List of Responses

Responds to the Anonymous Referee #2's comments:

Special thanks for your good comments which are very useful for us to improve the paper.

1. Response to comment: - The English needs substantial improvements.

Response: As Reviewer1 suggested that we have tried our best to improve the presentation of this paper, and correct the syntax and spelling errors.

2. Response to comment: - At the moment the paper reads like an adapted/modified and shortened version of Zhang et al., without trying to get some 'added value'. Furthermore, at some places the meaning is not clear without the Zhang et al. paper (e.g. the definition of 'forecasting benefits' (Chapter 4.3.1), the pseudocode (Table 1 in particular 8,10,11)).

Response: It is really true as Rreview2 suggested that we should give more details about ACPW algorithm and other terms.

"The update rules of the PSO and WSA are descripted in the following.

The PSO use the classical formula (4) to update the individuals.

$$\begin{cases} v_i^{k+1} = \omega v_i^k + c_1\alpha\left(o_i^k - u_i^k\right) + c_2\beta(o_g^k - u_i^k) \\ u_i^{k+1} = u_i^k + \gamma v_i^{k+1} \end{cases} \tag{4}$$

where the superscript k is the current iteration and $k+1$ is the next iterative step. v_i^{k+1} is the updating velocity of the individual u_i^k. ω is the inertia coefficient. c_1 is the learning factor for self-awareness to track the historically optimal position, and c_2 for social-awareness of the particle swarm to track the globally. α and β are the random numbers uniformly distributing in (0, 1). o_i^k is the local optimum and o_g^k is the global optimum in the k^{th} iteration. γ is the restraint factor to control the speed. u_i^{k+1} is the updated individual.

There are two ways for updating individual in WSA, prey and escape, which represent the functions of searching in a local region and escaping from a local optimum.

$$\begin{cases} u_i^{k+1} = u_i^k + \theta \cdot r \cdot rand(\ ) & dist\left(u_i^k, u_i^{k+1}\right) < r.and.J(u_i^k) < J(u_i^{k+1}) \\ u_i^{k+1} = u_i^k + \theta \cdot s \cdot escape(\ ) & p > p_a \end{cases} \tag{5}$$

where the superscript k or $\mathrm{k}+1$ is also the iterative step, θ is the velocity, r is the local optimizing radius, which smaller than the global constraint radius δ. *rand()* is the random function, whose mean value distributed in [-1,1]. *escape ()* is the function of calculating a random position, which is larger 3 times than r. s is the step size of the updating individual. p is a random number in [0,1], p_a is the probability of individual escaping from the current position."

3. Response to comment: - As the authors note (P2 L10ff, P10L28), the adjoint version of WRF-ARW used for this study appears not very well suited for the present purpose (typhoon prediction). It is not clear how important this issue is for the conclusions drawn by the authors.

Response: In this paper, the purpose of solving CNOP is to identify sensitive areas of typhoon target observations. The sensitive areas are used to improve the forecast skills. To evaluate the ACPW, we need compare it with the classical method, i.e. ADJ method. And the ADJ method must use the adjoint model. Hence, we also use the adjoint model.

“Recently, there is only one study which identify sensitive areas by using the WRF-ARW model (Yu et al., 2017). Yu et al. (2017) use the SPG2 (spectral projection gradient 2) algorithm (Ernesto et al., 2001) to solve CNOP. As we all know that the SPG2 algorithm must use the adjoint model to obtain the gradient information for updating the search direction. But the adjoint model of WRF-ARW only has one gravity dragging boundary layer parameterization scheme for such study, which limits the simulation of typhoon. In addition, when the horizontal resolution is higher than 30km, the gradient information calculated by the adjoint model has errors and omissions, which results in falling into the local optimum or optimization failure. Hence, an algorithm without using the adjoint model is needed.”

“To compare with the ADJ method, it is limited when we construct the physical parameterization schemes of WRF-ARW. Because the corresponding adjoint model only provides one physical parameterization scheme. And that may be the reason of bad simulated Fitow typhoon track. Since the ACPW method is free of the adjoint model, we will try more complicated physical parameterization schemes and improve the horizontal resolution to do such research. Moreover, ACPW can be used to solve CNOP in the numerical models no having adjoint model, such as GFDL (Geophysical Fluid Dynamics Laboratory) and CESM (Community Earth System Model).

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