Application of Computational Intelligence Techniques to an Environmental Flow Formula

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Abstract

Manning formula is one of the most famous functions used in hydraulics and hydrology, which calculates the average flow velocity based on roughness coefficient, hydraulic radius, and slope. This study intends to improve the original formula by minimizing the deviation error between calculated flow velocity and observed one. The first improvement approach was to estimate the exponent values of hydraulic radius and slope, instead of using current 2/3 and 1/2, while fixing the roughness value. When logarithm-converted multiple linear regression, calculus-based BFGS technique, and meta-heuristic genetic algorithm were applied to the problem, genetic algorithm found the best exponent values in terms of sum of squares error and coefficient of determination. The second approach was to estimate the individual roughness value, instead of a constant one, which is the function of hydraulic radius and slope. When multiple linear regression, artificial neural network with BFGS, and artificial neural network with genetic algorithm tackled the problem, the latter found the best solution. We hope these approaches will be utilized more practically in the future.

Keywords: Computational intelligence, Manning equation, Hydraulics, Curve fitting, Genetic algorithm, Artificial neural network

1. Introduction

The Manning formula, also referred to as Gauckler-Manning formula (or Gauckler-Manning-Strickler formula) in Europe [1] or Manning’s equation in the United States [2] and English-speaking countries [3], is a simple-structured empirical formula which calculates the average velocity of uniform or gradually varied flow [2] in an open channel. The common form of the formula is

\[ V = \frac{a}{n} R^{2/3} S^{1/2}, \]  

(1)

where \( V \) is cross-sectional mean velocity (L/T); \( n \) is roughness coefficient (T/L \(^{1/3}\)); \( R \) is hydraulic radius (L), which is calculated from the cross-sectional area \( A \) (L\(^2\)) divided by wetted perimeter \( P \) (L) of the flow. For wide rectangular channels, \( R \) is approximated by flow depth [1][4]; \( S \) is channel slope (L/L) which is assumed to be equal to friction slope [5]; and \( a \) is conversion factor between SI (\( a=1 \)) and English (\( a = 1.49 \)) units. This paper will follow the SI unit.
we can rearrange Eq. (1) as follows:

\[ V \left( \frac{m}{s} \right) = \frac{R^{\alpha_S \beta}}{S^{1/n}} \]

Also, Eq. (2) can be plotted using the dataset [8] as shown in Figure 1.

In order to find fixed \( n \), the dataset was analyzed using a linear regression with zero intercept (0I-LR; \( y = cx + 0 \)) which passes the origin point (both \( x \) and \( y \) are equal to zero) and whose slope becomes \( 1/n \) [9]. The regression result shows that \( 1/n = 74.202 \) or \( n = 0.013477 \) with the coefficient of determination \( (R^2) \) of 0.4861.

In this situation, is there any way to further improve the Manning formula with fixed roughness coefficient? For this “empirical” formula, the exponent values, such as \( 2/3 \) of hydraulic radius and \( 1/2 \) of slope, appear somewhat arbitrary and those values can be optimized using several techniques [10] such as multiple linear regression (MLR), calculus-based optimization, and meta-heuristic optimization.

For an optimal exponent estimation using MLR, we can first apply a logarithm to both sides of Eq. (1):

\[
\ln(V) = \ln \left( \frac{1}{n} R^{\alpha_S \beta} \right) = \ln \left( \frac{1}{n} \right) + \alpha \ln(R) + \beta \ln(S). \quad (3)
\]

And, the common form of MLR is

\[ Y = c_0 + c_1 X_1 + c_2 X_2. \quad (4) \]

Since we already have the dataset of \( V, R (X_1 = \ln(R)), \) and \( S (X_2 = \ln(S)) \), the optimal values of \( \alpha, \beta, \) and \( n \) can be obtained using the following relations:

\[
\alpha = c_1, \quad \beta = c_2, \quad n = 1/e^{c_0}. \quad (5)
\]

The regression result shows that \( \alpha = 0.785254, \beta = 0.31775, \) and \( n = 0.03037 \) with \( R^2 \) of 0.8294, which means that \( \alpha \) increased from 0.6667 to 0.7853, \( \beta \) decreased from 0.5 to 0.3178, \( n \) increased from 0.0135 to 0.0304 (since the exponent values were changed, we might not fairly compare the magnitude of two roughness coefficients), and \( R^2 \) soared from 0.4861 to 0.8294 as shown in Figure 2.

