Convergence Improvement of Surrogate Based Optimization for Reconfigurable Antenna Design Using Knowledge Based Inverse 3-step Modeling

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Abstract

Engineering design process requires modeling and optimization to find optimum design parameters. While direct optimization only exploits time consuming but accurate fine model, surrogate based optimization exploits less accurate but fast coarse model to reduce the overall computational effort. In this work, space mapping with inverse difference technique is applied to antenna design problem together with efficient 3-step modeling. The combination of two techniques provides less computational effort and better convergence through the accuracy improvement based on the new inverse 3-step modeling strategy. The inverse coarse model which is used for the parameter extraction process during the optimization is realized by knowledge based inverse 3-step modeling. Inverse 3-step coarse model is obtained by multi layer perceptron in MATLAB ANN toolbox. The efficiency of the combination of space mapping with inverse difference technique and 3-step modeling strategy will be demonstrated by reconfigurable antenna design example in terms of their convergence and accuracy through its multiple operating frequency characteristic.

1. Introduction

Surrogate based optimization techniques [1] have emerged to remove expensive and time consuming calculations of a direct optimization process. In these techniques, more accurate but time consuming fine model evaluation is utilized in limited number of iterations. Moreover less accurate but cheaper coarse model evaluation is mainly utilized during optimization process, hence the time consumption of surrogate based techniques can be less than conventional optimization techniques.

The aim of Space Mapping (SM) which is one of the surrogate based optimization techniques is to constitute mathematical link from the fine model parameter space to the coarse model parameter space. The coarse model becomes more related to the fine model through this mapping and it provides approximate responses more similar to the fine model responses. SM exploits affine mapping which needs coarse model parameters obtained by parameter extraction process [2].

The difference mapping idea was introduced to exploit the existing knowledge obtained from fine model. This knowledge is known as the coarse model in surrogate based techniques. The knowledge based techniques [3] use this knowledge but especially during modeling process as well. Through the combination of difference mapping and the inverse coarse model obtained from the fine model using the relationship between its input and output, Space Mapping with Difference [4] (SM-D) technique has been developed. Moreover to remove inverse matrix calculation, Space Mapping with Inverse Difference [4, 5, 6, 7] (SM-ID) technique has been developed by combining the inverse difference mapping and inverse coarse model. Both techniques show fast convergence performance as they are based on limited number of fine model execution. Difference mapping is based on Prior Knowledge Input with Difference [8, 4, 9, 10] PKI-D technique which is a part of knowledge based neural network techniques [3, 10], . Difference mapping is based on embedding knowledge into a mapping where the output is the difference between fine and coarse model parameters. Since this technique depends on forming a mapping based on the difference, it is called difference mapping to point out its difference from other SM based techniques.

The inverse coarse model determines the coarse model design parameters that's why directly effects the performance of SM-ID algorithm. The gap between the fine and the coarse model design parameters should be less for obtaining better convergence by conventional ANN based inverse coarse model [7]. In this study, knowledge based 3-step modeling strategy is used for improving the accuracy of inverse coarse model. Therefore the convergence of SM-ID will be shown for model improvement compared to previous results in terms of the required number of fine model evaluations.

Reconfigurable microstrip patch antennas [11] can be applied to cognitive radio, Multiple Input Multiple Output systems, satellites and other applications in wireless communications [12]. They provide the ability to tune various antenna parameters effectively such as the operating frequency, polarization and radiation pattern in a single antenna.In this study, return loss (S_{11}) of the ON-ON state reconfigurable antenna can be calculated by CST simulations for the operating frequency from 2 GHz to 6 GHz. ANN based and 3-step based inverse coarse models are generated by feed-forward Multi Layer Perceptron (MLP) through MATLAB Neural Network Toolbox.

