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Optimal Inner Case Design for Refrigerator by Utilizing Artificial Neural Networks and Genetic Algorithm

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Abstract : In this paper, an artificial neural network (ANN) was employed to build a predicting model for refrigerator structure. The predicting model includes three input variables of the plaque depth (D), width (W) and interval distance(S) on the inner wall. Finite element method was utilized to obtain the data, which would be necessary for the ANN training process. Finally, a genetic algorithm (GA) was applied to find the optimal parameters that leaded to the minimum inner case deformation under operating condition. The optimal combination found is the depth(D) of 2.63mm, the width(W) of 19.24mm and the interval distance(S) of 49.38mm which leaded to the smallest deformation of 1.88mm for the given refrigerator model.

Key words : Refrigerator, Artificial Neural Network(ANN), Genetic Algorithm(GA), Finite Element Method(FEM), Polyurethane Foam

1. Introduction

These years, as refrigerator case structure becomes more and more large and complicated, it is easier to cause crack during store process or under operating condition than before. The reason for the crack is very complicated; however, the main reason is the different thermal properties of the composite inner case materials under the great temperature differences.

Usually, engineers would rather design a lot of experiments of different refrigerator models in order to obtain an optimal structure with little inner case deformation, which would cause great waste of money and research and development (R&D) time. Consequently, there is a need for a tool that would make the evaluation of a refrigerator structure available for engineers during R&D process.

Kinds of numerical approaches such as gradient method, sequential quadratic programming, and approximation methods were applied to the optimization of structures.

These optimization method was reported that the initial point has great effect for the most optimal solution. It is a little

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difficult to obtain the global optimal solution but always convergent at local solution point [1]. But a GA would start from many points by utilizing selection, crossover and mutation operators so that local minimization could be avoided. There is no special restriction for functions of the calculating model by the GA. The GA is more suitable for complicated structure optimal project than any other traditional computing method in these days.

Artificial neural networks(ANN) is an empirical modeling tool analogous to the behavior of biological neural structures and can identify highly complex relationships by using input-output data. A common ANN model is established in a training process by using back-propagation(BP) with the gradient descent (GD) algorithm.

In this study, we used a method called BP-GA method to obtain the optimal plaque parameters for minimum refrigerator cabinet deformation. The training data were obtained by FEM model utilizing ANSYS because of lack of the experimental data. A total forty-five FEM models were analyzed among which twenty-five models were arranged by orthogonal test method according to plaque's depth (D), width(W) and interval distance (S). The FEM analysis results of thirty-eight models were inputted as training data and the other seven were taken as test data after BP network training process in order to know how perfect the predicting model obtained by ANN training would match with the actual FEM analysis results.

2. FEM modeling

2.1 Plaque effect on refrigerator deformation

Test results confirm that the plaques are effective as expansion joints to relieve liner surface tension. Table 1 below shows the results of tensile deflection testing on samples of plaqued and unplaqued HIPS refrigerator liners. The unplaqued samples exhibited yield forces which averaged 146,000psi at 1% tensile deflection[2]. The plaqued samples exhibited yield forces, which averaged 32,000psi at 1% tensile deflection. Because the plaqued liner samples have only 22% of the internal stiffness of the flat unplaqued liner samples, the plaqued material is more resistant to cabinet bowing due to the reduction of internal liner wall stiffness. So, many refrigerator inner cases have been designed as plaqued shape.

Table 1: Tensile deflection testing of plaqued and unplaqued HIPS liner samples

Sample Configuration	Tensile Deflection	Yield Fore(psi)
Unplaqued HIPS	1%	146,000
Plaqued HIPS	1%	32,000

Previous analysis results indicate that the degree of freezing inner case deformation is inversely proportional to the distance by which the plaque surface is offset from the surface of the liner.

In addition, the plaques' width and interval distance are the other two main parameters for the plaque shape designing. In this study, we put main attention on the plaque's depth, width and interval distance' effect on cabinet deformation, trying to find out the regular pattern between the three plaque parameters and cabinet deformation. The plaque structure is shown as in **Figure 1 ~ Figure 3**.

