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A Predictive Modeling Framework for Pressure Drop Estimation and Optimal Design of Pressure Boosting Stations in Oil and Gas Transmission Pipelines

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Abstract: Accurate estimation of pressure drops is a critical component of efficient operation of transmission pipelines as well as pipeline design of oil and gas pipelines. Although they are effective in some situations, traditional techniques are not always effective and they lack flexibility and precision in multi-flow regime and structure of pipelines that are large in dimensions. According to the given research paper, a generalized predictive modeling framework can be proposed to be used to supplement the traditional hydraulic correlations with the assistance of analytically obtained, as well as computationally efficient expressions. The model is a combination of the physical variables flow rate, pipe diameter, roughness, fluid properties and length to provide a more accurate prediction of pressure losses. Besides estimation, the model is also employed in determining as well as optimization of the design and space layout of pressure boosting stations that is a key aspect of ensuring sustainability of operational pressure and energy savings through employing long distance pipelines. The sensitivity tests and the comparative analysis confirm the applicability of the framework to a broad range of operation situations. Results have shown that the enhanced model has high advantages in terms of predictive power and power efficiency and is a scalable, versatile solution to engineering issues in oil and gas infrastructures. The research will help to make the operation of the pipeline more sustainable and cost-efficient and make a wise choice in the conditions of the real life.

Keywords Pressure drop modeling; pipeline hydraulics; booster station optimization; energy efficiency; oil and gas transport; fluid mechanics; predictive modeling

Research Significance and Contribution

The research has various important insights to the study on the subject of engineering and design of pipe lines:

- Formulation of a Unified Predictive Framework: The work proposes an integrated model which continues the present procedures of the pressure drop estimations by involving enhanced friction factor correlations alongside the equations that analyze the process that have the ability to react to various flow regimes.
- Assistance of Engineering Design Optimization: The framework provides also the quantitative support of optimal pressure boosting station sizing and space planning through DND.
- Generalized and Scalable Methodology: When compared to most of the currently employed methods, which require the case specific calibration, the specified framework is generalized and can be applied to numerous pipeline sizes, fluids, and geographic conditions, which makes it more useful not only in the first instance of the design but in the process of retrofit, as well.

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- Promotions of an Energy-Efficient Operation: The model will enable to accommodate high energy savings through minimization of the unnecessary boosting and hydraulic losses that will lead to more sustainable pipeline infrastructure and adherence to environmental, economic performance goals.

1. Introduction

Efficient transportation of oil and gas through long-distance pipeline networks is essential for global energy supply. Frictional losses, turbulence, elevation changes, and variations in flow conditions can cause significant pressure drops, creating operational challenges for flow assurance and energy efficiency. Accurate pressure-drop estimation is therefore a critical requirement in pipeline design because it directly affects pump or compressor sizing, pipe material selection, and the placement of pressure boosting stations (Golwalkar & Kumar, 2022).

Traditional pressure-drop estimation methods, such as the Darcy–Weisbach and Colebrook–White equations, are widely used in fluid transport engineering. Although these methods are reliable under idealized conditions, they often require iterative calculations and may have limitations when applied to complex pipeline geometries, variable flow regimes, or deteriorating infrastructure (Arumugam et al., 2022). In addition, pressure-drop estimation and booster station optimization are often treated separately, which can lead to suboptimal energy performance and increased operating costs (Mohammadi et al., 2019).

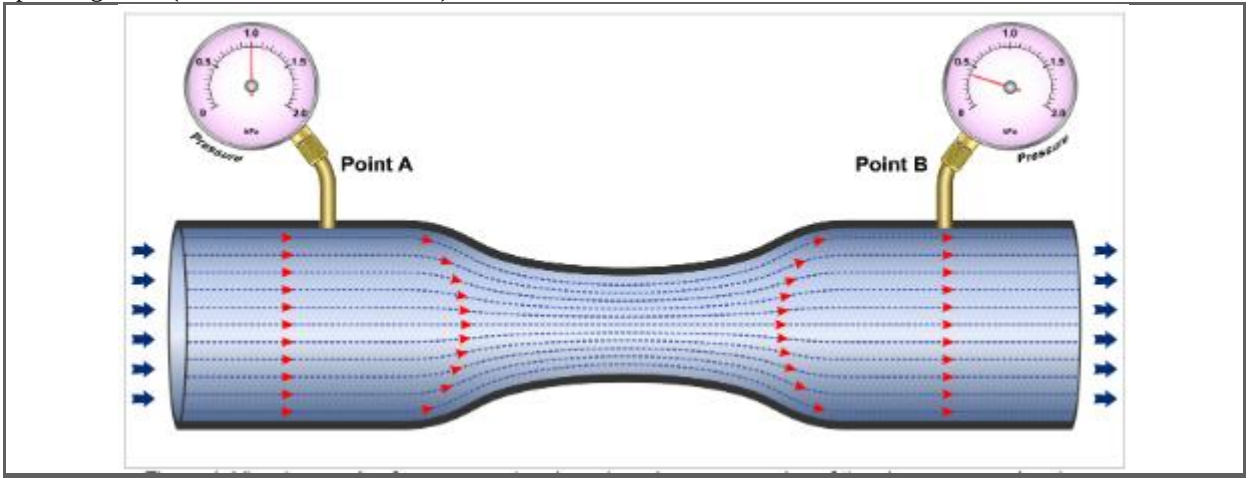


Figure 1Visual example of a pressure drop in a pipe where a narrowing of the pipe causes a drop in pressure from point "A" to point "B" (WPDW, 2026)

