Analysis of RC T-Beams Strengthened with CFRP Plates under Fire Loading using ANN

M. Naser¹; G. Abu-Lebdeh²; R. Hawileh²,*

¹ Research Assistant, Department of Civil & Environmental Engineering, 3580 Engineering Building, Michigan State University, East Lansing, MI 48824-1226; Email: nasermoh@msu.edu

² Associate Professor, Department of Civil Engineering, American University of Sharjah, P.O. Box 26666, Sharjah; Email: gabulebdeh@aus.edu

²,* Associate Professor, Department of Civil Engineering, American University of Sharjah, P.O. Box 26666, Sharjah; Email: rhaweeleh@aus.edu

Abstract This paper presents an alternative approach to predicting fire resistance of reinforced concrete (RC) T-beams strengthened with Carbon Fibre Reinforced Polymers (CFRP) plates, insulated with different protecting materials and exposed to different fire scenarios. Based on both, experimental and Finite Element (FE) studies, Artificial Neural Networks (ANN) were used to extend earlier research. The developed ANN can be used to predict the fire endurance of RC T-beams strengthened with CFRP laminates and subjected to elevated temperatures. Different insulation thicknesses, materials types and fire curves were the main input parameters in the presented ANN. The predicted fire endurance and time to failure results are compared with obtained experimental and validated FE simulation results. Strong correlation between the predicted ANN and both the experimental and FE results was obtained. The developed ANN model was then expanded in an extensive parametric study to predict the fire resistance of the strengthened beam using different insulation thicknesses, insulation material types, and fire
scenarios. Design charts were also developed to be used as preliminary guidelines to aid designers in selecting the required insulation thickness for specific insulation systems and fire exposure scenarios. It was concluded that the developed and validated ANN could be used as a computational tool in the analysis and design of RC beams strengthened with CFRP plates and subjected to thermal fire loadings. Other conclusions and observations were also drawn.

**Subject Headings:** Artificial Neural Networks, Reinforced Concrete, Finite Element, Fire, CFRP

### 1. Introduction

In the last few decades, there have been a fair number of attempts to study the effect of fire actions on RC structural members [1-4] in which both experimental tests and numerical models were developed [3, 5]. Because of their high strength to weight ratio, ease of installation and resistance to corrosion [3, 4], the use of FRP materials as new strengthening systems seems very promising. Because mechanical properties of FRP materials degrade rapidly with the increase of temperature [1-5], further studies on the performance of such hybrid structural elements under elevated temperatures are warranted.

It is widely recognized that full scale fire tested experiments are very costly and require tremendous amount of time, preparation, and monitoring [6]. This is besides the fact that the number of special research facilities and test furnaces is limited. Such issues impose obstacles to performing parametric studies and detailed testing on the structural performance of strengthened RC members under elevated temperatures. Furthermore, consistency is hard to achieve between
different furnaces since lining materials, fuel used and loading rigs differs greatly [6]. Thus, the thrust to develop numerical methods that can accurately predict the behavior of strengthened RC beam is gaining momentum [7].

FRP composite laminates are composed of two parent materials, FRP fibers and resin matrix. Despite the fact that the FRP fibers can withstand high temperatures, the epoxy matrix that holds the fibers together has a low glass temperature and tendency to rapidly lose its bonding ability [8-12]. Hence the composite plate experiences large loss of the strength and stiffness during the course of fire because of the loss of the interlock bonding between the fibers and matrix. The strength and stiffness of the FRP, mechanical properties of the matrix, fibre's cross sectional area and orientation, fiber-resin volume fraction, parent materials and manufacturing process can all govern the material properties of the FRP composite [8]. There has been a good number of studies on the effect of high temperatures on epoxies and composites material used in the aerospace, marine and naval application [9-13]. Furthermore, a fair amount of experimental programs on the tensile strength of different FRP materials, specially glass, has been conducted by Sen [14] and Rostasy [15]. Still further research is needed on the fire performance of FRP composites in civil engineering applications [2, 4, 5].

