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Performance Evaluation of Selected Explicit Friction Models In Pipe Network Analysis

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Abstract: The Accurate estimation of friction factor is essential for determining head loss and flow distribution in pipe networks. Although the Colebrook equation remains the benchmark, its implicit nature makes it computationally intensive. As a result, many explicit friction factor models have been developed as alternatives. This study evaluated the performance of 38 selected explicit models in solving pipe network problems using a non-linear gradient-based method in MATLAB. Four networks of increasing complexity (10, 24, 34, and 74 pipes) were used to assess each model's computational efficiency, accuracy, numerical stability, and complexity. The Colebrook equation, solved using the Clamond method, served as the benchmark.

Across all networks, the number of iterations remained nearly constant for most models, but convergence times and computational efficiencies varied widely. Computational efficiencies ranged from 1.042 to 2.791 for network 1, 1.122 to 8.227 for network 2, 1.023 to 2.050 for network 3 and 1.001 to 1.794 for network 4. Although some explicit models, such as Swamee-Jain, Cojbasic Brkic A, Niazkar A, and Serghides A, showed good performance, the Colebrook equation remained the fastest and most stable across all networks.

Error analysis using mean square error (MSE) across four pipe networks showed that Niazkar A, Cojbasic Brkic A, and Serghides A consistently produced the lowest errors and they closely matched Colebrook's results in both nodal heads and flow rates. For these models, nodal head MSE values ranged from 6.26×10^{-12} to 6.75×10^{-12} and flow rate MSE values from 6.61×10^{-11} to $6.17\times10^{-}10$ in Network 1; 1.415×10^{-17} to 1.3529×10^{-16} for nodal head and 3.980×10^{-19} to 9.579×10^{-18} for flow rate in Network 2; 1.14×10^{-10} to 1.88×10^{-5} for nodal head and 2.179×10^{-14} to 1.0795×10^{-12} for flow rate in Network 3; and 2.46×10^{-18} to 5.43×10^{-18} for nodal head and 2.851×10^{-18} to 4.449×10^{-18} for flow rate in Network 4. In contrast, models such as Avci Karagoz, Buzzelli, and Fang exhibited convergence failures in the most complex network, indicating numerical instability in highly interconnected systems.

In conclusion, while a few explicit models are suitable alternatives in specific scenarios, the Colebrook equation remains the most reliable choice for pipe network analysis.

Keywords: Pipe Network Analysis, Friction Factor, Colebrook Equation, Explicit Models, Hydraulic Engineering

I. INTRODUCTION

A pipe network is a system of interconnected pipes designed for transporting fluids such as water, oil, and gas. Pipe networks are vital to modern infrastructure, including water distribution, oil and gas transport, and HVAC systems (Chaudhry, 2014). Their efficiency depends on accurately predicting fluid behaviour, particularly frictional losses that occur due to interactions between the fluid and pipe walls, which cause energy dissipation and pressure reduction along the pipeline. Correct estimation of these losses ensures optimal system performance and resource utilization (García, 2022).

In pipe systems, head loss in turbulent flow is commonly determined using the Darcy–Weisbach relation given in Equation (1):

$$h_f = f \times L/D \times V^2/2g \qquad (1)$$

where h_f is head loss, L is pipe length, D is diameter, V is velocity, g is gravitational acceleration, and f is the friction factor.

The friction factor (f), which accounts for resistance due to pipe roughness, flow velocity, and fluid properties, is most accurately defined by the Colebrook–White (C–W) model (Equation 2):

$$1/\sqrt{f} = -2\log_{10}((\epsilon/D)/3.7 + 2.51/(Re\sqrt{f})) \qquad (2)$$

Although accurate, the Colebrook–White or simply Colebrook equation is implicit in f, meaning it cannot be solved directly and requires iterative computations. This implicit nature of 'f' adds complexity to hydraulic analyses and underscores the importance of accurately estimating its value for precise predictions of frictional losses in pipe networks. To overcome this limitation, several explicit friction factor relations have been proposed to approximate the Colebrook–White model, each with varying degrees of performance across different criteria such as computational efficiency, accuracy, numerical stability and model complexity.

Although numerous explicit friction factor relations exist, the majority of their evaluations in past studies have been carried out without applying them to pipe networks, which are the real environment for head-loss analysis. Very limited works have been reported on their evaluation when used specifically in pipe network analysis. Over the years, researchers have compared these explicit models under various conditions. Niazkar and Talebbeydokhti (2019) applied non-linear solution methods in the evaluation of explicit friction factor relations on pipe networks, where number of iterations was used as a measure of computational speed of these models. Using number of iterations as a measure of computational speed among other factors, may be erroneous as some relations may take more time to converge but with smaller or the same number of iterations.