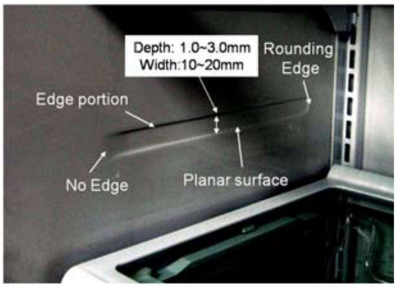

Figure 1: Plaques in refrigerator

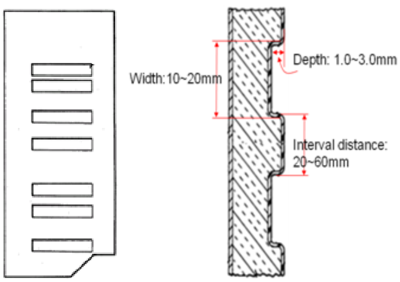

Figure 2: Description of the plaque parameters

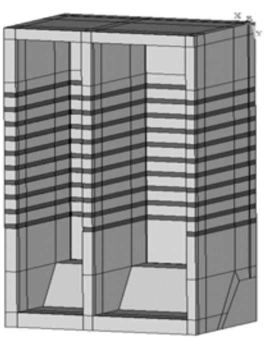

Figure 3: FEM plaqued refrigerator model

2.2 FEM analysis

We designed a series of FEM models instead of taking so many experiments to obtain the data for ANN model. The FEM models were analyzed in ANSYS V11.0 with APDL program. The parameters of refrigerator models for APDL including outline dimensions, materials properties, real constants, parameters of plaque, and load conditions and so on were arranged as in **Figure 4**. We only designed plaques on the freezing room of refrigerator in which maximum temperature difference emerged. If the room temperature would be 32°C and the freezing room temperature be -22°C, the maximum temperature difference would be 54°C on the freezing room wall which separate freezing room from outside environment. The plaque numbers were set to be ten according to the actual refrigerator. The plaques were linked up through the inner case walls.

The whole refrigerator model consists of four materials, the material properties are shown in the following **Table 2**. And we took use of solid70, solid185 and shell63 element to simulate the PU foam, steel plate and ABS plate in FEM model. First, we executed thermal analysis process to obtain temperature-distribution data, and then we executed structural analysis process by loading temperature data obtained in the preceding thermal analysis process. The reference convective heat transfer coefficients were tested as shown in **Table 4** obtained from experiment. The equivalent convective heat transfer coefficients on the refrigerator walls were calculated as shown in **Table 5**. After we loaded the equivalent convective heat transfer coefficients and temperature condition under strong condition as shown in **Table 3**, the temperature distribution condition could be calculated as shown in **Figure 6**. In structural analysis process, we loaded such temperature distribution condition and fixed the four bottom points according to the actual refrigerator condition. In order to make it visible and more efficient, we also designed a Visual Basic program for carrying out APDL program[3], as shown in **Figure 5**.

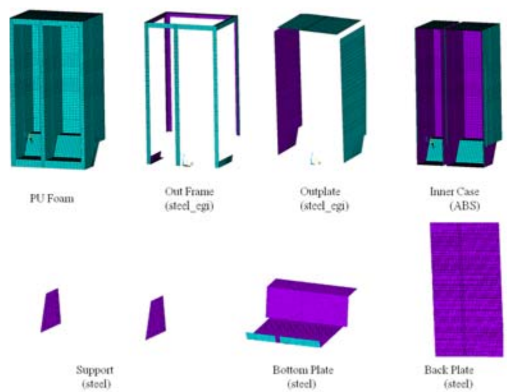

Figure 4: Shell and solid elements applied to FEM model

Table 2: Material properties

Material Type	Young's Modulus (GPa)	Poisson's Ratio	Density (kg/m^3)	Thermal Conductivity (W/m/^{o}C)	Coefficient of Thermal Expansion (1/^{o}C)
Steel	206.8	0.29	7820	45	1.17E-5
Steel	131.7	0.31	7820	45	1.17E-5
ABS	2.11	0.38	1085	0.02056	6.9E-5
PU Form	3.63E-3	1E-9	33.5	0.02054	8.0E-5

Table 3: Actual refrigerator temperature condition under operating

Storage room (^{o}C)	Freezing room (^{o}C)	Environment (^{o}C)
-1	-22	32

We take D, W and S as design variables, and maximum inner case deformation as objective function. A series of models could be designed according to such three design variables. In this study, total thirty-eight sets of FEM models were analyzed for the training data of ANN model, including twenty-five sets of FEM models arranged by L25_5_3