2. Space Mapping with Inverse Difference Technique

Space Mapping with Inverse Difference (SM-ID) technique [4, 5, 6] involves inverse coarse model usage to eliminate parameter extraction process. The inverse coarse model can be formed by ANN modeling. The considered ANN can be trained either with a small data set obtained from fine model or with a

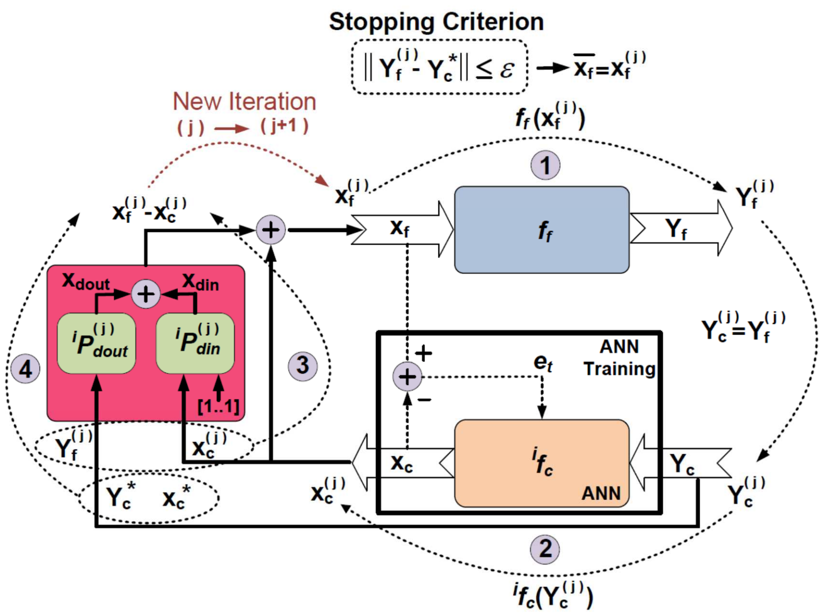


Figure 1. Main iteration steps of space mapping with inverse difference (SM-ID) techniue.

larger data set obtained from the coarse model. Model parameters and model responses are used as inputs and outputs during training process of feed-forward MLP. More training data is required to increase the accuracy of the inverse coarse model. One hidden layer would be sufficient for ANN but two hidden layer is very convenient to solve highly nonlinear complex modeling problems. After training process is completed, inverse coarse model can generate coarse model input parameters to construct difference mapping from coarse model parameters to fine model parameters.

Difference mapping utilizes fine model responses without extra computational burden. This existing knowledge is embedded to mapping structure, hence the mapping constitutes the connection between optimum coarse model and desired fine model parameters. This connection as it depends on fine model responses provides extra knowledge during generation of new iteration point. Before main iteration steps of SM-ID, desired response should be taken as coarse model optimum response and coarse model optimum input parameters should be calculated by inverse ANN coarse model. The main iteration of SM-ID starts with fine model input parameters which are equal to coarse model optimum input parameters. Main iteration steps of the SM-ID technique is denoted in Figure1. Algorithm of SM-ID is given below:

Step 1 - Stopping Criterion :

calculate ${Y_f}^{(j)}{=}f_f({x_f}^{(j)})$ and if $\|{Y_f}^{(j)} - {Y_c}^*\| \leq \varepsilon$

then $\overline{x_f} = {x_f}^{(j)}$ else go to step 2.

Step 2 - Inverse Coarse Model Response :

find ${x_c}^{(j)}$ using ${x_c}^{(j)} = {^i}f_c({Y_c}^{(j)})$

Step 3 - Forming ${^i}P_d$:

form ${^i}P_d^{(j)}{=}\begin{bmatrix} \begin{bmatrix} {^i}P_{din}^{(j)} \end{bmatrix} & \begin{bmatrix} {^i}P_{dout}^{(j)} \end{bmatrix} \end{bmatrix} = Q^{(j)} {D^{(j)}}^{\dagger}$

$Q^{(j)} = \begin{bmatrix} ({x_f}^{(1)} - {x_c}^{(1)}) & \ldots & ({x_f}^{(j)} - {x_c}^{(j)}) \end{bmatrix}_{n \times j}$

$$D^{(j)} = \begin{bmatrix} 1 & \ldots & 1 \\ {x_c}^{(1)} & \ldots & {x_c}^{(j)} \\ {Y_f}^{(1)} & \ldots & {Y_f}^{(j)} \end{bmatrix}^T_{(n+k+1)\times j}$$

where k denotes the number of coarse model outputs.

