A NEURAL NETWORK APPROACH FOR PREDICTING HARDENED PROPERTY OF GEOPOLYMER CONCRETE

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ABSTRACT: This paper presents the application of an Artificial Neural Network (ANN) approach to predict the 28-day compression strength of Geopolymer concrete (GPC) from the input ingredients. A total of 190 test samples collected from previously published were employed for training and validating the ANN model. Additionally, a test project was also implemented to collect the experimental data for verifying the prediction ability of the ANN model. Different learning algorithms were investigated to obtain the optimal algorithm for the GPC data. Results from the study revealed that the ANN model using the “trainlm” learning algorithm provided the best prediction results. The average prediction error about 8 MPa was found for the unseen data set. Besides, the effects of changing input variables to the output of the model were also explored by conducting the sensitivity analysis. It was shown that the 28-day GPC compression strength was more sensitive to the change of coarse aggregate (CoAg) and sodium silicate (Na₂SiO₃) variables.

Keywords: Geopolymer Concrete (GPC); Compression Strength; Artificial Neural Networks (ANN); Sensitivity Analysis.

1. INTRODUCTION

Conventional concrete using Ordinary Portland cement (OPC) as the primary binder is one of the widely employed materials all over the world. However, the production of OPC consumes a substantial amount of natural resources. It emits a significant volume of carbon dioxide to the air, leading to a severe impact on the global environment. According to a study of Malhotra [1], the entire cement industry annually releases about 7% of the total human-made (around 2.8 billion tons) of the greenhouse gas to the atmosphere. A feasible solution to reduce the adverse effects for the environment in the production of the conventional concrete is to replace OPC with by-product or geological origin materials. This leads to the development of a new type of concrete called Geopolymer concrete.

Geopolymer concrete (GPC) is an environmentally friendly material that uses fly ash to replace cement as the primary binder. Fly ash is a by-product material from power plants containing aluminous and siliceous ingredients. Geopolymer concrete is a promising alternative candidate to replace OPC in providing sustainable material with excellent resistance for the chemical attack and fire performance [2,3]. According to Davidovits [4], geopolymer paste is formed by the chain and ring polymers with Si⁴⁺ and Al³⁺ in IV-fold coordination with oxygen (polysilanes). The empirical formula of polysilanes is presented as below

\[ M_n \left( \left( \text{SiO}_2 \right)_x - \text{Al}_2 \text{O}_3 \right)_k \cdot \text{wH}_2 \text{O} \]  (1)

where “z” is 1, 2, or 3 or higher up to 32; M is a monovalent cation such as potassium or sodium, and “n” is a degree of polycondensation [4].

Geopolymer production is required for rich alumino-silicate materials and alkaline solutions. The material with rich in silicon (Si) and aluminum (Al) content may come from natural sources such as kaolinite, clays, and micas or the by-product material, including fly ash, silica fume, slag. The alkaline liquids can be obtained from solvable alkali metals such as Sodium or Potassium based. Intensive research has been conducted to explore the effects of ingredients on the GPC compressive strength. For example, Xu and Van Deventer [5] stated in their study that the GPC using potassium hydroxide as the alkaline liquids produced a better compressive strength than that of sodium hydroxide.

In another study, Palomo et al. [6] investigated various combinations of alkaline liquids. The conclusion from the study revealed that among different combinations, a mixture of sodium silicate and sodium hydroxide could result in the highest compressive strength of GPC. Related to the effects of calcium content in by-product materials to the compressive strength of GPC, Gourley [7] recommended in his study that the GPC using materials with low calcium (ASTM Class F) would provide a higher compression strength compared to that of the materials with high calcium (ASTM Class C).

Traditionally, the experimental method is often used to determine the compression strength and other properties of different materials [8-11]. This
method provides the compression strength of concrete with a high level of accuracy. However, this technique is destructive and time-consuming. Recently, an alternative approach using Artificial Intelligence (AI) to predict the strength of materials has been broadly employed. This novel technique involves two steps. In the first step, the approach using the available experimental data to establish the relationship between the input variables and outputs. In the second step, the successfully established connections are then applied to predict the outputs of an unseen input dataset.