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Udoh (2023) attempted to evaluate the performance of several explicit friction factor relations, primarily focusing on simple pipe networks and comparing their performances with that of Colebrook equation. He found that Colebrook equation converges faster than most explicit models when applied to simple pipe networks using linear solution method. This finding suggested that there may not be the need for explicit models in such scenarios, as the Colebrook equation demonstrated superior convergence performance. However, since Udoh's analysis was limited to simple networks and linear solution method, it is not clear what the performances of these explicit models would be, in more complex systems or when non-linear solution methods are employed.

Consequently, in this study, based on a number of criteria such as accuracy, convergence speed, numerical stability, and computational efficiency, a comprehensive performance evaluation of selected explicit friction factor equations when applied to pipe networks of varying complexity using a non-linear gradient-based solution method was done. The remaining sections present the methodology, followed by the results and discussion, and finally the conclusions.

II. COMPUTATIONAL METHODOLOGY

A. Pipe Networks

Four different pipe networks of increasing complexity were obtained from the literature and were analyzed to assess the performance of 38 selected explicit friction factor relations. The first pipe network consists of 10 pipes and 7 nodes (Figure 1). The second pipe network consists of twenty-four pipes and seven nodes (Figure 2). The third pipe network consists of 34 pipes and 32 nodes, and is fed by gravity from a reservoir with a 100 m fixed head (Figure 3). The fourth pipe network contains 74 pipes and 48 nodes (Figure 4).

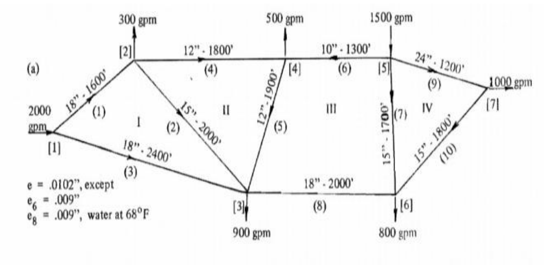

Fig. 1. Network 1 *(Source: Jeppson (1974))*

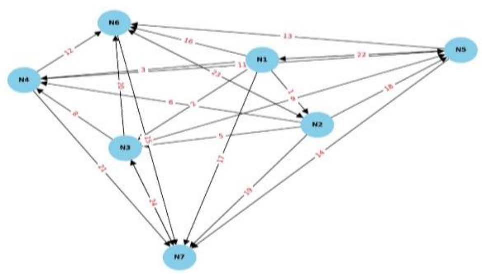

Fig. 2. Network 2 *(Source: Ciaponi et al. (2015))*

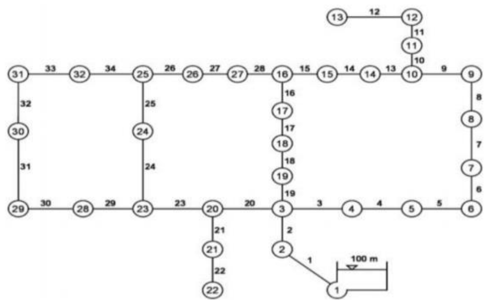

Fig. 3. Network 3 *(Source: Fujiwara and Khang (1990))*

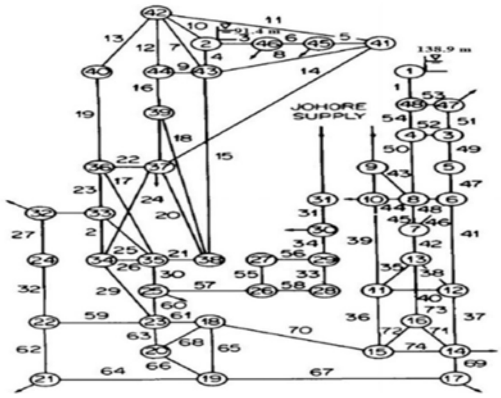

Fig. 4. Network 4 *(Source: Chin et al. (1978))*

B. Friction Factor Relations

In this study, 38 explicit friction factor models were evaluated to compare their performance against the Colebrook–White (CW) equation. These 38 models were chosen to provide a representative mix of the most established, widely referenced, and recently developed explicit friction factor equations, enabling a fair and comprehensive comparison. They include relations developed by Avci and Karagoz (2009), Azizi (2008), Barr (1981), Beluco and Schettini (2001), Biberg (2017), Brkić (2011), Brkić and Parks (2019a), Brkić and Parks (2011b), Brkić and Parks (2011c), Buzzelli (2008), Chen (1979), Churchill (1977), Cojbasic and Brkić (2013a), Cojbasic and Brkić (2013b), Eck (1973), Fang et al. (2011), Ghanbari et al. (2011), Haaland (1983), Jain (1976), Swamee and Jain (1976), Li et al. (2011), Manadili (1997), Niazkar (2019a), Niazkar (2020b), Offor and Alabi (2016), Papaevangelou et al. (2010), Rao and Kumar (2010), Romeo et al. (2002), Round (1980), Serghides (1984a), Serghides (1984b), Shacham et al. (1980), Shaikh (2012), Sonnad and Goudar (2006), Vatankhah (2018), Vatankhah and Kouchakzadeh (2008), Zigrang and Sylvester (1982a) and Zigrang and Sylvester (1982b).