Instead of using the above logarithm-converted multiple linear regression (Ln-MLR), we can adopt optimization techniques for estimating the roughness coefficient and two exponent values. In this optimization process, we have to minimize the sum of squares error (SSE) as follows:

\[
\text{Minimize} \sum_{i=1}^{n} \left( V_i - \hat{V}_i \right)^2, \quad \hat{V}_i = \frac{1}{n_i} R_i^{\alpha_S \beta}, \quad (6)
\]
Table 1. Experimental dataset and calculated velocities with fixed \( n \)

| Run No. | \( V_i \) (m/s) | \( R_i \) (m) | \( S_i \) | \( \hat{V}_i \) (m/s) |
|---------|----------------|-------------|---------|----------------------|
|         |                 |             |         | 0I-LR                | Ln-MLR | BFGS     | GA          |
| 1       | 0.400945        | 0.060583    | 0.00113 | 0.384760             | 0.421653 | 0.427683 | 0.424328    |
| 2       | 0.440086        | 0.070916    | 0.00112 | 0.425455             | 0.475809 | 0.481878 | 0.480858    |
| 3       | 0.493025        | 0.073364    | 0.00113 | 0.437130             | 0.510328 | 0.518989 | 0.519815    |
| 4       | 0.557127        | 0.078054    | 0.00112 | 0.453548             | 0.513028 | 0.518989 | 0.519815    |
| 5       | 0.340164        | 0.044717    | 0.00116 | 0.382025             | 0.376098 | 0.377570 | 0.375687    |
| 6       | 0.421810        | 0.056999    | 0.00117 | 0.449112             | 0.455053 | 0.455539 | 0.457541    |
| 7       | 0.443044        | 0.066841    | 0.00115 | 0.466432             | 0.513707 | 0.513518 | 0.518728    |
| 8       | 0.540074        | 0.074797    | 0.00115 | 0.535074             | 0.561193 | 0.560194 | 0.568344    |
| 9       | 0.263983        | 0.019121    | 0.00332 | 0.305722             | 0.240101 | 0.237589 | 0.234723    |
| 10      | 0.304127        | 0.026482    | 0.00331 | 0.379283             | 0.309773 | 0.305399 | 0.305505    |
| 11      | 0.379098        | 0.032199    | 0.00333 | 0.433381             | 0.361859 | 0.355859 | 0.358765    |
| 12      | 0.454098        | 0.039972    | 0.00333 | 0.500578             | 0.428822 | 0.420646 | 0.427642    |
| 13      | 0.369026        | 0.060583    | 0.00111 | 0.381340             | 0.419267 | 0.425532 | 0.421913    |
| 14      | 0.401014        | 0.062495    | 0.00112 | 0.391069             | 0.430846 | 0.436987 | 0.439396    |
| 15      | 0.438431        | 0.065183    | 0.00113 | 0.403997             | 0.446593 | 0.452592 | 0.450315    |
| 16      | 0.561799        | 0.073882    | 0.00112 | 0.437237             | 0.491367 | 0.497396 | 0.497130    |
| 17      | 0.565847        | 0.074797    | 0.00112 | 0.440840             | 0.496139 | 0.502155 | 0.502126    |
| 18      | 0.363013        | 0.038834    | 0.00168 | 0.348775             | 0.337300 | 0.339108 | 0.335656    |
| 19      | 0.430440        | 0.051457    | 0.00165 | 0.416984             | 0.418323 | 0.419451 | 0.419442    |
| 20      | 0.477283        | 0.055201    | 0.00167 | 0.439616             | 0.443742 | 0.444382 | 0.445783    |
| 21      | 0.500336        | 0.059032    | 0.00166 | 0.458349             | 0.466977 | 0.467263 | 0.469848    |
| 22      | 0.556912        | 0.064065    | 0.00167 | 0.485498             | 0.498785 | 0.498636 | 0.503096    |
| 23      | 0.282029        | 0.024382    | 0.00333 | 0.360036             | 0.290865 | 0.286975 | 0.286223    |
| 24      | 0.283186        | 0.025394    | 0.00332 | 0.369376             | 0.300019 | 0.295897 | 0.295552    |
| 25      | 0.383270        | 0.034578    | 0.00331 | 0.453106             | 0.381960 | 0.375394 | 0.379418    |
| 26      | 0.394911        | 0.040649    | 0.00332 | 0.505460             | 0.434107 | 0.425792 | 0.433106    |

where \( V_i \) is \( i \)th observed mean velocity in dataset; \( \hat{V}_i \) is calculated mean velocity using \( i \)th hydraulic radius \( R_i \) and slope \( S_i \) in the dataset.