In a recent study, Dao et al. [12] used two AI-based approaches, namely Adaptive Neuro-Fuzzy Inference (ANFIS) and Artificial Neural Network (ANN) to predict the compression strength of GPC. Four parameters, namely Fly Ash, Na$_2$SiO$_3$, NaOH, and H$_2$O, were utilized as the inputs of the model, and the 28-day compression strength of GPC was used as the output. A total of 210 data samples were employed for training, validation, and testing the proposed models. The results from the study revealed that the models showed strong potential for the prediction of the GPC compression strength.

Besides the applications for estimating the compression strength of GPC, the AI-based approaches were also used to tackle various engineering topics. For instance, in the study of Nguyen and Dinh [13], and Nguyen et al. [14], the AI-based methods were applied to predict the compression strength of conventional and high-performance concrete. Other researchers applied AI-based technique to identify structural damage [15], to estimate fire resistance ratings for wood structures [16], to predict the ultimate shear strength of steel fiber reinforced concrete [17], to predict the bridge desk rating [18], to predict the compression strength of the different types of concrete [19,20], or to optimize the performance in the wastewater treatment plant [21].

AI-based methods were also popular among researchers recently. As an example, Truong et al. [22] employed different AI-based approaches to evaluate the safety of steel trusses. The finding of the study revealed that the Gradient Tree Boosting algorithm provided the best performance. Elevado et al. [23] applied k-nearest neighbor model to predict the compression strength of the concrete made of fly ash and waste ceramics. Results from the study showed an acceptable prediction capacity of the model.

In this study, a supervised learning model using the ANN technique was developed to predict the compression strength of GPC concrete at 28 days old. The structure of the ANN model was built in MATLAB R2020a Runtime Environment with six input variables and one output. Two steps involving different datasets were performed to create the ANN model. In the first step, the ANN model was trained and validated using available data collected from the previous publications. In the second step, experimental work was implemented in the lab to collect the experimental dataset for verifying the prediction capacity of the proposed ANN model. The 28-day GPC compression strength collected from the destructive tests of specimens were compared to the non-destructive compression strength data generated from the proposed ANN model.

2. DATA PREPARATION

2.1 Experimental Data

A series of nine GPC specimens were fabricated and tested in the lab at the National of Civil Engineering University to collect the GPC 28-day compression strength. Three GPC mixtures with the ratio of alkaline activator over the paste varied from six to ten were used to cast specimens. All specimens were cured in the water in 28 days before conducting the compression tests. Details of material components, mixtures, specimen preparation, and data collection are presented in the subsequent sections.

2.1.1 Materials

Fly Ash (FA) was collected from the Pha Lai coal-fired power station in the Northern part of Vietnam was used in this study. The average particle diameter of FA is 15.5μm. Another by-product material, Blast Furnace Slag (BFS), gathering from the Thai Nguyen Steel factory, was also utilized along with FA as the cement replacement material. The specific surface area by Blaine of BSF is 4520 cm$^2$/g, with an average diameter of 7.63μm. The chemical composition of FA and BSF in terms of percentage by mass is listed in Table 1.

| Oxides | SiO$_2$ | Al$_2$O$_3$ | Fe$_2$O$_3$ | CaO | MgO | K$_2$O | Na$_2$O | SO$_3$ | TiO$_2$
|--------|--------|-----------|-------------|-----|-----|-------|--------|------|------|
| FA (%) | 57.3   | 25.2      | 6.06        | 1.09| 1.68| 5.29  | 0.16   | 0.09 | 0.83 |
| BFS (%)| 43.7   | 12.9      | 1.47        | 28.7| 6.29| 1.22  | 0      | 1.35 | 0.84 |
The sodium silicate \((\text{Na}_2\text{SiO}_3)\) was used as the alkaline activator for producing GPC in this study. The amount of alkaline activator was calculated to ensure the ratio of \(\text{SiO}_2/\text{Al}_2\text{O}_3\) in the input ingredients maintains between two to three. Natural crushed rock with a maximum size of 10 mm was selected for coarse aggregate. The natural sand with a particle size less than 5 mm was chosen for fine aggregate. Details of sieve analysis followed by TCVN 7572-2 are presented in Table 2.