Step 4 - New Iteration Point :

$x_f^{(j+1)} = {^i}{P_{din}}^{(j)}(1, {x_c}^*) + {^i}{P_{dout}}^{(j)}({Y_c}^*) + {x_c}^*,$

set $j = j + 1$ go to step 1.

3. Inverse ANN Modeling Concept

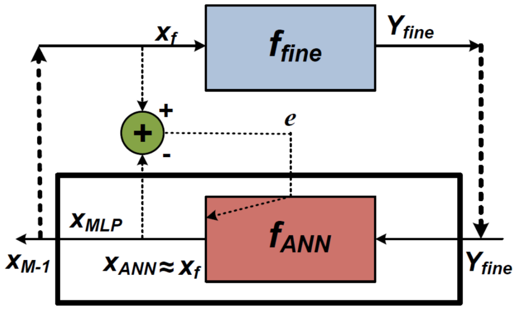
Artificial neural network (ANN) has been used as an important technique in engineering modeling and optimization. ANN has been widely preferred for modeling purposes in many disciplines such as function approximation, pattern recognition, signal processing, microwave design and so on [3, 8]. The main reason for ANN being so popular among other modeling techniques is that ANN needs only input-output information obtained from the detailed physical/EM simulation models. The main purpose of the training process is to reduce the error value as given in Figure 2 (a) and to increase the generalization capability of the ANN model. Inverse ANN modeling is usually preferred to determine design parameters during engineering design process. Weight coefficients can be obtained by the optimization process as shown in (2).

$$w^* = \arg\min_{w} \left\| \ldots \quad e^{(i)T} \quad \ldots \right\| \qquad i = 1, 2, ..., N \tag{1}$$

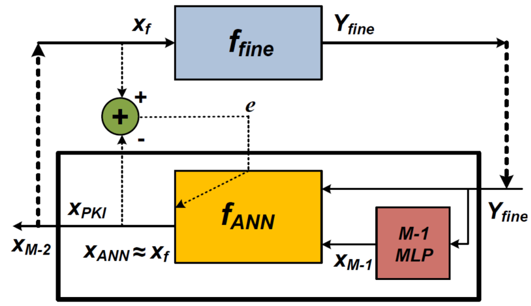
where w indicates weight coefficient of the inverse ANN model and N indicates the number of training data. i represents which training data is evaluated by the training process. The error term in (1) can be defined by (2).

$$e^{(i)} = x_f^{(i)} - f_{ANN}\left(Y_{fine}^{(i)}\right) \tag{2}$$

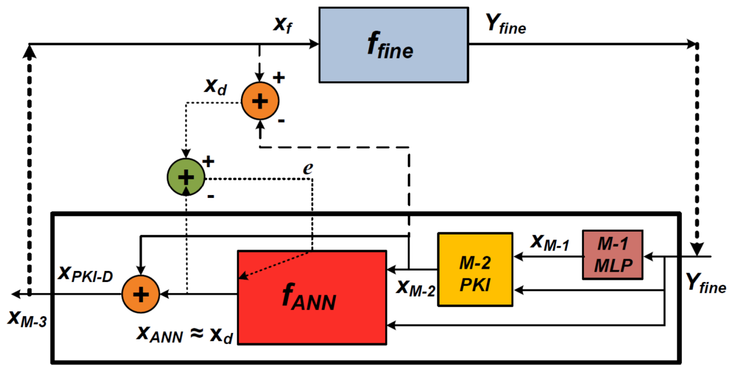
where f_{fine} and f_{ANN} indicate the fine model and the ANN model, respectively. x_f indicates design parameters of



(a) MLP structure of $M-1$ for generating knowledge (inverse ANN coarse model).