According to the guidelines of the ACI440 440.2R-08 document [16], "unless it can be shown that the FRP temperature remains below its critical temperature, the strength of externally bonded FRP systems is assumed to be lost completely in a fire". Such challenges limit the use of FRP strengthening systems in locations where fire action is more likely to occur, such as apartments and buildings.
Due to the above mentioned reasons and the limited number of experimental tests, a large number of parameters and material combinations need to be verified and tested. The use of numerical and computational models for investigating the fire performance of externally strengthened RC members with FRP laminates is also warranted. Among the many modeling techniques, artificial neural networks (ANN) are robust techniques that are especially suited for capturing the behavior of RC members strengthened with CFRP plates in the event of fire.

Artificial Neural Networks: Background

Artificial neural networks, or simply neural networks, are relatively crude computer-based systems that learn models and patterns within data through systematic and repeated exposure to the data sets. ANNs are built of simple processing units called neurons. The arrangement of neurons within a network and their connectivity and functioning are all based on the neural structure of the brain. The most common ANN model is the multilayer perceptron model, the details of which are provided in Haykin [17]. The most frequently used computer neural network consists of nodes, or neurons, arranged in layers. The input layer contains the independent, or predictor variables. The output layer contains the target variable or variables. One or more hidden layers may be used between the input and output layers to build non-linear models. Nodes are connected across layers. Knowledge in a neural network is stored in the interneuron connection weights. At the start, connection weights between layers are set to random values. In a forward pass, the inputs are fed into the input nodes. A given node sums the weights coming into it. The sum is then used to activate a transfer or node function (sigmoid or other type). Transformed output
signals from all hidden nodes are then summed to produce predicted values, which are then compared to known experimental values. The amount of error in the prediction is calculated and then fed back into the network (a backward pass). The forward and backward passes are then repeated and the weights are adjusted iteratively until the calculated outputs match the experimental (observed) ones to within a preset level of accuracy.

Neural networks do not use an algorithmic approach to modeling and, unlike statistics, require no assumptions a priori about the functional form of the input-output relationship. ANNs learn by example. The examples must be selected carefully otherwise the ANN will not train properly. But, if trained carefully, ANN may exhibit some capability for generalization beyond the training data. That is, to produce approximately correct results for new cases or data patterns that were not used for training. ANNs are not a cure-all for solving complex problems but, if used sensibly, they can produce some remarkable results. They are especially useful when there are many input variables, and when the relationship between the inputs and outputs is poorly understood. A successful ANN model is one that captures the logic, or patterns, in the data - thus able to generalize, or predict - and not simply memorize the data. This is typically accomplished by both ensuring that the training data actually spans the entire modeling space, and reserving some of the known data patterns (i.e., not using them in the training process) and using them to validate the model.

The computational efficiency of the ANN lies in its interconnection weights. The number of hidden layers and number of neurons within each layer are unknown prior to the development of the network, and they depend largely on the complexity of the relationship between the inputs
For a successful ANN model, determining the number of hidden layers and processing neurons in the hidden layers are the main operations of the development stage. There are no well established procedures for this determination; some rules of thumb along with trial and error approach may be used. ANNs have proven to be a good modeling technique in different domains including the different specialty areas within civil engineering.

ANNs have been used successfully to study fire-induced structural behavior. Hozjan et al. [7] used ANN in the formulation of a material model for structural steel at elevated temperature levels using experimental data. According to Erdem [17], the ultimate moment capacity of reinforced concrete slabs under fire conditions can be predicted using a well-trained ANN. Zhao [18] presented a strength model for steel columns under elevated temperatures using hybrid ANN and compared modified Rankine formula. Al-Khaleefi et al. [19] used ANN to predict the fire resistance of concrete filled tubular steel columns by monitoring various factors influencing the fire resistance such as structural and material factors in addition to loading conditions.

