model. As far as the second aspect concerns, I really appreciate both the idea of considering the inputs

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of the FNN as fuzzy numbers and the approach used to define these fuzzy inputs."

AUTHOR RESPONSE:

Thank you for these positive comments. We will endeavour to shorten the length of the final revised manuscript where possible.

RC 2. "Unfortunately, the manuscript misses to point out the benefits of using the fuzzy inputs. A comparison of the performances of the prediction model featuring fuzzy inputs with respect to the prediction model using non-fuzzy inputs is completely missing. Does the application of fuzzy inputs allows for a more accurate prediction of the DO and, most important, for a reduction of the output uncertainty? Indeed, the discussion of the result is mainly focused on the benefits of using a FNN with respect to a traditional NN in which uncertainty is disregarded, but this should not be the main task of the manuscript, given that benefits of FNN have already been pointed out in other studies, whereas the attention should be focused on the application of Fuzzy inputs."

AUTHOR RESPONSE:

We apologise for not including more details of the specific advantages of the fuzzy number inputs in the FNN. We did include the following statement in the original manuscript:

"The method is adapted to be able to handle fuzzy number inputs to produce fuzzy weights and biases, and fuzzy outputs. The advantage is that the uncertainties in the input observations are also captured within the model structure." (Section 1.2, page 12318, line 3).

We will make an effort to highlight this in the revised manuscript, along with the fact that, if possible (i.e. data is available as is the case with this research), the uncertainty in the input data should not be ignored and should be included in the model, and our method proposes a method to do this. Existing methods do not allow for this and thus, this is the major advantage of our research.

We will also highlight the fact that the proposed method to create the fuzzy inputs have

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limited assumptions of the underlying distribution of the data and relies only on objective information (i.e. no subjective information is used to construct the fuzzy numbers as is the case in many studies). This addresses a major concern when using fuzzy numbers for many numerical applications.

We are happy to include the suggested comparison (between the existing FNN method with crisp inputs and the proposed FNN with fuzzy inputs) in the in final revised manuscript. However, for clarification we would like to highlight a few issues related to this comparison:

1. Conceptually, an FNN model with crisp inputs and fuzzy inputs are completely different, making a direct comparison difficult (or at least not straightforward). It is not just a case of comparing error metrics, or percent of data captured within intervals (e.g. as shown in Tables 3 and 4 in the initial manuscript). This is because these two approaches are essentially modelling the system completely differently. In the crisp input case, the input uncertainty is completely ignored even though this data is available. This is essentially making a complex problem less complex by limiting the amount of data that is used in the model. Also, there is no definitive answer to what the crisp input should be: is it the mean daily value? The median value? Or the corresponding value from the fuzzy number at $\mu = 1$? (n.b. this final option is what we have selected for our comparison to allow for the closest approximation between the two approaches). On the other hand, the fuzzy number based input use all the available information (i.e. hourly observations), and condenses it into one fuzzy number. Arguably, in this approach the complexity of the system is not being ignored (by reducing the highly variable/uncertain inputs into crisp, single-values inputs). Thus, any analysis of the performance of these two methods should highlight that the proposed method accomplishes something that the existing method cannot.

2. Currently, they are no suitable performance metrics to compare fuzzy number based models with each other (or for that matter even with other crisp models). While the Nash-Sutcliffe Efficiency (or other similar metrics) can be calculated on an α-cut in-

terval basis, these values do not represent the overall model performance nor does calculating the amount of extreme values within the fuzzy interval. A suitable alternative may be to use the training method of the FNN: to see if the percentage of data captured within each interval is similar (see Table 4 in the manuscript). However, given that this is an optimisation problem, and both methods will have the same tolerances, the result is expected to be the same for both (at least for the training dataset), although the computation time will differ. Thus, the computation time may be used as an effective metric, but even this does not account for the fact that in the proposed method the uncertainty in the inputs is being included in the model, and hence, the extra computational cost is acceptable if the input uncertainty is high (as in the case in this research where flowrate and water temperature are used as inputs).

3. With respect to "more accurate predictions": please refer to Figure 1 attached to this response that includes a comparison of trend plots for 2004 for crisp and fuzzy inputs, as an example of a comparison between both methods. Using fuzzy inputs means that the output is not necessarily symmetrical about the modal value (as is the case with this crisp inputs). This means that the outputs are more skewed, resulting in more of the "very low DO" values being captured within the predicted intervals. It also shows that the upper limit for fuzzy inputs is much closer to the observations. Thus, from this point of view, the benefits of using fuzzy number inputs are clear, though the accuracy (in this case this may be the amount of data captured within intervals, which by definition is the same for both) or precision (e.g. width of various α-cut intervals) may not be different. Again, it is worthwhile to point out that in the proposed system more data (due to the construction of fuzzy numbers) was used to train the model, and represents the real uncertainty in the system.

4. With respect to a "reduction in output uncertainty": the uncertainty is reduced because by using fuzzy inputs all the observed data is used to calibrate the model, and this gives a full spectrum of possible outcomes. In other words, the uncertainty is lower because all possibilities of the output value have been mapped out using all available

input data. In the crisp input case, the uncertainty is by definition higher, since the variability or uncertainty in the input data has not been accounted for (only one crisp value is used). Using this definition of uncertainty means that there is a reduction in output uncertainty (since more information is used), while not necessarily meaning that the predicted intervals are smaller.