The Colebrook–White equation was used as the benchmark for all comparative analyses, and the solution was computed using the Clamond (2009) method, which provides a fast and accurate iterative solution for the implicit relation.

C. Evaluation Criteria

The performance of each explicit model was assessed using four key criteria. These comparison indices help highlight the strengths and limitations of each model, particularly when applied in computational frameworks for fluid flow analysis.

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The most commonly used criteria in the literature are outlined below:

1. Accuracy: This was evaluated by comparing each model's nodal head and pipe flow results against those derived from the Colebrook equation. To quantify this closeness, Mean Square Error (MSE) criterion was used. MSE calculates the average of the squares of the differences between the model's predicted values and those from the Colebrook equation. It penalizes larger errors more than smaller ones, making it useful for identifying models that deviate significantly under certain conditions. A lower MSE indicates a better overall fit to the reference values.

2. Computational Efficiency: Computational efficiency was calculated as the ratio of the model's convergence time (seconds) to that of the Colebrook equation. A value greater than one (1) indicates that the model is slower than the Colebrook equation while the value less than one (1) indicates that the model is faster than the Colebrook equation and a value equal to one (1) means the model is exactly as fast as the Colebrook equation.

3. Numerical Stability: Stability was judged based on whether the solver successfully converged for each network. Models that failed to converge, particularly in larger or more complex systems, were classified as numerically unstable.

4. Number of Iterations to Convergence: The total number of iterations required by the solver to converge was recorded for each model. This helped in identifying whether faster convergence corresponds to reduced computational cost.

D. Computational Procedure

The h-based gradient method of solution was used in analyzing the four complex pipe networks. This method applies the Newton-Raphson technique in terms of pipe flows and nodal heads to obtain a simultaneous solution to the mass and energy balance system of equations. The pipe networks were solved through an iterative solution of a system of non-linear equations. The pipe properties, fluid properties and other data needed to start the analysis were inputted into Excel spreadsheet. The gradient algorithm method was coded into MATLAB using appropriate formulated codes. The formulated code was designed to call in the input data from the Excel spreadsheet into MATLAB environment.

The results of the analysis were displayed and the best-performing relations were selected based on number of iterations, computational time, accuracy, and stability of the iteration scheme. The displayed results include head losses, flow rates, number of iterations, and computational time taken by each relation. The obtained results from each explicit friction factor relation were compared with the results from the Colebrook solution. The error for each explicit relation was computed for both nodal heads and flow rates using mean square error as an accuracy metric. The error measure was used to comprehensively evaluate the performance of each explicit friction factor relation.

III. RESULTS AND DISCUSSION

A. Solver Convergence and Computational Performance

This section presents the results of the iteration count, computational time, and computational efficiency for each of the four pipe networks. These three metrics are combined into a single table per network, allowing a clearer comparison of solver performance for each explicit friction factor relation.

1. Network 1 (10 Pipes): The computational performances of the explicit models for Network 1 are as shown in Table I. It is obvious that all the models converged successfully with nearly the same number of iterations. However, the total computational time vary due to differences in the model complexity.

Models such as Biberg, Swamee Jain, Vantankhah A, Serghides A and Niazkar A demonstrated the fastest convergence among the explicit relations as shown in Table 1, while Colebrook remained the overall fastest. The computational efficiency results show that all the explicit relations had efficiency ratios slightly greater than 1, indicating that they were slower than the Colebrook relation, although the differences were relatively small for the top-performing models. This overall result suggests that the number of iterations alone is not a reliable indicator of a model's overall computational performance in pipe network analysis. This finding directly contradicts the conclusion of Niazkar and Talebbeydokhti (2019), who suggested that iteration count reflects performance (convergence speed).

TABLE I. CONVERGENCE AND COMPUTATIONAL PERFORMANCE OF NETWORK 1 (10 PIPES)

Friction Model	Number of Iteration	Computational Time (s)	Computational Efficiency
Avci Karagoz	5	0.0279799	1.1704279
Azizi	5	0.0421797	1.7644202
Barr	5	0.0296128	1.2387338
Beluco Schettini	6	0.0667423	2.7918990
Biberg	5	0.0249097	1.0419983
Brkic	5	0.0373603	1.5628197
Brkic Parks A	5	0.0295799	1.2373576
Brkic Parks B	5	0.0373603	1.5628197
Brkic Parks C	5	0.0319264	1.3355141
Buzzelli	5	0.0296187	1.2389806
Chen	5	0.0363211	1.5193489
Churchill	5	0.0525646	2.1988312
Cojbasic Brkic A	5	0.0356075	1.4894983
Cojbasic Brkic B	5	0.0373603	1.5628197
Eck	7	0.0641269	2.6824941
Fang	5	0.0298192	1.2473677
Ghanbari	5	0.0314821	1.3169285
Haaland	5	0.0538186	2.2512873
Jain	5	0.0356453	1.4910795