When a calculus-based optimization technique, named BFGS [11], was applied to the identical dataset, we could obtain \( \alpha = 0.773554, \beta = 0.282297, \) and \( n = 0.039360 \) with \( R^2 \) of 0.8295 and SSE of 0.0347, which means that \( R^2 \) was slightly improved from 0.8294 to 0.8295 and SSE was also slightly improved from 0.0347 to 0.0345 when compared with the results from Ln-MLR.

When a popular meta-heuristic algorithm, named genetic algorithm (GA) [12], was also applied to the identical dataset, we could obtain \( \alpha = 0.812227, \beta = 0.319725, \) and \( n = 0.027611 \) with \( R^2 \) of 0.8309 and SSE of 0.0342, which means that \( R^2 \) was even improved from 0.8295 to 0.8309 and SSE was also even improved from 0.0345 to 0.0342 when compared with the results from BFGS. The fifth to eighth columns of Table 1 show the calculated velocities from different techniques, and Table 2 summarizes corresponding parameter values and fitness indexes.

3. Improvement of the Formula with Varied Roughness Coefficient

Roughness value \( n \) varies along the reach in a river, and even varies in an identical reach with different flow amount [4].
value of $n$ generally decreases as discharge (or depth or hydraulic radius) increases [13–15] although sometimes a direct proportion between the two occurs in sand-bed, instead of this inverse proportion [3, 14]. Anyhow, this discharge-dependency is seldom considered, and most cases adopt a fixed roughness value [3] for a given reach.

If the Manning’s roughness coefficient $n$ is assumed to be varied, we can calculate individual roughness coefficient as follows:

$$n_i = \frac{R_i^{2/3} S_i^{1/2}}{V_i}.$$ \hspace{1cm} (7)

The individual roughness value is shown in the third column of Table 3. When a graph of $R_i$ versus $n_i$ is drawn as shown in Figure 3, we can confirm the previous studies where roughness decreases with increasing hydraulic radius.

Furthermore, when a graph of $S_i$ versus $n_i$ is drawn as shown in Figure 4, we can also confirm the previous research where roughness increases with increasing slope [15].

With the above relationships among hydraulic radius, slope and roughness, we can derive a two-independent-variable function using MLR as follows:

$$n_i = c_0 + c_1 R_i + c_2 S_i.$$ \hspace{1cm} (8)

MLR could obtain $c_0$ of 0.014049, $c_1$ of $-0.04483$, and $c_0$ of 1.00974 with $R^2$ of 0.8367 and SSE of 0.0333. The corresponding $n_i$ and $\hat{V}_i$ values can be found in the seventh and fourth columns of Table 3, and Figure 5 shows the relationship between observed and calculated velocities. This varied roughness approach by MLR slightly enhanced the solution quality in terms of $R^2$ from 0.8309 to 0.8367, and SSE from 0.0342 to 0.0333 when compared with those from the fixed roughness approach by GA.

In the varied roughness approach by MLR, the roughness $n_i$ was the function of hydraulic radius $R_i$ and slope $S_i$. We can ask if there is any way to improve this linear relationship among them.

This study introduces an artificial neural network (ANN)
Table 3. Experimental dataset and calculated velocities with varied $n$

