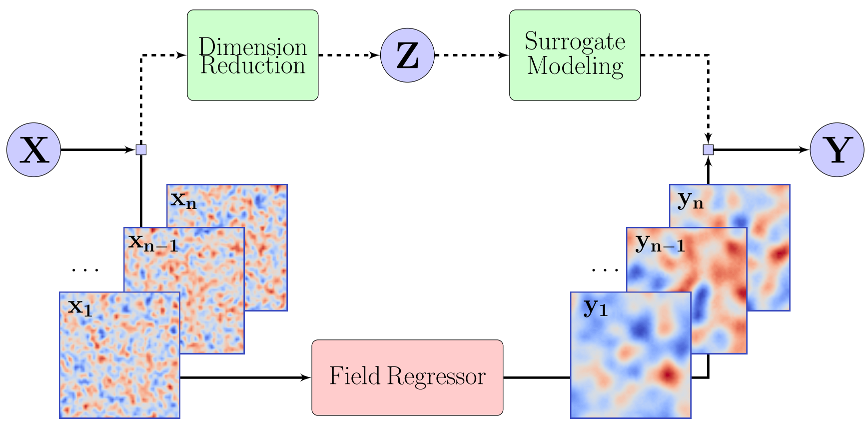
To Reviewer # 5:

We appreciate the positive feedback from the reviewer. We found the carefully marked comments are very helpful.

To Comment # 1:

Concern: ***The third part of Fig. 1 is not clear.***

Response: Yes, thank you for bringing this to our attention. To address this, we have prepared another plot illustrating this idea.

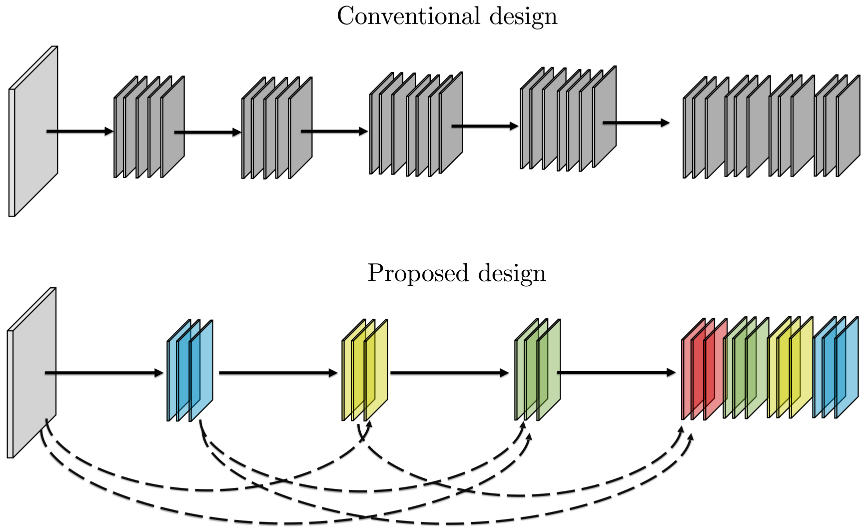


where X/Y is the high-dimensional input/output and Z denotes the dimension-reduced space. The point we want to raise is that compared to conventional approaches, the proposed method directly deal with high-dimensional systems.

To Comment # 2:

Concern: ***Explanation of the strengthening mechanism by skip connections.***

Response: Yes. Compared to the conventional design, skip connections represented by the dashed lines allow the network to reuse the information extracted from previous layers, and hence strengthen the learning mechanism. Moreover, skip connections improve the efficiency of model learning by fast extracting sufficient information for the output prediction. However, conventional approaches address this sufficiency issue by adding more layers, which in turn increase the model parameters. A graphic illustration is given below.



To Comment # 3:

Concern: ***Is this procedure also appropriate on large scale problems?***

Response: Yes, the core idea of the proposed method is to replace the time-consuming finite element model by an easy-to-evaluate surrogate model. In the context of structural analysis, we have tested the proposed method on computing linear and nonlinear responses. With the aim of applying this method to more application problems, we will share the code upon publication of this manuscript. Meanwhile, a detailed guidance regarding potential applications has been added to the conclusion section of the revised manuscript.