(b) PKI structure of $M-2$ for improving the accuracy of inverse ANN coarse model $M-1$ and reducing complexity of the ANN model.



(c) PKI-D structure of $M-3$ for more accuracy via $M-2$ usage as the extra input and the target difference between $M-2$ and the fine model design parameters.

Figure 2. Each discrete and also sequential training process of 3-step modeling strategy to improve the accuracy of design parameters which are obtained by ANN based inverse coarse model $M-1$.

the fine model. After the training process is completed, the final response of the inverse ANN model can be formulated by (3).

$$x_{ANN} = f_{ANN}\left(Y_{fine}\right). \tag{3}$$

4. Inverse 3-step Modeling Strategy Exploiting Knowledge Based ANN

Although conventional ANN modeling provides easily applicable model in terms of input-output relationships only, the modeling results are not always successful for highly nonlinear and time consuming engineering problems. More accuracy with less time consumption is desired for computationally expensive modeling. More training data can improve the accuracy but more number of iterations is required to satisfy the stopping condition in this case. If an engineering problem is handled in terms of difficulty level from easy to hard, less complex part of the problem requires less complex ANN model.

3-step modeling strategy has been developed to deal with more complex, highly nonlinear and time consuming modeling in engineering design problems. Main contribution of the new strategy is that former model improves latter model via knowledge based modeling techniques. The contribution is to provide step by step improvement and final one is generally better than conventional ANN modeling.

3-step modeling strategy starts with knowledge generation using conventional ANN modeling. This knowledge generating model is called the coarse model which is necessary for KBANN techniques. In this study, first model is considered to obtain more accurate model using 3-step modeling strategy as depicted in Figure 2 (a). In the second step, PKI utilizes this coarse model as an extra input besides input parameters of the problem to reduce ANN complexity, which constitutes general correction instead of detail one as depicted in Figure 2 (b). PKI-D utilizes coarse model two times. While coarse model is firstly used as extra input, it also redetermines the ANN target using the output difference Y_d at the same time as shown in Figure 2 (c). Since PKI-D utilizes new target in terms of the output difference between the fine model and the coarse model obtained by PKI model in the second step, third step is used to enable more improvement in 3-step modeling. Step 1 and step 2 generate $M-1$ and $M-2$ which are shown in Figure 2 (a) and (b). Step 3 is used for PKI-D training and data generation of step 3 in terms of $M-1$ and $M-2$. All necessary steps for 3-step modeling are given below:

3-step Modeling Algorithm:

- ***Inverse coarse model M-1 is generated by conventional ANN:***

  ANN training by using (1).

  $e^{(i)} = x_f^{(i)} - f_{ANN}(Y_{fine}^{(i)}).$ i = 1, 2, ..., N.

  $x_{M-1} = x_{MLP} = f_{ANN}\left(Y_{fine}\right).$

- ***M-2 is generated by PKI:***

  PKI training by using (1).

  $e^{(i)} = x_f^{(i)} - f_{ANN}(Y_{fine}^{(i)}, x_{M-1}^{(i)}).$

  $x_{M-2} = x_{PKI} = f_{ANN}\left(Y_{fine}, x_{M-1}\right).$

- ***M-3 is generated by PKI-D:***

  PKI-D training by using (1).

$$e^{(i)} = \left(\underbrace{x_f^{(i)} - x_{M-2}^{(i)}}_{x_d}\right) - f_{ANN}(Y_{fine}^{(i)}, x_{M-2}^{(i)}).$$

$$x_{M-3} = x_{PKI-D} = f_{ANN}\left(Y_{fine}, x_{M-2}\right) + x_{M-2}.$$

Since 3-step modeling requires three discrete and sequential training processes, the training process of $M-2$ utilizes generated responses by $M-1$ and the training process of $M-3$ utilizes generated responses by $M-2$. Finally $M-3$ generates the responses in terms of $M-1$, $M-2$ and its ANN model.