| Run No | $V_i$ (m/s) | $n_i$ (s/m$^{1/3}$) | $\hat{V}_i$ (m/s) | $\hat{n}_i$ (s/m$^{1/3}$) |
|--------|-------------|---------------------|-------------------|---------------------|
|        | MLR        | ANN+ BFGS | ANN+ GA | MLR | ANN+ BFGS | ANN+ GA |
| 1      | 0.400945   | 0.412319 | 0.418819 | 0.410950 | 0.012576 | 0.012381 | 0.012618 |
| 2      | 0.440086   | 0.473793 | 0.487133 | 0.471736 | 0.012102 | 0.011770 | 0.012155 |
| 3      | 0.493025   | 0.490799 | 0.505732 | 0.496809 | 0.012003 | 0.011649 | 0.011858 |
| 4      | 0.557127   | 0.518795 | 0.538541 | 0.585896 | 0.011782 | 0.011350 | 0.010432 |
| 5      | 0.340164   | 0.370899 | 0.364315 | 0.379831 | 0.013881 | 0.014132 | 0.013555 |
| 6      | 0.421810   | 0.454040 | 0.445487 | 0.453332 | 0.013330 | 0.013586 | 0.013351 |
| 7      | 0.443044   | 0.519934 | 0.512035 | 0.509077 | 0.012867 | 0.013066 | 0.013142 |
| 8      | 0.540074   | 0.576392 | 0.570223 | 0.560367 | 0.012511 | 0.012646 | 0.012868 |
| 9      | 0.263983   | 0.244620 | 0.252857 | 0.254519 | 0.016843 | 0.016294 | 0.016188 |
| 10     | 0.304127   | 0.309751 | 0.315694 | 0.316054 | 0.016502 | 0.016191 | 0.016173 |
| 11     | 0.379998   | 0.359028 | 0.363260 | 0.361278 | 0.016268 | 0.016118 | 0.016166 |
| 12     | 0.454098   | 0.423771 | 0.421844 | 0.417734 | 0.015919 | 0.015992 | 0.016149 |
| 13     | 0.369026   | 0.409370 | 0.416470 | 0.407822 | 0.012554 | 0.012340 | 0.012602 |
| 14     | 0.401041   | 0.422327 | 0.430116 | 0.419148 | 0.012479 | 0.012253 | 0.012574 |
| 15     | 0.438431   | 0.440150 | 0.449151 | 0.435160 | 0.012370 | 0.012122 | 0.012512 |
| 16     | 0.561799   | 0.492323 | 0.508122 | 0.502058 | 0.011969 | 0.011597 | 0.011737 |
| 17     | 0.565847   | 0.498087 | 0.514702 | 0.514645 | 0.011928 | 0.011543 | 0.011544 |
| 18     | 0.363013   | 0.332046 | 0.326778 | 0.343594 | 0.014156 | 0.014384 | 0.013680 |
| 19     | 0.430440   | 0.41518  | 0.406985 | 0.419285 | 0.013557 | 0.013808 | 0.013403 |
| 20     | 0.477283   | 0.441769 | 0.433391 | 0.442782 | 0.013411 | 0.013670 | 0.013380 |
| 21     | 0.500336   | 0.469555 | 0.458501 | 0.464440 | 0.013228 | 0.013472 | 0.013300 |
| 22     | 0.556912   | 0.502771 | 0.494049 | 0.494495 | 0.013014 | 0.013243 | 0.013232 |
| 23     | 0.282029   | 0.291977 | 0.298950 | 0.299863 | 0.016618 | 0.016231 | 0.016181 |
| 24     | 0.283186   | 0.307571 | 0.307062 | 0.307717 | 0.016562 | 0.016212 | 0.016177 |
| 25     | 0.383270   | 0.378361 | 0.380001 | 0.377960 | 0.016139 | 0.016069 | 0.016156 |
| 26     | 0.394911   | 0.429020 | 0.426441 | 0.421927 | 0.015878 | 0.015974 | 0.016145 |

approach with optimization technique, which can consider nonlinearity among variables. Actually ANN approaches have been applied to various prediction problems such as energy demand [17] or water pipe deterioration [18]. While those approaches used error-back-propagation technique to adjust the weight values among layers, a recent ANN approach hybridized ANN with an optimization algorithm to search the solution space of an ocean engineering problem more efficiently [19]. The basic ANN model, named feed-forward multilayer perceptron, can be structured as shown in Figure 6. As shown in the figure, there are three layers (input layer in left column, hidden layer in middle column, and output layer in right column). If we put certain values for hydraulic radius $R_i$ and slope $S_i$ in the left input layer, these values are multiplied by weighting values (such as 16.18) on the links. Then, those multiplied values are summed at each node (for example, $v_1 = 16.18 \times R_1 + (-9.36) \times S_1 + (-18.21)$) in the middle hidden layer. Again, Sigmoid-functioned nodal values (for example, $\frac{1}{1+e^{-z}}$) in the middle layer are multiplied by weighting values (such as $-97.43$), then the multiplied values are finally summed (for example, $z = \frac{-97.43}{1+e^{-z}} + \frac{-1.65}{1+e^{-z}} + 2.52$) in the right output layer and Sigmoid functioned.