Table 2 Sieve analysis results

| Type of agg. | Sieve size (mm) | Cumulative retained (%) | Standards |
|--------------|-----------------|-------------------------|-----------|
| Coarse       | 40              | 0                       | TCVN 7572-2 |
|              | 20              | 8.2                     |           |
|              | 10              | 50.3                    |           |
|              | 5               | 95.5                    |           |
|              | < 5             | 100                     |           |
| Fine         | 5               | 0                       |           |
|              | 2.5             | 8                       |           |
|              | 1.25            | 27.6                    |           |
|              | 0.63            | 52.3                    |           |
|              | 0.315           | 78.4                    |           |

2.1.2 Mixture proportions and specimen preparation

Table 3 presents the composition of three GPC mixtures. The ratio of alkaline activator over the paste (FA and BSF) in the mixture of MIX1, MIX2, and MIX3 was six, eight, and ten percent, respectively. For each mixture, a set of three specimens using a standard cube with the dimensions of 150×150×150 mm was cast. These specimens were then cured in water for 28 days until the compression tests were implemented.

Table 3 Mix proportions and compression strength of test samples

| No. | Mixture | Test Sample | FAsh (kg) | CoAg (kg) | FiAg (kg) | NaOH (kg) | Na\(_2\)SiO\(_3\) (kg) | H\(_2\)O (kg) | \(f_{c'}^{28}\) (MPa) |
|-----|---------|-------------|-----------|-----------|-----------|-----------|------------------------|--------------|---------------------|
| 1   | MIX1    | 1           | 520       | 1050      | 760       | 25        | 31.2                   | 240          | 38                  |
| 2   |         | 2           | 520       | 1050      | 760       | 25        | 31.2                   | 240          | 41                  |
| 3   |         | 3           | 520       | 1050      | 760       | 25        | 31.2                   | 240          | 38                  |
| 4   | MIX2    | 1           | 520       | 1050      | 760       | 30        | 41.6                   | 240          | 43                  |
| 5   |         | 2           | 520       | 1050      | 760       | 30        | 41.6                   | 240          | 46                  |
| 6   |         | 3           | 520       | 1050      | 760       | 30        | 41.6                   | 240          | 45                  |
| 7   | MIX3    | 1           | 520       | 1050      | 760       | 45        | 52                     | 240          | 54.2                |
| 8   |         | 2           | 520       | 1050      | 760       | 45        | 52                     | 240          | 56                  |
| 9   |         | 3           | 520       | 1050      | 760       | 45        | 52                     | 240          | 52.1                |

2.2 Data from Previous Study

Information of seven GPC properties, namely Furnace ash (FAsh), Coarse aggregate (CoAg), Fine aggregate (FiAg), Sodium hydroxide solution (NaOH), Sodium silicate (Na\(_2\)SiO\(_3\)), Water (H\(_2\)O), and GPC 28-day compression strength \((f_{c'}^{28})\) was collected from the previously published research [26, 27]. Data of the 190 test samples were then employed to train and validate the proposed ANN model. The characteristics of the data are presented in Table 4.

Table 4 Characteristics of data from previously published

| No. | FAsh (kg) | CoAg (kg) | FiAg (kg) | NaOH (kg) | Na\(_2\)SiO\(_3\) (kg) | H\(_2\)O (kg) | \(f_{c'}^{28}\) (MPa) |
|-----|-----------|-----------|-----------|-----------|------------------------|--------------|---------------------|
| 1   | 350       | 1200      | 645       | 41        | 103                    | 35           | 20                  |
| 2   | 428       | 1170      | 630       | 57        | 114                    | 86           | 20                  |
| 3   | 400       | 950       | 850       | 57        | 143                    | 80           | 22.6                |
3. ARTIFICIAL NEURAL NETWORK APPROACH

3.1 ANN Structures

An ANN structure is a supervised learning system that mimics the operation of the human brain. The typical shallow ANN system often consists of an input layer, a hidden layer, and an output layer. Each layer includes one or several inter-layers connected processing units, also known as a neuron. Fig. 1 depicts the structure of a typical ANN system. The neurons in the hidden layer are linked to the neurons of adjacent layers (input and output layer) through the adjustable weighting factor ($w_{ij}$). The value of the factor would be adjusted during the network training process to obtain the best relationship between input and output variables.