5. Reconfigurable Antenna Design Example

Reconfigurable microstrip patch antennas [11] can be chosen for design example in this work. Return loss (S_{11}) of the ON-ON state reconfigurable antenna can be calculated by CST simulations for the operating frequency from 2 GHz to 6 GHz as given in Figure 3. f_{opt} in (4) which is obtained by minimum value of S_{11} is desired response for optimization in reconfigurable microstrip patch antenna. Minimum S_{11} and its frequency f_{opt} corresponding to 3125 geometries are used as inputs and five optimization parameters are used as outputs for training data of inverse coarse model (feed-forward MLP), respectively.

$$f_{opt} = \min_f \left(S_{11}(f)\right) \qquad 2Ghz \leq f \leq 6Ghz \quad (4)$$

Feed-forward MLP for inverse ANN modeling is obtained by MATLAB Toolbox which utilizes Levenberg-Marquard algorithm and such parameters (two hidden layer with 30 and 40 neurons, learning rate = 0.1, momentum = 0.2 and regularization = 0.2.) during training. Moreover Feed-forward MLP for second and third steps of 3-step inverse ANN modeling is obtained by MATLAB Toolbox which utilizes Levenberg-Marquard algorithm and such parameters (two hidden layer with 70 and 50 neurons for the second step and 60 and 40 neurons for the third step , learning rate = 0.05, momentum = 0.1 and regularization = 0.2.) during training. After training is completed, inverse coarse model can generate necessary inputs of coarse model in order to form inverse difference mapping in SM-ID optimization. The performance of ANN and 3-step modeling can be checked by %20 (625 geometry)of the training samples (3125 geometry) and average normalized errors are found as 0.1721 for ANN based inverse coarse model and 0.1280 for 3-step based inverse coarse model. This means 3-step modeling improves the accuracy of ANN based inverse coarse model from 0.1721 to 0.1280. Two different frequencies (3.54 GHz and 4 GHz) are chosen for desired responses. The aim of design example is to find design parameters corresponding to f_{opt} through SM-ID optimization algorithm. Each convergence of SM-ID algorithm based on ANN based and 3-step based inverse coarse model are given in Figure 4 and Figure 6) for two different frequencies (3.54 GHz and 4 GHz).

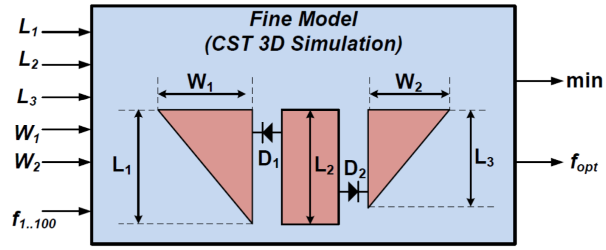


Figure 3. Optimization parameters and fine model input-output relationships of reconfigurable microstrip patch antenna.

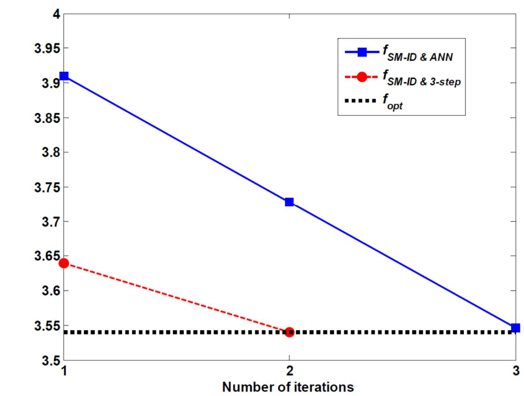
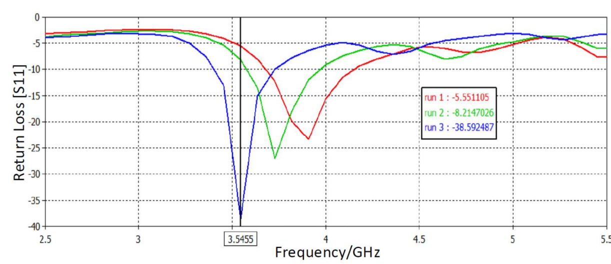
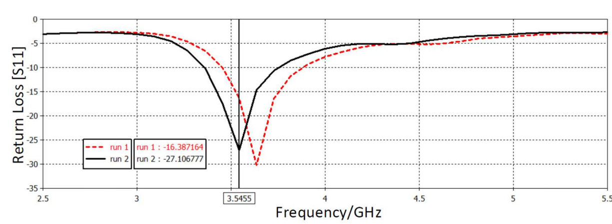