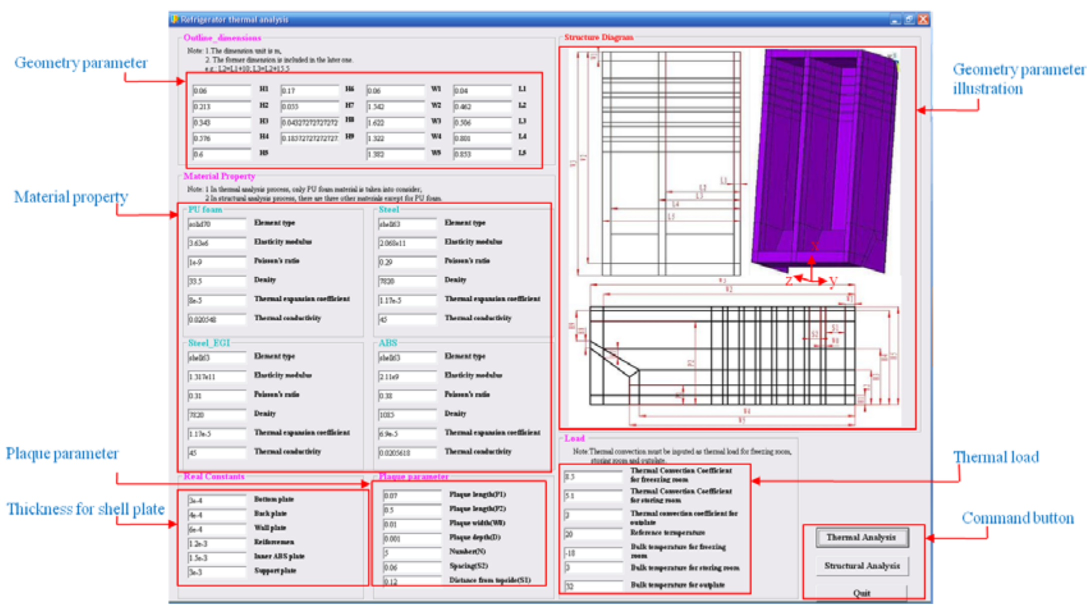

Figure 5: FEM modeling for ANSYS

orthogonal test method and another thirteen sets of additional FEM models arranged by author in order to make the ANN model more reliable by providing more training data. The FEM analysis results are shown in Table 6 and Table 7.

Table 4: Reference heat transfer coefficient

Location	Reference Convective Heat Transfer Coefficient ($W/m^2/^oC$)
Outer Plate (Outside)	3
Inner Case (Storing Room)	8
Inner Case (Freezing Room)	22

Table 5: Equivalent convective heat transfer coefficient

Location	Thermal Resistance $\left(\frac{1}{h}+\frac{L}{k}\right)$	Equivalent Convective Heat Transfer Coefficient ($W/m^2/^oC$)
Outer Plate (Outside)	$R_{outer}=\frac{1}{3}+\frac{0.0005}{45}=0.333$	$h_{o,eq}=2.9999\approx 3$
Inner Case (Storing Room)	$R_{StoringR}=\frac{1}{8}+\frac{0.0015}{0.0206}=0.1978$	$h_{S,eq}=5.0551\approx 5.1$
Inner Case (Freezing Room)	$R_{FreezingR}=\frac{1}{22}+\frac{0.0015}{0.0206}=0.1182$	$h_{F,eq}=8.45523\approx 8.6$

h:Convective heat transfer coefficient [$W/m^2/K$]