![Fig. 1 Structure of a typical ANN system](image)

Of all the popular training algorithm, the backward propagation of errors, or backpropagation, is the most widely used for the supervised learning ANN system. This algorithm consists of two reverse stages, called forward and backward stage. In the first stage, an arbitrary weight value is assigned for each connection in the entire network to establish the initial connection between input and output. In the second phase or backward phase, the difference (error) between the actual and the desired output is calculated and propagated back into the network. The connection weight is adjusted during these iterative processes to minimize the input and output error.

3.2 Model Assessment

Performances of the ANN model was assessed based on three factors: coefficient of determination ($R^2$), Mean Squared Error ($MSE$), and Root Mean Squared Error ($RMSE$). The coefficient of determination measures the correlation between input and output parameters using eq. (2)

\[
R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}
\]  

(2)

where $y_i$ is the $i^{th}$ actual output, $\bar{y}$ is the mean of the actual outputs, $\hat{y}_i$ is the $i^{th}$ predicted outputs, and $n$ is the total number of data samples. $MSE$ is the average squared difference between predicted outputs and actual outputs. $MSE$ can be computed using eq. (3)

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2
\]  

(3)

Root Mean Squared Error is the square root of Mean Squared Error and can be calculated by eq. (4)

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}
\]  

(4)

3.3 Model Development

Six parameters, including FAsh, CoAg, FiAg, NaOH, Na$_2$SiO$_3$, and H$_2$O were selected as the input variables for the ANN model, and the GPC 28-day compression strength (fc'$_{28}$) was designated as the output. The dataset from the previous studies was randomly divided into two subsets in which 85% (i.e., 160 data points) of the entire dataset was employed for training model, 15% (i.e., 30 data points) for validation. The experimental dataset with 9 data samples was utilized for testing the prediction accuracy of the ANN model.

Multiple learning algorithms with variations of neuron numbers in the hidden layer were investigated in this study. The purpose of these tasks was to obtain the optimal ANN model for the GPC data. The performance of the ANN model was
evaluated based on the MSE value. For each model configuration, the potential model was run for 10 trials to find the best performance result for both training and validation datasets. Figure 2a shows the performance of the ANN models with different learning algorithms. The performance of the ANN models with changing neuron numbers in the hidden layer from one to 20 is presented in Fig. 2b.

4. RESULTS AND DISCUSSIONS

4.1 Model Performance

As mentioned above, the proposed ANN model was trained and validated with the dataset collected from previously published research. Three indicators, namely, $R^2$, MSE, and RMSE, were employed to assess the performance of the ANN model. Table 6 lists the values of these indicators for the training dataset, validation dataset, and overall. As can be observed from the table, the ANN model performed well with a coefficient of determination was 0.7209 and 0.6192 for the training and validation dataset, respectively. It is worth noting that the larger value of $R^2$, the better the prediction capacity of the model.

Table 6 Performance results of ANN model

| Parameter   | Training | Validation | Overall |
|-------------|----------|------------|---------|
| $R^2$       | 0.7209   | 0.6192     | 0.7047  |
| MSE         | 81.71    | 73.93      | 80.56   |
| RMSE        | 9.04     | 8.59       | 8.97    |
| Samples     | 160      | 30         | 190     |

Fig. 3 Performance of selected ANN model

Table 5 Details of the selected ANN model

| Parameter                  | Information |
|----------------------------|-------------|
| # neurons in the input layer | 6           |
| # neurons in hidden layer   | 19          |
| # neurons in the output layer | 1          |
| Training method             | backpropagation |
| Learning algorithm          | trainlm     |
| Activation function         | sigmoid     |

![Graph of different learning algorithms](image)