There has been limited number of studies on the use on ANNs in the fire performance of structural members used in civil engineering applications [21-23]. Among them, Cachim [23] used ANNs for calculation of temperatures in timber members under fire loading. Cachim [23] trained different ANNs that varied the number of neurons and hidden layers. The input parameters were timber density, time after fire initiation, and distance from the side exposed to the fire. It was concluded that the use of ANNs allows designers and engineers to simplify the process of calculating the temperatures in timber members without the need of performing thermal-stress...
analysis The current state of the art still lacks studies on the fire performance of RC beams strengthened with CFRP plates.

This paper presents an ANN models to predict the temperature variations within a RC beam strengthened externally with CFRP plate. The developed model is based on the experimental tests conducted by Williams et al. [4]. The validated model is expanded into a parametric study to investigate the effect of different fire scenarios, insulation thicknesses and material types. Design charts are also generated from the outcomes of the parametric studies that would aid designers and engineers in the design process of such strengthening systems. Successful modeling of this problem using ANNs could serve as a valid tool to predict the performance of such system instead of expensive and time-consuming fire experimental testing.

2. Neural Network Architecture

The multilayer perception model shown in Figure 1 with feed-forward backpropagation and supervised learning was used in this project. This particular model has been used in many applications in science and engineering. The term “supervised” means that the network requires a target output in order to learn. Therefore, the goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce or predict the output for a given set of inputs.

An ANN was used that dynamically grows hidden neurons to build a model that generalizes well. In this paper, 30 insulation thicknesses were selected ranging from 10 to 125 mm in 2.5 mm increment up to 40 mm; and continues with a 5-mm increment afterwards. It should be noted that
the insulation thickness was used as a continuous variable. Three insulation materials and fire curves were used as categorical variables. Temperature of the CFRP/concrete interface at 30, 60, 90 and 120 minutes was the output of the developed ANN. Hence, 120 data points (calculated as 30 insulation thicknesses × 4 time increments) were collected for each of the combinations used in the developed ANN; except for the Compartment fire curve that will be discussed in details later on. Table 1 shows the values and categories of the input variables, and the combinations thereof used in in the ANN model.

Of the 120 patterns (observations) generated from the finite element (FE) design/experiments (presented next section), seventy five percent (75%) of the observations were used to train the ANN and the remaining 25% were used to test the best network model. A data pattern corresponds to a particular combination of insulation material, material thickness, fire curve, and the corresponding temperature variation within the beam.

3. Finite Element Model Validation

The data points used in developing the ANNs were collected from the finite element (FE) model developed by Hawileh et al. [24]. Hawileh et al. [24] developed a 3D nonlinear FE model using the finite element (FE) software, ANSYS [25] based on the results of the experimental study of Williams et al. [4]. The T-beam has a depth and length of 400 and 3900 mm, respectively. The flange has a width of 1220 mm, while the width of the web is 300 mm. Two 20 mm diameter steel rebars were used to model the internal steel reinforcement, and a 100 mm wide CFRP layer was externally attached to the soffit of the beam. Finally, three sides of the T-beam web were insulated with a 25 mm layer of Vermiculite/Gypsum (VG) up to a distance of 125 mm into the bottom
underside surfaces of the flange. The developed FE model incorporates the same geometry, nonlinear temperature-dependent material properties as well as boundary conditions and loading of the tested specimen. Thermal SOLID70 and LINK33 [25] elements were used in the development of the thermal FE model. The total number of elements in the adopted model was 55000. Further details on the temperature-dependent material properties and simulation techniques can be found elsewhere [24]. The obtained temperature variation results at specified locations within the beam were compared with the measured experimental data of Williams et al. [4]. The validated FE model achieved good matching with the experimental results. Hence, it was used in this study as a benchmark to produce additional data points that were the used to train and test the developed ANN.

Given the good matching between the experimental and predicted results, a parametric study was carried out. The effect of using different insulation thicknesses and materials as well as various fire curves were investigated. The thickness of the insulation was varied from 10 to 125mm in 2.5mm increment up to 40mm; afterward a 5-mm increment was used. To study the effect of different insulation materials, three different insulation materials were studied separately. The different protecting materials along with their material properties were collected from the fire protection industry.