To Comment # 4:

Concern: ***What is the prescribed statistics?***

Response: Yes. The prescribed statistics in this manuscript indicate the mean and covariance functions of a lognormal random field.

To Comment # 5:

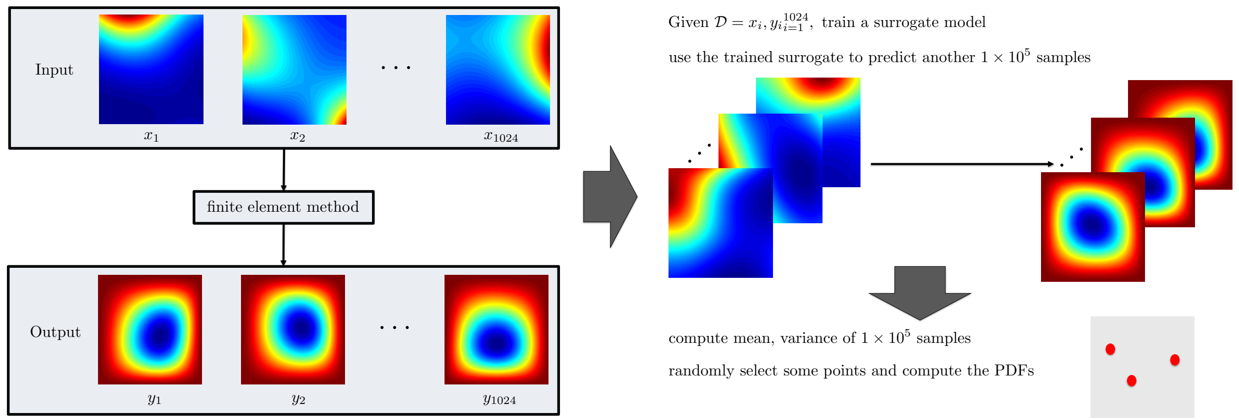
Concern: ***There is some jump in the methodology section.***

Response: Yes, we agree with the reviewer. Therefore, we have rewritten Section 3, explicitly stating the state-of-the-art techniques we have used. A section discussing model architecture and hyperparameter identification is added before the model construction part to make the whole presentation more consistent.

To Comment # 6:

Concern: ***In the case study, what is the process of computing statistical moments and PDFs?***

Response: Yes, thank you for raising this point. Take case 1 for example, input is the random material field and output is the structure deflection. We generate 1024 input samples and use finite element (FE) method to solve the problem. Then, we train the surrogate model using these 1024 samples. Next, we generate another 1×10^5 samples and use the FE and trained surrogate to obtain the corresponding outputs respectively. Finally, we compute the mean and variance of these 1×10^5 samples. Also, we randomly selected some points in the domain and check their associated PDFs. A graphic representation of the workflow is given below.



To Comment # 7:

Concern: ***What is the error shown in the results plot?***

Response: Yes, thank you for the question. In the model validation phase, let y denote the truth value computed by the finite element method and $\hat{y}$ be the predicted value via the surrogate model. The error is defined as $y - \hat{y}$. In the revised manuscript, we have also added a new accuracy indicator that is defined as:

$$\mathcal{E}\left(\mathbf{u}_{\mathrm{FR}}, \mathbf{u}_{\mathrm{FEM}}\right) = \frac{\left|\sum_{i=1}^{n_x} \sum_{j=1}^{n_y} \left|\mathbf{u}_{\mathrm{FEM}}\right| - \sum_{i=1}^{n_x} \sum_{j=1}^{n_y} \left|\mathbf{u}_{\mathrm{FR}}\right|\right|}{\sum_{i=1}^{n_x} \sum_{j=1}^{n_y} \left|\mathbf{u}_{\mathrm{FEM}}\right|}$$

It shows the relative error in terms of the whole field.