Fig 2 Performance of potential ANN models

As can be seen clearly in Fig.2a, the ‘trainlm’ (Levenberg-Marquardt) algorithm generated the best performance result for the proposed ANN model. The outcome was in line with the previous study [15]. Additionally, the ANN model with 19 neurons in the hidden layer was found to produce optimal performance results, as presented in Fig. 2b. Other information about the selected ANN model to employ in this study is listed in detail in Table 5.
An alternative method to present the performance results of the ANN model is using regression plots. Fig. 3 shows the performance results of the proposed ANN model for different datasets. In these figures, the horizontal axis represents the actual value, and the vertical axis represents the predicted values generated by the proposed ANN model. The samples located on the diagonal lines show an ideal prediction of the model.

4.2 Error Evaluation

The error histogram with 20 bins (columns) of the performance errors of the proposed ANN model is presented in Fig. 4. The error was the difference between the predicted value produced by the ANN model and the actual value. In this figure, the vertical axis represents the number of samples from a dataset, while the horizontal axis presents the error corresponding to the bins. The zero-line is the zero error on the horizontal axis. As can be seen, most samples had errors between -7.56 MPa and 8.48 MPa. The negative errors indicated that the predicted value from the ANN model was smaller than the experimental one.

4.3 Application of Artificial Neural Network for Experimental Data

The successful ANN model was then employed to predict the compression strength of GPC. The input data for the model was the ingredients for mixtures, as presented in Table 3. The output of the model was the predicted GPC 28-day compressive strength. The compressive strength produced by the ANN model was then compared to the experimental compression strength obtained from the destructive tests. Table 7 presents the performance results of the model for the experimental data set.

| No. | Experimental (MPa) | Predicted (MPa) | Error (MPa) | Error (%) |
|-----|-------------------|----------------|-------------|-----------|
| 1   | 38.0              | 31.5           | 6.48        | 17.0      |
| 2   | 41.0              | 31.5           | 9.48        | 23.1      |
| 3   | 38.0              | 31.5           | 6.48        | 17.0      |
| 4   | 43.0              | 36.6           | 6.40        | 14.9      |
| 5   | 46.0              | 36.6           | 9.40        | 20.4      |
| 6   | 45.0              | 36.6           | 8.40        | 18.7      |
| 7   | 54.2              | 43.1           | 11.1        | 20.4      |
| 8   | 56.0              | 43.1           | 12.9        | 23.0      |
| 9   | 52.1              | 43.1           | 8.97        | 17.2      |

As can be seen from Table 7, the ANN model performed reasonably well for the experimental dataset with an average error of about 8 MPa. It is worth pointing out that the experimental dataset was unseen for the proposed ANN model. The ANN model could predict the compressive strength of GPC in a wide range from 38 MPa to 56 MPa with an approximate error of 20 percent. That means the ANN model could generalize the nonlinear relationship between the inputs and output.

4.4 Sensitivity Analysis

The sensitivity analysis was conducted for each input variable by changing its value from low to high while keeping the value of others at the mid-value. To do that, the input data were divided into five groups including the Low (the smallest value of each input parameter), the Mid Low (a halfway from Low to Mid), the Mid (a halfway from Mid to High), the Mid High (a halfway from Mid to High), and the High (the largest value of each input parameter), as listed detail in Table 8.

Fig. 4 Error assessment for the selected ANN model
Table 8 Data for sensitivity analysis

| Input parameter levels | FAsh (kg) | CoAg (kg) | FiAg (kg) | NaOH (kg) | Na$_2$SiO$_3$ (kg) | H$_2$O (kg) |
|------------------------|-----------|-----------|-----------|-----------|-------------------|------------|
| Low                    | 254       | 723       | 535       | 22.8      | 48                | 0          |
| Mid Low                | 315       | 985       | 614       | 47.1      | 72                | 28.4       |
| Mid                    | 376       | 1247      | 692       | 71.4      | 96                | 56.8       |
| Mid High               | 437       | 1509      | 771       | 95.7      | 120               | 85.2       |
| High                   | 498       | 1772      | 850       | 120.0     | 144               | 114        |

Fig. 5 presents the sensitivity analysis results of all input variables in the form of a parallel coordinate diagram. This graph has five vertical axes arranged from left to right along with the horizontal axis; each of the axes corresponds to a different level of the input parameters. The vertical axis represents the GPC 28-day compression strength. As can be observed clearly, the 28-day compression strength of GPC was responsive to the change of coarse aggregate and sodium silicate parameters.