The ANN was trained to predict the temperature at the interface between the CFRP/concrete and steel reinforcement. Since the glass temperature of the CFRP material is relatively low (in the range of 60 to 82 °C [4]). It was shown that CFRP materials lose 50% of their strength at 250 °C; therefore it is important to predict the temperature at the CFRP/concrete
interface to determine the point at which the CFRP material reaches 250 °C to decide the corresponding fire resistance duration. For example, the steel reinforcement critical temperature according to ASTM E119 [26] is 593 °C. The same concept is used in this study by monitoring the steel temperature via the FE simulations.

4. Neural Network Model Development and Validation

Upon the validation of the FE model developed by Hawileh et al. [25], the FE model was used to generate multiple data patterns that were then used to train the ANN. The successfully trained ANN was then used to predict the temperature at the CFRP/Concrete interface. As mentioned earlier, seventy five percent 90 data points (75% of the total 120 data points) and 30 data points were used to train and test the developed ANN, respectively. Figure 2 shows a comparison between the FE observed and ANN predicted temperatures at the CFRP/Concrete interface at specified time intervals.

It is evident that the ANN succeeded in achieving a close match with the FE results. The total average error is 8.6 °C and the network coefficient of determination (R^2) is 98.05%. Figure 3 shows the accuracy of the ANN prediction. With a perfect prediction all data points would lie on the 45-degree line. It is noted that the data points in Figure 3 all lie within a ±10% bound. It can be concluded from Figures 2 and 3 that there is a close enough match between the ANN prediction and the observed FE results. Hence the ANN models can be used, with confidence, to study the behavior of the structure with different CRFP strengthening schemes subjected to different fire exposure scenarios... . To further validate the ability of the developed ANN, the temperature of
the CFRP/concrete interface of the second strengthened RC beam tested by Williams et al. [4] was studied. It should be noted that the only difference between the tested beams was the applied insulation thickness. The first and second beams had thicknesses of 25 and 38 mm, respectively. Comparisons after 30, 60, 90 and 120 minutes between the temperatures predicted by the FE simulation and that by the ANN was carried out and provided in Table 2. The ANN was able to achieve excellent matching (less than 10% deviation) with the experimental results of Williams et al [4]. Upon the completion of the ANN training, an extensive parametric study was carried out. The parametric study investigated the effects of using different insulation materials as well as different fire curves.

5. Parametric Study: Results and Discussion

The parametric study was divided into two parts. In the first part, the insulation material was varied while the second part presents the effect of different fire curves.

6.1. Different Insulation Materials:

Information on properties of different insulating materials was collected from the fire protection industry. PROMATECT®-H and PROMAGLAF®-HTI [27] were chosen to represent a good range of insulating materials. PROMATECT®-H can resist temperatures up to 400 °C; on the other hand, PROMAGLAF®-HTI can withstand temperatures till 1250 °C. In order to accurately simulate the material degradation at elevated temperatures, temperature-dependent material properties were used based on the manufacturing data sheets as shown in Figure 4. It should be noted that the specific heat and density of PROMATECT®-H and PROMAGLAF®-HTI
were 870 and 100 Kg/m³ 0.92 and 1.13 kJ/Kg.K, respectively. Figures 5-8 show the effect of using different insulation materials on the thermal response of the strengthened RC beam at different times measured from the onset of the fire exposure. The benchmark for comparison is the validated beam 1 noted earlier.

PROMAGLAF®-HTI insulation material seems to perform better than PROMATECT®-H and VG at least for the lower range of thicknesses. As thicknesses increase, the trend reverses and that reversal happens later for higher thickness. In other words, the Insulation materials used behaves better in the longer term (after longer time) if used in higher thickness. All the studied insulation materials herein seem to behave similarly after the use of an insulation thickness of 60-70 mm; in this range of thickness type of insulation material does not matter. This information can be used to reduce costs by replacing relatively expensive insulation by less expensive ones. In practice, however, the average thickness is between 20 and 50 mm, and therefore the cost issue may be a significant factor only in large scale projects where exceptionally thicker insulations than normal are used. Another use of the produced charts is that they can be used as benchmarks for choosing insulation thickness based on the fire resistance rating needed given other constraints.