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Friction Model	Number of Iteration	Computational Time (s)	Computational Efficiency
Li	6	0.0604117	2.5270834
Manadili	5	0.0356075	1.4894983
Niazkar A	5	0.0274535	1.1484081
Niazkar B	5	0.0362512	1.5164249
Offor Alabi	5	0.0303333	1.2688731
Papaevangelou	5	0.0330365	1.3819507
Rao Kumar	5	0.0383431	1.6039312
Romeo	5	0.0295799	1.2373576
Round	5	0.0275689	1.1532354
Serghides A	5	0.0267423	1.1186578
Serghides B	6	0.0653564	2.7339253
Shacham	5	0.0337999	1.4138845
Shaikh	5	0.0392573	1.6421732
Sonnad Goudar	5	0.0442266	1.8500441
Swamee Jain	5	0.0258499	1.0813278
Vantankhah A	5	0.0263246	1.1011850
Vantankhah-Kouchakzadeh	5	0.0282276	1.1807895
Zigrang-Sylvester	5	0.0547462	2.2900898
Zigrang-Sylvester B	5	0.0543566	2.2737924
Colebrook	**5**	0.0239057	

2. Network 2 (24 Pipes): The computational performances of the explicit models for Network 2 are as shown in Table II. It is obvious that all the explicit models converged within similar iteration ranges (19 to 34), but the computational times increased compared to Network 1, which is expected because the larger network contains more pipes and nodes, resulting in more head-loss evaluations and matrix updates per iteration. Models such as Brkic Parks A, Cojbasic Brkic-A, Romeo, and Niazkar A, recorded shorter convergence times compared to other explicit relations, though still slower than the Colebrook equation. The computational efficiencies for these models were greater than 1, showing that they were slower than the Colebrook reference. This study confirms that, for this network, iteration count does not correlate with computational time, and therefore cannot be used as a reliable indicator of solver performance.

A consistent trend observed in this network is the influence of model complexity, measured by the number of internal iterations. Models with higher internal complexity, such as Serghides A (10 internal iterations), Niazkar A (6 internal iterations), Biberg (4 internal iterations), and Vantankhah A (4 internal iterations), achieved shorter computational times and therefore exhibited better computational efficiency. In contrast, low-complexity models such as Azizi (1 internal iteration), Beluco–Schettini (1 internal iteration), Eck (1 internal iteration), etc. despite having the simplest algebraic structures, recorded higher convergence times. This reinforces the finding that model simplicity does not translate to computational speed within network solvers.

TABLE II. CONVERGENCE AND COMPUTATIONAL PERFORMANCE OF NETWORK 2 (24 PIPES)

Friction Model	Number of Iteration	Computational Time (s)	Computational Efficiency
Avci Karagoz	19	0.3549771	1.3603506
Azizi	30	0.7049535	2.7015374
Barr	19	0.4102749	1.5722639
Beluco Schettini	31	0.4215987	1.6156592
Biberg	19	0.314825	1.2064789
Brkic	19	0.4230497	1.6212198
Brkic Parks A	19	0.2928519	1.1222731
Brkic Parks B	19	0.4793162	1.8368455
Brkic Parks C	19	0.3509846	1.3450504
Buzzelli	20	0.446381	1.7106305
Chen	19	0.3021765	1.1580070
Churchill	19	0.3758147	1.4402049
Cojbasic Brkic A	19	0.2989579	1.1456726
Cojbasic Brkic B	33	1.106872	4.2417778
Eck	19	0.3053319	1.1700992
Fang	35	1.3462864	5.1592667
Ghanbari	19	0.3994126	1.5306372
Haaland	31	0.4526304	1.7345796
Jain	19	0.4361855	1.6715591
Li	19	0.3004665	1.1514539
Manadili	35	2.1467053	8.22664865
Niazkar A	19	0.3001856	1.1503774
Niazkar B	19	0.4052987	1.5531940
Offor Alabi	19	0.4110778	1.5753408
Papaevangelou	19	0.4075448	1.5618016
Rao Kumar	19	0.4212987	1.6145096
Romeo	19	0.2990844	1.1461574
Round	33	0.4545118	1.7417895
Serghides A	19	0.3089729	1.1840523
Serghides B	19	0.3075095	1.1784442
Shacham	19	0.360168	1.3802432
Shaikh	29	0.3477332	1.3325903
Sonnad Goudar	19	0.3361595	1.2882374
Swamee Jain	19	0.3108572	1.1912734
Vantankhah A	19	0.3974598	1.5231537
Vantankhah-Kouchakzadeh	19	0.3689207	1.4137855
Zigrang-Sylvester	19	0.4043953	1.5497320
Zigrang-Sylvester B	19	0.3906788	1.4971674
Colebrook	**19**	0.2609453	

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3. **Network 3 (34 Pipes)**: The computational performances of the explicit models for Network 3 are as shown in Table III. This result shows that although the explicit models converged within a relatively narrow iteration band (mostly 20–24 iterations), the convergence times varied substantially, ranging from 0.2288 s to 0.4584 s. This confirms again that iteration count does not correlate with computational time, as several models with identical iteration counts produced widely different convergence times.