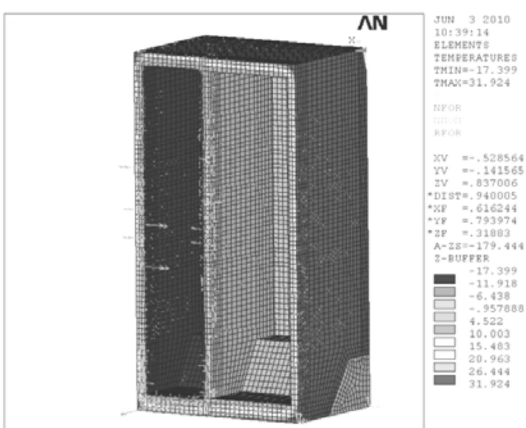

Figure 6: Cabinet Temperature Distribution

Table 6: FEM analysis data by L25_5_3 orthogonal test method for ANN training

Factor	Depth (mm)	Width (mm)	Interval Distance (mm)	Result (mm)
Test-1	1.0	10	20	2.771
Test-2	1.0	12	30	2.745
Test-3	1.0	15	40	2.711
Test-4	1.0	18	50	2.755
Test-5	1.0	20	60	2.751
Test-6	1.5	10	30	2.572
Test-7	1.5	12	40	2.478
Test-8	1.5	15	50	2.411
Test-9	1.5	18	60	2.435
Test-10	1.5	20	20	2.496
Test-11	1.8	10	40	2.420
Test-12	1.8	12	50	2.320
Test-13	1.8	15	60	2.286
Test-14	1.8	18	20	2.450
Test-15	1.8	20	30	2.364
Test-16	2.0	10	50	2.286
Test-17	2.0	12	60	2.213
Test-18	2.0	15	20	2.448
Test-19	2.0	18	30	2.347
Test-20	2.0	20	40	2.220
Test-21	3.0	10	60	1.984
Test-22	3.0	12	20	2.317
Test-23	3.0	15	30	2.247
Test-24	3.0	18	40	2.090
Test-25	3.0	20	50	1.927

Table 7: Additional FEM analysis data

Factor	Depth (mm)	Width (mm)	Interval Distance (mm)	Result (mm)
Test-26	1.0	20	45	2.772
Test-27	1.5	15	35	2.464
Test-28	2.0	18	35	2.298
Test-29	2.0	15	45	2.242
Test-30	1.8	18	45	2.269
Test-31	1.5	12	50	2.446
Test-32	1.2	16	40	2.578
Test-33	1.5	17	42	2.409
Test-34	1.5	16	50	2.406
Test-35	2.0	18	55	2.152
Test-36	1.3	16	33	2.558
Test-37	1.7	20	41	2.320
Test-38	2.1	16	45	2.214

Moreover, seven sets of additional FEM models have been prepared for test of the ANN training model. Such test data would be compared with the predicting results by

ANN model that we obtained by training process. The analysis results of FEM model for test are shown in Table 8.

3. The BP network for ANN model

3.1 ANN model

This paper applied BP Neural Networks [4] in MATLAB V7.0. The structure of the BP network includes three layers: an input layer, a hidden layer and an output layer, as illustrated in **Figure 7**. The input layer receives three input parameters (D, W, and S) of the refrigerator model and the output layer provides the output of the deformation, which is shown as follow:

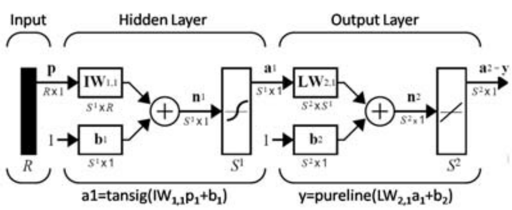

Figure 7: The ANN structure for predicting refrigerator deformation

The input D, W and S have bound as follow:

$$\begin{aligned} 1\ \text{mm} \le D \le 3\ \text{mm} \\ 10\ \text{mm} \le W \le 20\ \text{mm} \\ 20\ \text{mm} \le S \le 60\ \text{mm} \end{aligned} \tag{1}$$

The maximum cabinet deformation in FEM analysis would be collected as the input data for training the BP neural network. For the BP neural network, we want to know under what condition of the D,W and S parameters that the minimum inner case deformation would emerge. The minimum inner case deformation is the final goal of our optimal structure design, and the regular pattern between the three design variables and the minimum inner case deformation is what we want to find out by training the BP neural network to obtain a reliable ANN model.

With the specified transfer functions 'tangent sigmoid' and 'pureline', the unknown function relationship between input of 'D', 'W', 'S' and outputs of 'minimum deformation' could be determined iteratively along with the iterations of the weights W(1) and W(2), and biases b(1) and b(2). By learning the patterns of these inputs and outputs, the weights and biases are adjusted iteratively during the training procedures.

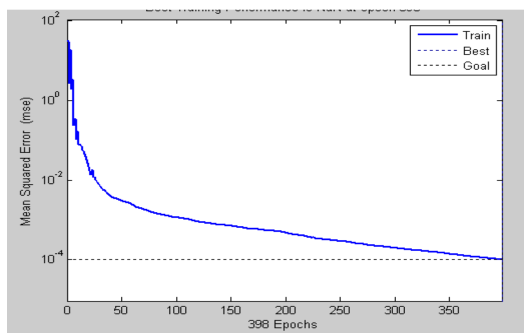

Figure 8: Training process

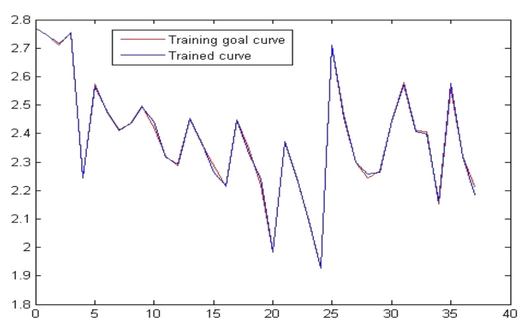

Figure 9: Training Data and Training Result

3.2 The BP training results and discussions

The ANN mathematical predicting

model, i.e., ANN output layer, that describes the relation between three refrigerator structure parameters and refrigerator deformation.