5. Based on our experience using fuzzy number based data-driven methods for hydrological and environmental applications, there is still a need and demand to compare new methods (like the one proposed in this research) with existing non-fuzzy methods to provide a baseline reference with other literature (see a brief discussion on page 12331, line 4). Thus, we think it is important to include this comparison in this manuscript so that readers who may be unfamiliar with fuzzy number and possibility theory based methods may be able to directly compare results from this research to other NN based results. Secondly, while we agree that the benefits of the FNN method has been highlighted in previous studies, we would like to highlight that the FNN used in this research uses a different training criteria (i.e. the selection of PCI shown in Table 2 in the manuscript) compared to previous work, so there is a benefit in showing the results for this comparison.

RC 3. "Furthermore, I have some concerns also on the benefits of using the FNN with respect to a deterministic NN. Indeed, the authors state that (page 12351) "the FNN method predicts a probability of low DO (even if it is relatively small) on days when the crisp ANN does not predict a low DO event. This value can be used as a threshold by water resource managers for estimating the risk of low DO. For example, if forecasted water temperature and flow rate are used to predict minimum fuzzy DO using the calibrated model, if the risk of low DO reaches 14 %, the event can be flagged." Capability of the FNN of identifying very low DO values is certainly appreciable, but on the other hand, by looking at figure 6, it seems that most of the predicted fuzzy DO numbers features a support which in some way intersects very low (i.e. <5 mg/l) DO values. In other words, according to the criteria proposed by the authors how many events would

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be flagged? And, how many of these flagged events were low (i.e. <5 mg/l) observed DO events and how many would have been false alarms?"

AUTHOR RESPONSE:

First, we would like to highlight that the data has been filtered to include only data from the April to October period for each year (to remove the ice-free period in the river). This means that the entire analysis has been conducted on the time period that is most susceptible to low DO (due to high water temperature). In other words, we are focusing on the most critical time period already. Thus, it is expected that the majority of the days will have some possibility of low DO. This phenomenon is correctly reproduced in Figure 6 that shows that indeed there is a possibility (though typically at low membership levels) to predict "very low DO" (< 5mg/L) values.

Second, it is worth noting that using possibility theory means that "something should be possible before it is probable", i.e. Zadeh's consistency principle. Thus, the fact the FNN model predicts a possibility of very low DO does not necessarily mean that there will be a significant or high probability of this event to occur. In fact, this can be seen in the trend plots (Figs. 7 and 8 in the manuscript) that show that the produced fuzzy number membership functions are highly skewed (see page 12348 Line 10 and more examples in Figure 10), i.e. the predictions at the lower limit of the α-cut at μ = 0 are much lower than the rest of the membership function. In the possibility-probability framework adopted in this research (see Sections 2.2 and 2.4 in the manuscript), this means that the highly skewed membership functions translate into very low probability events (based on Equation 20 in the manuscript).

Third, we have identified (page 12348, Line 20) that the 2004 data has contributed to the wide intervals in the predictions. The rapid decrease in DO in the 2004 data (which are likely due to instrument error), along with the optimisation constraints that requires 99.5% of the data to be included in the predicted interval at μ = 0, means that the produced output will include these outliers at the expense of creating wider intervals.

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However, we have noted that as more data is available and include in the model, the 0.5% of data points that will no longer be captured within the $\mu = 0$ interval are likely to be these outliers.

Finally, we are happy to include in the final revised manuscript a summary of the flagged days using our criteria for low DO as well as those incorrectly identified at the given threshold. We hope that this will satisfy all of the Referee's comments.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 12, 12311, 2015.

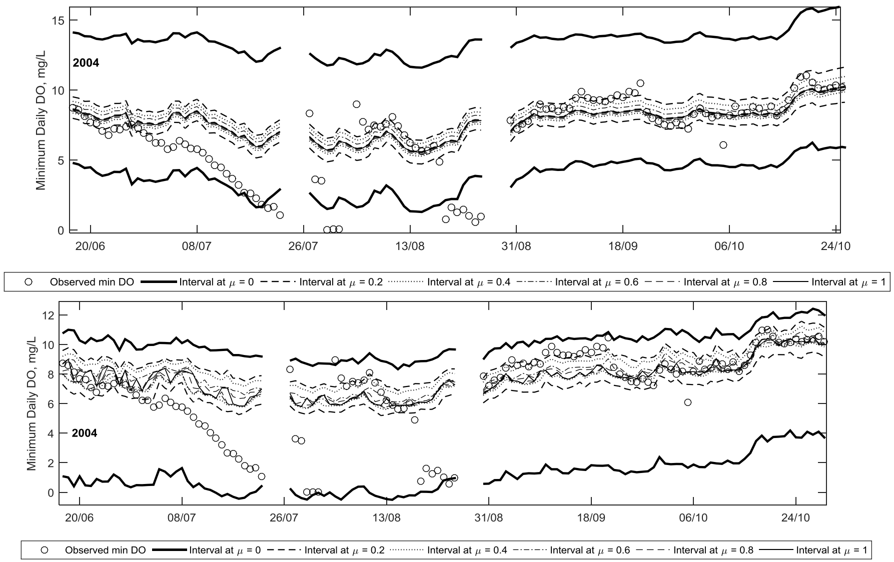

Figure 1: A comparison of trend plots for 2004 using (top) crisp inputs, and (bottom) fuzzy inputs in the FNN

Fig. 1.

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