Models such as Serghides A, Biberg, Swamee Jain, Niazkar A and Cojbasic Brkic A were among the top 5 performers, converging more rapidly and efficiently than most models. A closer inspection shows that there is no simple, monotonic relationship between the number of internal iterations and convergence time. High-complexity models (in terms of number of internal iterations), such as Serghides A, Cojbasic–Brkic A, Niazkar A, achieved fast convergence, but relations such as Swamee–Jain, and Biberg, which have lower number of internal iterations also recorded short runtimes.

In contrast, some of the simpler, low-complexity models such as Azizi, Avci–Karagoz, Beluco–Schettini, and Chen exhibited much longer convergence times. This confirms that simpler expressions do not necessarily compute faster in network simulations; the internal numerical stability and structure matter more than algebraic simplicity.

Despite the strong performance of several explicit relations, the Colebrook equation again showed the fastest convergence for Network 3 (0.2236 s), confirming that even with increasing network complexity, the implicit formulation remains computationally superior when solved using the Clamond method.

TABLE III. CONVERGENCE AND COMPUTATIONAL PERFORMANCE OF NETWORK 3 (34 PIPES)

Friction Model	Number of Iteration	Computational Time (s)	Computational Efficiency
Avci Karagoz	24	0.4584391	2.0505550
Azizi	23	0.3500506	1.5657434
Barr	20	0.3094163	1.3839900
Beluco Schettini	23	0.3592821	1.6070350
Biberg	20	0.2288322	1.0235449
Brkic	20	0.4007588	1.7925564
Brkic Parks A	20	0.2484558	1.1113194
Brkic Parks B	20	0.2815977	1.2595600
Brkic Parks C	20	0.2404098	1.0753304
Buzzelli	20	0.3134542	1.4020511
Chen	23	0.4105554	1.8363757
Churchill	20	0.3691923	1.6513624
Cojbasic Brkic A	20	0.2358404	1.0548919
Cojbasic Brkic B	20	0.3634816	1.6258190
Eck	20	0.3214455	1.4377955
Fang	20	0.2577506	1.1528942
Ghanbari	20	0.3607775	1.6137238
Haaland	20	0.2370852	1.0604598
Jain	20	0.2684554	1.2007757
Li	20	0.2476071	1.1075232
Manadili	20	0.3653969	1.6343860
Niazkar A	20	0.2324601	1.0397721
Niazkar B	20	0.2604652	1.1650363
Offor Alabi	20	0.2844972	1.2725292
Papaevangelou	20	0.2830856	1.2662152
Rao Kumar	20	0.2849943	1.2747527
Romeo	20	0.2530465	1.1318532
Round	23	0.2898574	1.2965049
Serghides A	20	0.2287812	1.0233168
Serghides B	20	0.2462684	1.1015354
Shacham	20	0.3731537	1.6690814
Shaikh	20	0.2897913	1.2962092
Sonnad Goudar	20	0.3170146	1.4179765
Swamee Jain	20	0.2305696	1.0313161
Vantankhah A	20	0.2477378	1.1081079
Vantankhah-Kouchakzadeh	20	0.2468879	1.1043063
Zigrang-Sylvester	20	0.2573534	1.1511175
Zigrang-Sylvester B	20	0.2670543	1.1945087
Colebrook	20	0.2235683	

4. **Network 4 (74 Pipes)**: This network represented the most complex case analysed in this work. As shown in Table 4, almost all explicit models converged within 41 to 45 iterations, indicating that the iteration count remained consistent despite the larger system size. However, three models such as Avci–Karagoz, Buzzelli, and Fang, failed to converge, demonstrating numerical instability when applied to a highly interconnected network.

Although the iteration counts were nearly identical, the computational times varied significantly, ranging from approximately 0.339s to 0.608s among models that converged. This reinforces the established finding that iteration count does not correlate with computational speed, especially in complex networks. Among the convergent models, Serghides A, Cojbasic Brkic A, Brkic Parks C and Niazkar A continued to show superior performance, though still slower than the Colebrook equation.

A closer look at model complexity reveals that there is no direct relationship between the number of internal iterations and computational speed. High-complexity models (in terms of number of internal iterations), such as Serghides A and Cojbasic Brkic A, delivered the fastest runtimes, while low-complexity models such as Azizi, Beluco Schettini, Eck, were among the slowest. This shows that in a gradient-based solver, numerical behaviour and structural stability of a model determines practical performance.