Figure 4. Convergence of SM-ID optimization algorithm depending on inverse coarse models obtained by conventional ANN $M-1$ and 3-step modeling $M-3$ for $f_{opt} = 3.54GHz$.



(a) Inverse coarse model obtained by conventional ANN $M-1$.



(b) Inverse coarse model obtained by knowledge based 3-step modeling $M-3$.

Figure 5. CST 3D-simulation results for each iteration of SM-ID optimization process for $f_{opt} = 3.54GHz$

CST simulation results for fine model evaluation in terms of ANN based and 3-step based inverse coarse model are shown in Figure 5 for 3.54 GHz and Figure 7 for 4 GHz.

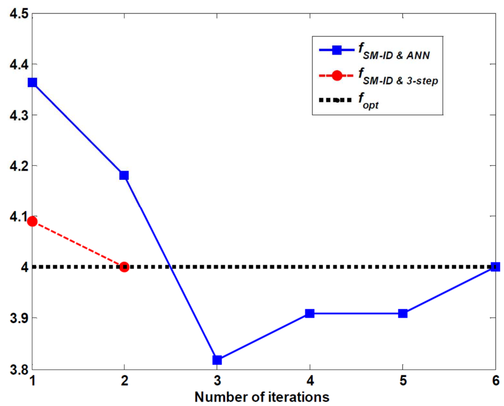
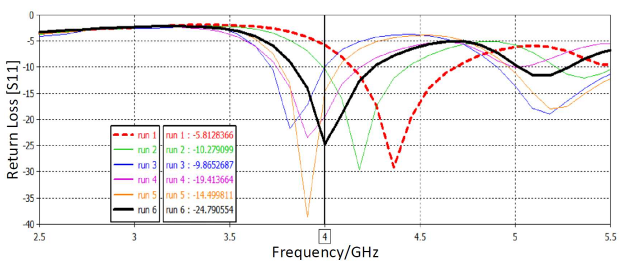
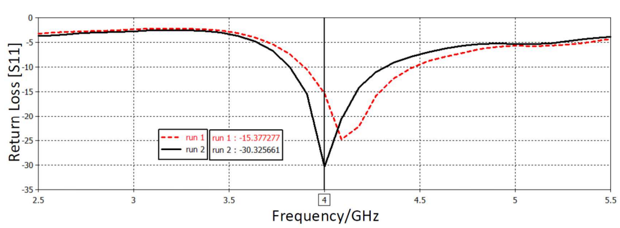


Figure 6. Convergence of SM-ID optimization algorithm depending on inverse coarse models obtained by conventional ANN $M-1$ and 3-step modeling $M-3$. for $f_{opt} = 4GHz$



(a) Inverse coarse model obtained by conventional ANN $M-1$.



(b) Inverse coarse model obtained by knowledge based 3-step modeling $M-3$.

Figure 7. CST 3D-simulation results for each iteration of SM-ID optimization process for $f_{opt} = 4GHz$

6. Conclusion

Space mapping with inverse difference technique is applied to design problem relevant to reconfigurable microstrip patch antenna together with knowledge based 3-step modeling strategy. The aim of this design problem is to obtain antenna geometry corresponding to optimum frequency condition for minimum S_{11}. The convergence of $SM-ID$ & $3-step$ combination can require less number of fine model evaluations than $SM-ID$ & ANN combination to find optimum frequencies. In addition 3-step based inverse coarse model can generate closer coarse model input parameters to the fine model input parameters through its better accuracy than ANN based inverse coarse model. As all things considered, $SM-ID$ & $3-step$ combination can provide efficient optimization technique for design problems.

7. References

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