After the training process, the general ability of the ANN model must be tested by using seven sets of random combinations of testing data shown in **Table 8**. **Figure 9** shows the comparison between predicting data predicting data computed from ANN and FEM computed results for the test data. In addition, **Table 9** shows the test errors of the ANN model, in which, the maximum errors is -0.49%. Such an ANN model is thought to be a reliable mathematical model in predicting the effect of plaque parameters on refrigerator inner case deformation.

Table 8: Results comparison

Factor	Depth (mm)	Width (mm)	Interval Distance (mm)	test result (mm)	Error(%)
Test-39	1.2	15	32	2.61	0.44
Test-40	1.4	17	34	2.50	-0.05
Test-41	1.5	18	38	2.44	-0.49
Test-42	1.6	19	40	2.38	-0.33
Test-43	1.8	19	42	2.29	-0.11
Test-44	1.9	18	43	2.26	-0.06
Test-45	2.0	17	44	2.22	0.35

4. The optimization of refrigerator structure parameter using genetic algorithm

4.1 The GA optimization

After the nonlinear mapping between plaque parameters and refrigerator inner case deformation has been established in the use of the BP training algorithm, the desired target function approximation value for plaque parameter optimization could be obtained by a genetic algorithm.

GA and calculations were firstly introduced by Holland [5]. The algorithm is a computational search scheme according to the mechanics of natural selection and genetics and selection and is used to obtain optimal solutions [6]. The operation procedures are described by following steps.

① Start with a randomly generated population of 'n' m-bit chromosomes.

② Calculated the fitness value of each chromosome in the population. The larger the fitness value is, the better is the property. In this study, our target function is to get the minimum value, so the fitness function should be:

$$fit(f(x)) = -f(x) \tag{2}$$

③ Use three operators that are selection, crossover and mutation to create 'n' offspring from the current population.

④ The new population replaces the current population.

⑤ Go back to ② and recomputed fitness then repeat step ③, ④ and ⑤ until the termination criterion is reached.

In this study, we used the GAOT toolbox by Christopher R. Houck of MATLAB in 1996. Using GAOT, designers do not have to consider of genetic algorithm internal structure, only work on the fitness function program according to the design requirements. So GAOT toolbox simplified the originally complex genetic algorithm design process, which has been proved very helpful for numerical optimization.

After 50 generations, the best solution

is about D=2.63mm, W=19.24mm, S=49.38mm, minimum deformation is 1.91mm.

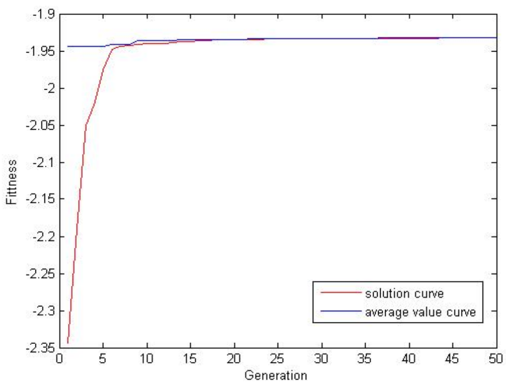

Figure 10: The GA optimization property

4.2 Verification for the GA optimization result

We made a FEM model with the GA optimization result of D, W and S, and obtained the FEM result of maximum inner case deformation, which is 2.066mm. The comparison of the FEM result and the GA optimization result is shown in Table 9:

Table 9: FEM Result and the GA optimization Result

The GA optimization parameter for FEM model	FEM result in ANSYS	The GA optimization result in MATLAB
D=2.627mm W=19.2396mm S=49.3762mm	2.066mm	1.9096mm
	Error	
	(2.066-1.9096)/2.066×100%=7.57%	

The error between the two results is very small, and the optimization result by the GA method is thought to be reliable. Figure 11 shows the regular pattern between plaque parameters and refrigerator minimum deformation.