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TABLE IV: CONVERGENCE AND COMPUTATIONAL PERFORMANCE OF NETWORK 4 (74 PIPES)

Friction Model	Number of Iteration	Computational Time (s)	Computational Efficiency
Avci Karagoz	-	-	-
Azizi	41	0.4894358	1.4440888
Barr	41	0.3929686	1.1594607
Beluco Schettini	45	0.6083332	1.7948977
Biberg	41	0.3770132	1.1123840
Brkic	41	0.502949	1.4839598
Brkic Parks A	41	0.4816927	1.4212427
Brkic Parks B	41	0.444987	1.3129419
Brkic Parks C	41	0.3509718	1.0355484
Buzzelli	-	-	-
Chen	41	0.469168	1.3842883
Churchill	41	0.3833203	1.1309932
Cojbasic Brkic A	41	0.3401325	1.0035668
Cojbasic Brkic B	42	0.5678299	1.6753920
Eck	41	0.54776	1.6161754
Fang	-	-	-
Ghanbari	41	0.3704834	1.0931177
Haaland	41	0.4175989	1.2321328
Jain	42	0.5090967	1.502099
Li	42	0.5043876	1.488204
Manadili	41	0.4364567	1.287773
Niazkar A	42	0.3617754	1.067425
Niazkar B	41	0.4533966	1.337755
Offor Alabi	41	0.5151997	1.5201057
Papaevangelou	41	0.4960696	1.463662
Rao Kumar	41	0.4254019	1.2551557
Romeo	41	0.5349866	1.5784873
Round	41	0.3962113	1.1690283
Serghides A	41	0.3393895	1.0013745
Serghides B	42	0.5452413	1.6087439
Shacham	41	0.4435457	1.3086893
Shaikh	41	0.3821235	1.1274621
Sonnad Goudar	41	0.4115435	1.2142662
Swamee Jain	41	0.3749543	1.1063092
Vantankhah A	41	0.4522207	1.3342850
Vantankhah-Kouchakzadeh	41	0.4768442	1.4069371
Zigrang-Sylvester	41	0.3782463	1.1160223
Zigrang-Sylvester B	41	0.3864233	1.1401486
Colebrook	41	0.3389236	

Summary, this study shows that the number of iterations is not a valid indicator of computational efficiency. All the explicit friction factor models tested converged with nearly the same number of iterations for each of the four networks, yet they produced varying convergence times due to differences in mathematical complexity. This study also shows the Clamond time function which was used to evaluate the Colebrook equation converged faster than all the explicit models across the four networks. Consequently, there may not be any need for the use of explicit models except there is a problem of numerical instability from the use of the Colebrook equation. In this study, however, the Colebrook equation, solved using the Clamond method did not exhibit any numerical instability across all four network case studies.

B. Accuracy

The nodal heads and flowrates errors obtained using each explicit model were compared to those derived from the Colebrook equation, which serves as the benchmark. Mean square error metric was used as a measure of accuracy. The performance of each model under mean square error metrics was evaluated across all four pipe networks.

1. Mean Square Nodal Error: Table V shows the mean square nodal error for each model across the four pipe networks. Across all four pipe networks, the mean square nodal error results revealed that only a few explicit friction factor models consistently achieved high accuracy when compared to the Colebrook equation. Models with lower errors demonstrated stable and precise behavior even in larger or more complex networks, while others, especially those with higher errors exhibited reduced reliability as network complexity increases.

TABLE V: MEAN SQUARE NODAL ERROR ACROSS ALL THE FOUR NETWORKS

Friction Model	Network 1	Network 2	Network 3	Network 4
Avci Karagoz	1.79E-10	260.84	22789	-
Azizi	7.50E-11	2.424	18262.7	10063.01
Barr	1.16E-11	0.009	5881.7	1.3442
Beluco Schettini	8.96E-12	2.403	18186.2	9968.61
Biberg	7.58E-12	5.35E-07	0.012	4.46E-05
Brkic	1.24E-08	7.68E-06	15.294	0.0245
Brkic Parks A	1.02E-10	7.69E-08	0.0106	0.0070
Brkic Parks B	1.74E-11	2.12E-07	0.0407	0.0084
Brkic Parks C	6.87E-11	1.04E-06	5.42E-05	0.0091
Buzzelli	1.17E-11	0.062	1176.05	-
Chen	1.25E-11	1.16E-05	0.0253	0.0006
Churchill	1.31E-11	0.0002	0.4194	0.1664
Cojbasic Brkic A	6.75E-12	8.94E-17	1.35E-05	2.46E-18
Cojbasic Brkic B	1.74E-11	32.813	248851.6	136037.8
Eck	6.06E-12	0.0003	123.3	0.0572

