1. My main concern at this moment is your claim on “usability and efficiency”, i.e., practical relevance of your brief. I just don’t see how the current brief can be more efficient than simply write 10 lines of code in R.   
     
   Therefore, it would be sufficient for me at least if you compare your current results to R package “forecast", and smart persistence model. The remaining suggested changes, we can leave them to the reviewers (or maybe they have other suggestions)  
     
     
   ***Response****: To the best of our knowledge, the mentioned tools do not automatically conduct statistical tests (such as for stationarity and residuals). We believe our main contribution is in providing a scheme which suggests “what to do when”, rather than inventing a new method. Also, we now compare results against a direct ARMA model (not hourly) and a smart persistence model.*

*In addition, we have added further details of the text, line 6.*

*[…] Representation of the uncertainty in renewable energy is typically done by either using samples or a set representation from the underlying stochastic process. The former generally requires forecasting tools for generating synthetic samples or scenarios that are used for feeding decision-making optimization models [1]. The latter requires a simple representation of the stochastic process in order to embed it into more sophisticated decision-making tools [2]. In both cases, but especially so in the latter, complex forecasting models result in models that are hard to integrate. […]*

Issues:

1. Please see Ref. [1] for a classification of solar forecasting methods. In that paper, the concerns on univariate methods have been clearly expressed, an not advised in general. Should you feel that a rebuttal is necessary, please give detailed reasons of choosing ARMA in your manuscript.

***Response****: We have now added a citation for Ref[1] and acknowledged that ARMA models have limitations. We also added that ARMA models are still widely used in literature for their simplicity and ease of implementation.*

1. The literature review on time-series-based solar forecasting is incomplete. At the very least, you are missing out my many previous works on the subject.

***Response****: While we cannot do a complete literature review in a 1500 word limit, we have now updated some of our citations for previous works as well as included three of your works.*

1. Most statistical/non-statistical tools such as R, SAS, Matlab or python, provide existing ARMA implementations using sophisticated, automatic, model identification and fitting procedures. In what way is your approach different from theirs, and why?

***Response****: We do use MATLAB for our computations. However, to the best of our knowledge, all the mentioned tools do not* automatically *check for stationarity, autocorrelation, and evaluate performance metrics. While all of these features are indeed available in nearly all packages, one needs to decide which statistical tests to use when. Our main contribution is in having a handy “cheat-sheet” which serves as a guide for future forecasting using ARMA models.*

1. I now see how you train your models with data from each hour separately. Firstly, I have seen this approach before in solar forecasting. The drawback of this kind of modeling is that you are missing out the autocorrelation among the different hours. On this point, Hugo has used a more advance input selection in his 2012 paper [2]. Since that paper, many variations have been proposed, you are missing out all of those.

***Response****: We acknowledge this limitation and mention it in the paper now as well as the Ref[2].*

1. Your confidence interval appear to be outside the physical range of solar radiation, see [3].

***Response****: We apologize but we do not understand this comment. We do not forecast solar radiation, but solar power directly from historical data.*

1. Lastly and most importantly, this manuscript lacks comparison with the existing

models. I require several things:  
a.      A comparison with the clear-sky persistence model, i.e., persistence forecasts with clear sky adjustment

b.      A comparison with an existing implementation from one of the packages I mentioned earlier (also train by hour).  
c.      A comparison with an implementation that trains the time series as a whole, with clear-sky detrending, or other time series deseasonalization (diurnal trend) method. If the numbers of day-light hours are different throughout the year, use dynamic time warping to align that.  
d.      A comparison with other time series methods, such as MLP, ETS, or SVM (there are hundreds of them, so pick three)

***Response****: We cannot perform a comparison with clear-sky models, as predict directly from historical data. However, we now do make a comparison with a “smart-persistence” model which assumes the next forecast is an average of some previous h forecasts and an ARMA model fit to the entire data. We report results in the Appendix.*  
  
References:  
[1] Dazhi Yang, Jan Kleissl, Christian A. Gueymard, Hugo T.C. Pedro, Carlos F.M. Coimbra, History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining, Solar Energy, 2018.  
  
[2] Hugo T.C. Pedro, Carlos F.M. Coimbra, Assessment of forecasting techniques for solar power production with no exogenous inputs,  
Solar Energy, Volume 86, Issue 7, 2012  
  
[3] Isaac Moradi, Quality control of global solar radiation using sunshine duration hours,  
Energy, Volume 34, Issue 1, 2009.