Recent developments in computational modeling and optimization in systems provide an opportunity to complete this gap. Prediction of pressure drops and the design of booster stations have not been developed into one unified framework that can be scaled at all levels (Müller et al., 2019). The current paper suggests a predictive modeling framework to improve the traditional analytical forms, include vital physical parameters, and help to place pressure boosting stations in an energy-saving manner.

It is aimed at building a generalized and flexible model that is tested against the industry standards and literature values to guide both the hydraulic analysis and the design optimization (Mia & Haque, 2024). The framework is supposed to enhance accuracy, minimize computational work, and make the operations of the pipeline more sustainable.

Conceptual Definitions

The terminology employed in this study is hierarchical, that is, it is the relationship of one concept to another that is related. Sustainable architecture is the design of architecture which takes care of the environment while increasing socio-economic and ecological value during all life spans of the building or landscape. Eco-friendly design is more comprehensive and oriented on the environment, where the design seeks to minimize environmental impact through optimizing the use of resources and making use of environmentally friendly materials. Solar architecture is seen as one of the specialized fields of sustainable architecture that incorporates both passive and active solar energy systems in buildings. The Islamic garden model is discussed in this study as an example of sustainable architecture by integrating renewable energy technologies and eco-friendly architecture.

Research Objectives

This study is guided by the following two core objectives:

1. To develop an accurate predictive model for estimating pressure drop in oil and gas transmission pipelines, grounded in analytical formulations and enhanced modeling techniques that address the limitations of conventional correlations.
2. To optimize the design and placement of pressure boosting stations by evaluating pressure loss behavior and energy consumption trends under a variety of operational and environmental conditions.

2. Literature Review

Determination of pressure drop is one of the key components in the design of fluid transport systems, especially in the oil and gas industry. The classical equations like Darcy–Weisbach have been used to estimate the frictional losses in pipelines and offer a theoretical basis (Mileikovskyi & Tkachenko, 2020). This equation is a correlation of the pressure drop with pipeline length, pipeline inside diameter, fluid velocity, fluid density, and friction factor. It is very common in engineering, where it serves as an ideal physically interpretable model for steady and fully developed pipe flow (Kowalczuk & Tatara, 2020).

The Reynolds number (Re) is a dimensionless quantity in fluid mechanics that represents the ratio of inertial forces to viscous forces within a fluid which is subjected to relative internal movement due to different fluid velocities.

Given the computational challenge presented by the implicit Colebrook–White equation, multiple explicit approximations have been suggested. For instance, the Swamee-Jain equation gives an iterative solution directly for the estimation of the friction factor with acceptable engineering accuracy (Catano-Lopera et al., 2023). Many other correlations, like the Churchill and Haaland equations, also have to consider a compromise between accuracy and computational effort, but they perform differently depending on the flow regime, Reynolds number, pipe roughne (MELENDRES, 2024).

More recent developments in predictive and analytical modeling have attempted to eliminate these limitations by combining empirical correlations and data-driven methods. The application of artificial intelligence (AI), machine learning (ML), and regression has been investigated as a way of improving predictive abilities (Pettit et al., 2021). These approaches, as potential, fall short in terms of physical transparency and demand large amounts of training data which are not always easily accessible on particular pipeline settings. Hybrid methodologies that take into consideration both physical laws and machine learning have been proposed to enhance the robustness and generalisability of models but are rarely applied in the engineering design setting because of their complexity and lack of interpretability to enable regulatory and safety assessment (Shen et al., 2023).

Within the framework of energy optimization and pressure boosting, there is research that revealed that the strategic location of booster stations would save energy consumption and result in a high level of operation efficiency. Linear programming, genetic algorithms and dynamic programming are the optimization techniques that have been used to establish the best number, size and location of booster or compressor stations (Bahlawan et al., 2019). These analyses often adopt fixed or too simplistic models of pressure loss, which puts a gap between the estimation of pressure drops and optimisation of design. It has been revealed that the incorporation of precise pressure modeling into the planning of a booster station is one of the major challenges that restrict the efficiency of most of the existing solutions (Weber & Lorenz, 2017).