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Friction Model	Network 1	Network 2	Network 3	Network 4
Fang	4.26E-11	19.467	8237.3	-
Ghanbari	2.06E-11	0.0004	3.9327	0.4364
Haaland	1.26E-11	2.406	18277.3	9967.7
Jain	1.50E-11	0.0001	0.7983	0.0672
Li	4.29E-11	0.0018	548.112	0.2044
Manadili	9.51E-12	1.1014	303.73	63.4013
Niazkar A	6.31E-12	1.41E-17	1.14E-10	5.43E-18
Niazkar B	3.60E-11	0.0007	17.89	0.2858
Offor Alabi	1.14E-11	0.0002	0.0148	0.1759
Papaevangelou	1.25E-11	7.69E-05	0.0707	0.0191
Rao Kumar	4.54E-11	0.0086	5884.5	1.4240
Romeo	6.87E-11	4.16E-08	0.0213	0.0027
Round	4.59E-11	2.5385	18383.4	10738.7
Serghides A	6.26E-12	1.35E-16	1.88E-05	3.67E-18
Serghides B	6.39E-12	5.04E-10	0.23786	5.68E-10
Shacham	5.58E-12	5.45E-08	1.5340	0.0033
Shaikh	5.37E-11	2.156	11257.2	9748.22
Sonnad Goudar	9.38E-12	2.32E-06	0.37839	0.00023
Swamee Jain	7.26E-12	0.0002	0.5979	0.1616
Vantankhah A	2.61E-12	1.30E-07	0.00150	0.1616
Vantankhah-Kouchakzadeh	1.15E-12	1.07E-08	0.30172	6.52E-06
Zigrang-Sylvester	1.83E-11	1.70E-10	0.02394	2E-10
Zigrang-Sylvester B	3.26E-11	9.46E-06	24.6564	0.0001

In Network 1, which consists of 10 pipes, the best-performing models were Vantankhah-Kouchakzadeh, Vantankhah A, Eck, and Serghides A. Models such as Niazkar A, Serghides B and Cojbasic Brkic A relations were the next best explicit relations, in no particular order. In Network 2, which consists of 24 pipes, the best-performing models were Niazkar A, Cojbasic Brkic A, and Serghides A. In Network 3, which consists of 34 pipes, the best-performing models were were Niazkar A, Cojbasic Brkic A, and Serghides A. In Network 4, which consists of 74 pipes, the best-performing models were Cojbasic Brkic A, Serghides A and Niazkar A.

Models such as Niazkar A, Cojbasic Brkic A, and Serghides A consistently exhibited the lowest MSE values across varying network sizes, indicating their ability to maintain high accuracy in predicting nodal heads. For instance, in smaller networks, these models produced mean square errors close to zero, and even in larger systems, they maintained minimal deviation from the Colebrook benchmark.

In contrast, models like Avci Karagoz, Azizi, Round, Cojbasic Brkic B, performed poorly as their mean square errors increase with the network size, confirming their limited applicability in complex or highly interconnected systems. Overall, the best-performing models with respect to accuracy across the four networks was Niazkar A and Cojbasic Brkic A.

2. Mean Square Flow Error: Table VI shows the mean square flow rate error for each model across the four pipe networks. Across all the four networks, the Mean Square Error values reveal notable variations in the accuracy of the explicit friction factor models. In general, models such as Niazkar A, Cojbasic Brkic A, and Serghides A, consistently record the lowest MSE values, indicating superior performance in estimating flowrate relative to the Colebrook equation.

TABLE VI: MEAN SQUARE FLOW ERROR ACROSS ALL THE FOUR NETWORKS

Friction Model	Network 1	Network 2	Network 3	Network 4
Avci Karagoz	9.173E-09	11.225	9.86E-07	-
Azizi	8.664E-09	0.0259	3.92E-05	1.265E-05
Barr	1.471E-08	0.00011	0.0013	0.1085
Beluco Schettini	6.475E-09	0.02552	2.3E-05	4.108E-05
Biberg	1.234E-11	6.613E-09	2.24E-11	6.279E-06
Brkic	8.627E-09	2.475E-07	1.71E-06	0.00044
Brkic Parks A	4.787E-09	2.315E-09	5.09E-11	3.747E-05
Brkic Parks B	8.627E-09	4.914E-09	2.61E-08	2.715E-05
Brkic Parks C	4.298E-09	1.355E-08	2.58E-10	1.392E-05
Buzzelli	1.471E-08	0.0012	0.0003	-
Chen	1.651E-08	1.39E-07	8.30E-08	0.00039
Churchill	1.302E-08	2.054E-06	3.57E-06	0.00285
Cojbasic Brkic A	6.17E-10	6.736E-18	7.21E-14	2.851E-18
Cojbasic Brkic B	8.627E-09	0.3835	1.44E-11	1.758E-05
Eck	4.235E-10	5.662E-06	0.0001	0.0048
Fang	2.018E-09	0.24416	0.0083	-
Ghanbari	1.782E-07	4.281E-06	4.88E-06	0.01181
Haaland	1.039E-08	0.02555	6.283E-06	0.00199
Jain	1.186E-08	1.422E-06	4.09E-06	0.0032
Li	2.233E-09	2.316E-05	0.0001	0.02371
Manadili	6.168E-09	0.00652	0.0006	6.1628
Niazkar A	6.61E-11	3.9801E-19	2.18E-14	4.449E-18
Niazkar B	3.912E-09	8.471E-06	2.59E-06	0.10278
Offor Alabi	1.834E-08	2.927E-06	5.76E-08	0.00358
Papaevangelou	8.252E-09	8.898E-07	9.22E-08	0.00099
Rao Kumar	1.361E-08	0.00011	0.0013	0.10767
Romeo	4.298E-09	1.1567E-09	4.89E-09	1.577E-05
Round	3.415E-05	0.0276	1.50E-05	0.8689
Serghides A	6.98E-11	9.580E-18	1.08E-12	4.152E-18
Serghides B	1.249E-08	2.083E-11	2.07E-07	4.575E-10
Shacham	1.757E-08	3.36E-09	1.53E-07	1.057E-05