6.2. Different Fire Curves

Because fire is a very random complex phenomenon and its behavior depends on many factors such as room size, ventilations, amount and type of fuel available, etc., it is difficult to simulate the exact action of fire in a fire furnace. To overcome such issue, standard fire curves have been developed. The standard fire curve can be thought of as a severe fire incident that might
occur in a structure. For the purpose of this study, Figure 9 shows the different fire scenarios used, namely the standard fire curves ASTM 119, the modified Hydrocarbon and a representative actual compartment fire curve. One of the main differences between a standard and a compartment fire curve is the absence of a decaying period in the standard fire curve, which can be also observed in Figure 9. Only the VG insulation material was used exclusively in this section. Figures 10-13 show the thermal response of the strengthened RC beam under different fire curves. During the first 30 minutes, the ASTM E119 and the compartment fire curve yield very close results. Both were less severe than the Modified Hydrocarbon curve. However, after longer exposure time, the results change dramatically whereby the standard ASTM E119 appears to have more detrimental impact (i.e., higher interface temperature) than the compartment fire curve. As expected, the Modified Hydrocarbon curve is the most severe one followed by the ASTM E119 and the compartment fire curve. Since the duration of the compartment fire scenario is 60min, no data were available for the 90 and 120min.

Table 3 shows the average error and coefficient of determination ($R^2$) between the ANNs and FE simulations for each of the ANN cases presented earlier in figures 5-8 and 10-13. The average error is average difference between the predicted results of the ANN and FE model. It can be noted that there is a very small average error and excellent coefficient of determination ($R^2$) which reflect the fact that the ANN was able to capture the behavior of the strengthened RC beam under different fire scenarios.
6.3. Case Studies

This section provides four case studies that present the proposed approach for predicting the temperature at the CFRP/Concrete interface. The case studies were chosen to provide the reader with different illustration examples to illustrate the proper use of the proposed charts. For the sake of illustration, different limiting temperatures were chosen for each study case. The limiting temperatures were taken to be 150, 200 and 250 °C for the first, second and third cases, respectively. Finally, case study 4 provides a comprehensive example that shows the proposed insulation thicknesses required to limit the temperature at the CFRP/concrete interface to 150 °C when the RC beam is subjected to different fire scenarios and insulated with different insulation thicknesses.

Case Study 1

Table 4 shows the proposed insulation thickness needed to limit the temperature at the CFRP/Concrete interface to 150 °C. The required insulation thicknesses are shown based on 30 min time increments for a RC T-beam protected with a U-wrap PROMATECT®-H insulation and exposed to the ASTM E119 fire scenario. The results are obtained from the proposed design charts shown in Figs. 5-8. It can be seen from Table 4 that an insulation thickness of 46.5 mm would be sufficient to limit the temperature at the CFRP/Concrete interface to 150 °C for two hours.

Case Study 2:

Similarly, Table 5 demonstrates the proposed insulation thickness required to keep the temperature at the CFRP/Concrete interface at 200°C. The required thicknesses are shown in 30
min increment for a RC T-beam insulated with a U-wrap VG insulation and exposed to the Modified Hydrocarbon fire scenario. The results are obtained from the proposed design charts shown in Figs. 10-13. It can be concluded that using an insulation thickness of 45 mm would be sufficient to limit the interface temperature at the CFRP/Concrete surface to 200 °C for two hours. Compared to the PROMATECT®-H insulation shown in the previous case study, it seems that the use of VG insulation would enhance the state of the insulated RC beam; taking into account that the Modified Hydrocarbon is more severe than the ASTM E119 used in the previous study case.