When the ANN was hybridized with BFGS (ANN+BFGS), this model slightly enhanced the solution quality when compared with MLR, obtaining $R^2$ of 0.8447 and SSE of 0.0315. The corresponding $n_i$ and $\hat{V}_i$ values can be found in the eighth
and fifth columns of Table 3.

When the ANN was hybridized with GA (ANN+GA), this model even enhanced the solution quality when compared with ANN+BFGS, obtaining $R^2$ of 0.8636 and SSE of 0.0277. The corresponding $n_i$ and $\hat{V}_i$ values can be found in the ninth and sixth columns of Table 3. The optimal weight values from ANN+GA are shown in Figure 6, and this result can be explicitly described as follows:

$$\hat{n}_i = \frac{0.0176}{1 + e^{-z_i}},$$

$$z = \frac{-97.43}{1 + e^{-v_1}} + \frac{-1.65}{1 + e^{-v_2}} + 2.52,$$

$$v_1 = \frac{R_i}{0.0781} \times 16.18 + \frac{S_i}{0.0033} \times (-9.36) - 18.21,$$

$$v_2 = \frac{R_i}{0.0781} \times 1.56 + \frac{S_i}{0.0033} \times (-8.06) + 4.47.$$  

(9)

4. Discussions

The amount of data (26 points) introduced in Table 1 does not appear very large. Nonetheless, this is not small for our regression-type neural-network calculation. In fact, a much larger dataset is required for unstructured data (pixel-type photos or sound wave files). However, because our hydraulic data is very structured (number-type), 26 points might be enough for devising the better formula, which could be verified with statistical indexes ($R^2$ and SSE) and our other papers for energy demand prediction [17] and pipe condition assessment [18].

Actually, Manning formula can be derived from Chézy formula [13] as follows:

$$V = C R^{1/2} S^{1/2},$$

where $C$ is Chézy number and can be represented as $C = R^{1/6} n^{-1}$. This is why the Manning formula is sometimes called as Chézy-Manning formula [20].

Since the basic structure of the Chézy formula relies on a physical relationship between the average velocity and the square root of the bed shear stress ($\tau \propto R S$), we may change only Chézy number while fixing the exponent 0.5. When BFGS tackled this situation (fixing $R^{1/2} S^{1/2}$ part of Chézy formula), we obtained a much higher exponent value (1.0024) for $R$ in Chézy number with $R^2 = 0.8075$ and SSE = 0.0412, which is a more theoretical approach but less accurate when compared with the approach of varied slope exponent.

Manning formula is usually used by engineers, who barely have much knowledge of cutting-edge computational intelligence techniques, such as artificial neural network and genetic algorithm. The ANN model in this study can be simply an improved model which considers higher nonlinearity between independent variables and a dependent one, than existing MLR model. And, the GA technique can be utilized for globally finding optimal weighting values of the ANN model. However, a calculus-based BFGS model, which finds optimal weighting values locally, could perform as well as GA in this study. In order for engineers to easily use these techniques, application software can be coded in the form of spreadsheet macros.
5. Conclusions

This study proposed various techniques to improve the original Manning formula. The approach was divided into two parts. The first approach was to estimate the exponents of hydraulic radius and slope while fixing the roughness value. When three different techniques, such as logarithm-converted MLR, gradient-based BFGS, and meta-heuristic GA as well as zero-intercept LR, tackled the problem, the GA technique found the best solutions with respect to determination coefficient and SSE.

The second approach was to estimate the individual roughness value while fixing the exponent values of hydraulic radius and slope. When three different techniques, such as MLR, ANN+BFGS, and ANN+GA, tackled the problem, ANN+GA found the best solutions with respect to determination coefficient and SSE.

Nonetheless, we have to admit that this study has a limitation when determining the Manning’s roughness $n$, which is also related with riverbed material, particle size distribution, and sediment transport, mainly because we do not currently have those detailed data. However, in order to fully investigate the roughness, we need such factors as riverbed type, flow depth, hydraulic radius, free surface width, $d_{50}$, $d_{75}$, $d_{84}$, $d_{90}$, cross section geometry, etc, as shown in previous studies [21]. While the goal of this paper to minimize any error between experimental data and corresponding hydraulic formula is accomplished by utilizing computational intelligence techniques, we have to consider more roughness-related data for implementing more practical and realistic formula in the future. Also, various soft computing techniques such as neural network [22], meta-heuristics [23], and fuzzy theory [24] will be utilized for this endeavor.

Conflicts of Interest

The authors declare no conflict of interest.

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