The ANN technique was employed in this study to predict the compression strength of GPC at 28 days old. In the first stage, available data were utilized to develop the ANN model. In the second stage, experimental data was used to test the prediction capacity of the model. Performance results revealed that the ANN model could predict the wide range of output for the unseen experimental data with an error of around 20 percent. In addition, the “trainlm” learning algorithm was found to generate the best results for the proposed ANN model.

With respect to the sensitivity analysis, the outcomes indicated that the coarse aggregate (CoAg) and sodium silicate (Na$_2$SiO$_3$) were among the two input variables, which had a significant influence on the output parameter of the ANN model. Finally, it was concluded that the ANN model could be used as an alternative method to predict the compression strength of GPC with an acceptable level of accuracy.

5. ACKNOWLEDGMENT

This research is funded by the National University of Civil Engineering (NUCE), Hanoi, Vietnam under a grant number 29-2019/KHXD-TD. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NUCE.

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Appendix A Experimental data from the previous study

| No. | F(kg) | CaO(kg) | SiO2(kg) | Al2O3(kg) | MgO(kg) | Fe2O3(kg) | SO3(kg) | H2O(kg) | C(kg) | S(kg) | P(kg) | Mg(kg) | Ca(kg) | Sr(kg) | Fe(kg) | Cu(kg) |
|-----|-------|---------|----------|-----------|---------|-----------|---------|---------|-------|-------|-------|--------|--------|--------|--------|--------|
| 1   | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 2   | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 3   | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 4   | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 5   | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 6   | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 7   | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 8   | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 9   | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 10  | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 11  | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |
| 12  | 100   | 200     | 300      | 400       | 500     | 600       | 700     | 800     | 900   | 1000  | 1100  | 1200   | 1300   | 1400   | 1500   | 1600   |

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| No. | Value   |
|-----|---------|
| 50  | 444.4   |
| 51  | 498.4   |
| 52  | 1153.5  |
| 53  | 599.5   |
| 54  | 89.7    |
| 55  | 26.5    |
| 56  | 39.9    |
| 57  | 103.2   |
| 58  | 20.7    |
| 59  | 103.2   |
| 60  | 20.7    |
| 61  | 103.2   |
| 62  | 103.2   |
| 63  | 103.2   |
| 64  | 103.2   |
| 65  | 103.2   |
| 66  | 103.2   |
| 67  | 103.2   |
| 68  | 103.2   |
| 69  | 103.2   |
| 70  | 103.2   |
| 71  | 103.2   |
| 72  | 103.2   |
| 73  | 103.2   |
| 74  | 103.2   |
| 75  | 103.2   |
| 76  | 103.2   |
| 77  | 103.2   |
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| 80  | 103.2   |
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| 83  | 103.2   |
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| 85  | 103.2   |
| 86  | 103.2   |
| 87  | 103.2   |
| 88  | 103.2   |
| 89  | 103.2   |
| 90  | 103.2   |
| 91  | 103.2   |
| 92  | 103.2   |
| 93  | 103.2   |
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| 95  | 103.2   |
| 96  | 103.2   |
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| 102 | 103.2   |
| 103 | 103.2   |
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| 105 | 103.2   |
| 106 | 103.2   |
| 107 | 103.2   |
| 108 | 103.2   |
| 109 | 103.2   |
| 110 | 103.2   |
| 111 | 103.2   |
| 112 | 103.2   |
| 113 | 103.2   |
| 114 | 103.2   |
| 115 | 103.2   |
| 116 | 103.2   |
| 117 | 103.2   |
| 118 | 103.2   |
| 119 | 103.2   |
| 120 | 103.2   |
| 121 | 103.2   |
| 122 | 103.2   |