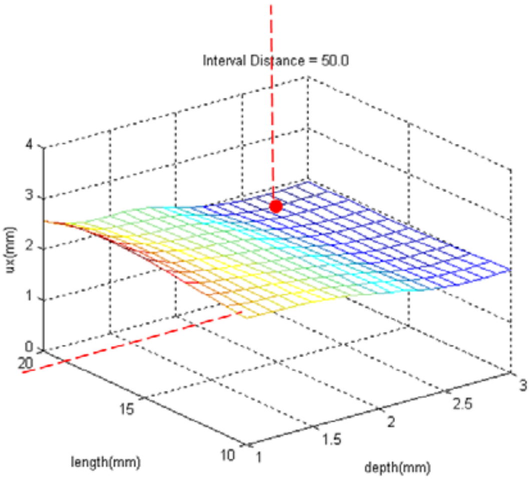

Figure 11: The GA optimization result

As shown in the figure, plaque depth parameter has stronger effect than width parameter, especially when depth approaches about 2.2mm, then the effect of plaque depth almost keeps the same from 2.2mm to 3mm.

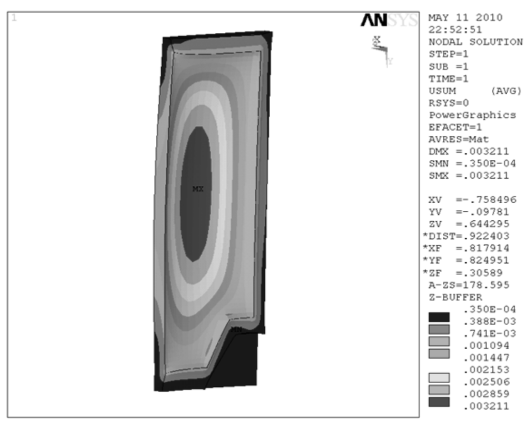

Figure 12: Freezing room inner case deformation without plaques

Compared to the unplaqued refrigerator model as shown in Figure 12, the plaques distributed evenly along the inner case wall according to the optimization result, so that the plaques separated the maximum deformation area to small areas with S=49.3762mm as shown in **Figure 13-14**. As a result, the inner case deformation could also be effectively reduced. The inner case deformation of FEM plaque model could be reduced from 3.21mm of the unplaqued model to 2.07mm according to the optimization result.

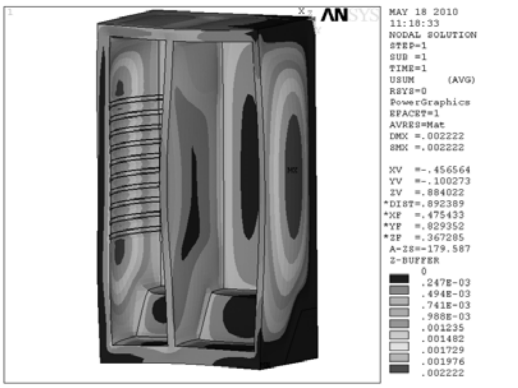

Figure 13: Structural FEM analysis result with the GA optimization paramter

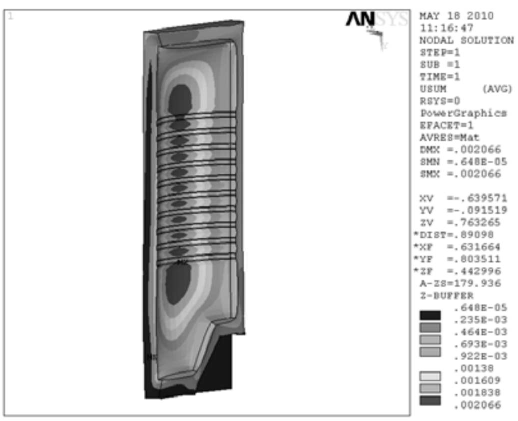

Figure 14: Freezing room inner case deformation

5. Conclusion

This paper reports the application of an artificial neural work (ANN) for building a feasible predicting model for refrigerator deformation. The back-propagation neural network has been applied to construct a mathematical model wherein the refrigerator inner case deformation function expressed as explicit nonlinear functions of the three structure parameters D (plaque depth), W(plaque width) and S(plaques interval distance). The established ANN model was trained from thirty-eight sets of FEM analysis data and tested by extra seven sets of FEM analysis data. The maximum test error is 7.57%.

Finally, a genetic algorithm is utilized to obtain the optimal structure parameters that provide the best refrigerator deformation quality. The best structure parameter is D=2.63mm, W=19.24mm, S=49.38mm, and minimum deformation is 1.91mm. The result of the GA optimization is considered reliable, and the method for refrigerator structural optimization is practicable.

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