**Case Study 3:**

Table 6 indicates the proposed insulation thickness necessary to keep the temperature at the CFRP/Concrete interface limited to 250 °C in 30 min increment for a RC T-beam insulated with a U-wrap VG insulation and exposed to the ASTM E119 fire scenario. The results are obtained from the proposed design charts shown in Figs. 10-13.

**Case Study 4:**

Table 7 indicates the proposed insulation thicknesses required to limit the temperature at the CFRP/concrete interface to 150 °C when the RC beam was subjected to different fire scenarios and insulated with different insulation thicknesses. As mentioned earlier, the FE simulation conducted on the different insulation materials were subjected to the ASTM E119 fire scenario, while the insulation materials used in the FE simulation on the different fire was the VG insulation material.
6. Conclusion:

This paper presented the use of Artificial Neural Networks (ANN) as an alternative approach of predicting the fire rating of RC strengthened with FRP plates and exposed to fire scenarios. The developed ANN can accurately predict the fire endurance of RC beams strengthened with Carbon FRP laminates and subjected to elevated temperatures during the whole course of fire. Different fire curves, insulation thicknesses and materials were the main parameter involved in the presented ANN. Different charts and figures were produced that would simplify the complex computational efforts required for practical design purpose. Future research will extend the developed ANN to predict mid span deflections and stress states during fire exposure.

In order to fully understand the effect of fire upon RC structural members strengthened with FRP materials, further numerical and experimental studies are still needed. The following conclusions could be also drawn from the results of this investigation:

- PROMAGLAF®-HTI insulation material seems to perform better than PROMATECT®-H and VG at all stages of the fire action.
- All the studied insulation materials in this paper seem to behave similarly after the use of a of 60-70mm thickness.
- For different fire curves and the worst case scenario presented in this study, the use of 35-40mm thickness of VG insulation seems to keep the temperature of the CFRP/concrete interface below 250 °C.
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Table 1. Input and output variables used in the development of the ANN

<table>
<thead>
<tr>
<th>No.</th>
<th>Input Variable</th>
<th>Type</th>
<th>Number of variables</th>
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<tr>
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<td>2</td>
<td>Insulation material</td>
<td>(categorical variable)</td>
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<td>3</td>
<td>Fire curve</td>
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Output Variable

1. Temperature at the interface between the CFRP/Concrete - -
Please cite this paper as:

Table 2. Comparison between the results of the FE simulation and ANN at different time increments.

<table>
<thead>
<tr>
<th>Time (min)/Beam</th>
<th>Temperature (°C)</th>
<th>Percentage difference (%)</th>
<th>Beam 1*</th>
<th>ANN</th>
<th>Percentage difference (%)</th>
<th>Beam 2*</th>
<th>ANN</th>
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<td>166</td>
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* Tested by Williams et al. (2008)
Table 3. Average error and coefficient of determination ($R^2$) between the ANNs and FE simulation results

<table>
<thead>
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<th>Case</th>
<th>Average error (°C)</th>
<th>Coefficient of determination ($R^2$) (%)</th>
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<tr>
<td><strong>Different insulation materials</strong></td>
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<td>PROMATECT®-H</td>
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<td><strong>Different fire curves</strong></td>
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<tr>
<td>Modified Hydrocarbon</td>
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<tr>
<td>Compartment fire</td>
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Table 4. Proposed insulation thicknesses needed to limit the temperature at the CFRP/Concrete interface to 150 °C.

<table>
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<th>Time (min)</th>
<th>Insulation Thickness (mm)</th>
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<tr>
<td>60</td>
<td>30.0</td>
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<tr>
<td>90</td>
<td>38.0</td>
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<td>46.5</td>
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Table 5. Proposed insulation thicknesses needed to limit the temperature at the CFRP/Concrete interface to 200 °C

<table>
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<tr>
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<td>90</td>
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Table 6. Proposed insulation thicknesses needed to limit the temperature at the CFRP/Concrete interface to 250 °C

<table>
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<table>
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