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Friction Model	Network 1	Network 2	Network 3	Network 4
Shaikh	2.517E-08	0.023248	0.0029	2.90004
Sonnad Goudar	3.509E-09	3.035E-08	4.30E-07	1.759E-05
Swamee Jain	1.097E-08	1.949E-06	3.83E-06	0.00270
Vantankhah A	1.322E-08	4.09E-09	4.97E-10	0.00270
Vantankhah-Kouchakzadeh	1.830E-08	1.959E-10	3.28E-07	1.904E-06
Zigrang-Sylvester	1.104E-08	5.063E-12	6.89E-09	1.368E-10
Zigrang-Sylvester B	6.312E-09	1.522E-07	2.54E-05	3.458E-05

In Network 1, which consists of 10 pipes, the best-performing models were Biberg, Niazkar A, Serghides A. Eck, Cojbasic Brkic A, Fang and Li relations were the next best explicit relations, in no particular order showing in Table 4. In Network 2, which consists of 24 pipes, the best-performing models were Niazkar A, Cojbasic Brkic A, and Serghides A. In Network 3, which consists of 34 pipes, the best-performing models were were Niazkar A, Cojbasic Brkic A, and Serghides A. In Network 4, which consists of 74 pipes, the best-performing models Cojbasic Brkic A, Serghides A and Niazkar A.

Models such as Niazkar A, Cojbasic Brkic A, and Serghides A consistently exhibited the lowest MSE values across varying network sizes, indicating their ability to maintain high accuracy in predicting flow heads. For instance, in smaller networks, these models produced mean square errors close to zero, and even in larger systems, they maintained minimal deviation from the Colebrook benchmark.

In contrast, models like Avci Karagoz, Azizi, Cojbasic Brkic B which performed poorly in mean square flow error evaluations, also showed relatively high MSE values, confirming their limited applicability in complex or highly interconnected systems. Overall, the best-performing models with respect to mean square flow error across the four networks was Niazkar A and Cojbasic Brkic A.

Overall, when both convergence behaviour and error metrics are considered together, models such as Niazkar A, Cojbasic–Brkic A, and Serghides A consistently offered the best balance of speed and accuracy. These models recorded some of the best computational efficiency values while simultaneously producing the smallest nodal head and mean square flow errors, and their performance remained stable as network size increases. Models such as Avci–Karagoz, Cojbasic Brkic B show comparatively high computational times and consistently larger flow-error magnitudes, indicating weaker suitability for network-based hydraulic analysis. Although few explicit models demonstrated good performance, the Colebrook–White equation remained superior, consistently exhibiting faster convergence, consistent numerical stability, and higher accuracy.

IV. CONCLUSION

This study evaluated the performance of 38 explicit friction factor equations within iterative pipe network solvers using MATLAB across four networks of increasing complexity. The results revealed notable differences in accuracy, numerical stability, and computational efficiency among the models when applied during pipe networks analysis.

A key finding is that the number of iterations required for convergence is not a reliable measure of computational efficiency. Although most models converged in a similar number of iterations, their computation times varied significantly due to differences in their mathematical complexity, particularly the presence of multiple logarithmic or exponential terms.

Among the selected models, Niazkar A, Cojbasic Brkic A, and Serghides A consistently delivered accurate and stable results across all networks. Their ability to balance computational speed and reliability makes them suitable for practical engineering applications.

In contrast, models like Avci–Karagoz, Buzzelli, and Fang failed to converge in the most complex network, suggesting that their structure might have made them prone to numerical instability when applied to large pipe networks.

Despite the good performance of a few explicit models, the Colebrook-White equation remained superior, consistently achieving faster convergence, consistent numerical stability, and higher accuracy. Consequently, there may not be any need for the use of explicit models except there is a problem of numerical instability from the use of the Colebrook equation. In this study, however, the Colebrook equation, solved using the Clamond method did not exhibit any numerical instability across all four network case studies.

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