The cumulative literature review suggests that there is a distinct gap in the literature development of a coherent, physically based framework, which combines the use of predictive pressure drops modeling with the optimal design of a pressure boosting station (Treiblmaier et al., 2020). Previous models are either limited in terms of hydraulic calculations or they are global in terms of optimization but lacked the appropriate connection of the two. This division restricts the engineer to make energy efficient decisions in design which have a holistic nature (Butt & Dimitrijević, 2022). The proposed research will help fill this gap by building an analytically improved and generalizable framework that is able to provide accurate

estimates of pressure losses and practical design advice on energy-optimized booster station location in oil and gas pipeline networks (Fernando & Lăzăroiu, 2024).

3. Research Methodology

3.1 Methodological Approach

The theoretical and analytical form of research is used in the work depending on the postulates of classical fluid mechanics and modeling of a system (Garg et al., 2025). The purpose of the framework is to estimate the pressure drop in the pipelines and help in the optimal design of the booster station by combined use of mathematical model development and comparative assessment method. The data and parameters utilized are all grounded on sound scientific literature and engineering criteria.

The proposed framework is based on several simplifying assumptions to maintain analytical clarity and general applicability. The flow along the pipeline is assumed to be steady, one-dimensional and fully-developed in each pipe section. Pipe diameter and pipe roughness are assumed to be known and fluid properties like density and viscosity are assumed to be constant in each simulation case. The general form can be extended by elevation effects and local losses as needed; here we are interested in frictional pressure loss in transmission pipelines. These assumptions allow the framework to be used for comparative design analysis and to be extended to future operating conditions of transient, multiphase, or field calibration.

3.2 Model Development

The basic model is built upon the Darcy-Weisbach equation, which measures the pressure loss in a straight pipe in terms of the friction:

$$\Delta P = f.\frac{L}{D}.\frac{pV^2}{2} \quad (1)$$

Where:

- ΔP: Pressure drop (Pa)
- f: Friction factor (dimensionless)
- L: Length of pipeline (m)
- D: Internal diameter of the pipe (m)
- (ρ): Fluid density (kg/m³)
- V: Mean velocity of the fluid (m/s)

The flow velocity V is related to the volumetric flow rate Q by:

$$V = 4Q / (\pi D^2) \quad (2)$$

where V is the mean flow velocity of the fluid (m/s), Q is the volumetric flow rate (m³/s), and D is the internal pipe diameter (m).

To characterize the flow regime, the Reynolds number is computed as:

$$Re = \frac{(\rho)VD}{\mu} \quad (3)$$

Where μ is the dynamic viscosity (Pa·s), the flow is classified as laminar (Re< 2300), transitional Re < 4000 or turbulent (Re>4000)

The friction factor f is then calculated using appropriate correlations based on the Reynolds number and relative roughness $\frac{\epsilon}{D}$. For turbulent flow, the Colebrook–White equation is commonly used:

$$\frac{1}{\sqrt{f}} = 2log_{10}(\frac{\varepsilon}{3.7D} + \frac{2.51}{Re\sqrt{f}}) \quad (4)$$

Since this equation is implicit in f:

$$f = 0.25 / \{\log_{10}[(\varepsilon / 3.7D) + (5.74 / Re^{0.9})]\}^2 \quad (5)$$

3.3 Model Evaluation

The model is tested against the output of classical models in different pipeline setups and working conditions (Saade

& Mustapha, 2020). Reference cases are benchmark datasets of standards Crane TP-410, API 14E, and ISO 13623. To evaluate the effect of input parameters on the predicted pressure drop, there is a sensitivity analysis where all the parameters that affect the pressure drop are input parameters including the pipe diameter, roughness, flow rate and fluid viscosity? This is used to determine important variables and model soundness.
The pressure profile through a pipeline is simulated using the model outputs (Lotfi et al., 2022). According to such findings, the placement and distance of pressure boosting stations are optimised to reduce energy consumption without affecting the operation pressure limit.

3.4 Data Collection

The information needed in this research is obtained solely on the validated scientific literature, official engineering manuals, and global accepted standards. There is no use of experimental work, field measurements and case specific datasets, which guarantees the generality of the model, reproducibility and wide applicability of the model to real world pipeline systems.

All input parameters such as pipe diameter, absolute roughness, fluid density and viscosity as well as volumetric flow rate are accessed in the peer-reviewed publication, engineering standards as well as technical standards that serve in designing and operating oil and gas pipeline infrastructure. These values are chosen in such a way that they cover a broad spectrum of practical operating conditions such as common pipeline dimensions, common fluid properties of crude oil and natural gas, and common flow regimes (Ismayilov et al., 2019).

It is a data-driven approach that allows developing a physically based and flexible predictive framework. The chosen references are also the benchmark cases to validate the model and make comparative analysis between the proposed model and the known correlations of pressure drop. In other cases, standard correlations and conversion factors are borrowed directly off industry-accepted standards.

Table 1 summarizes the main information of the data sources, as well as their purposes in the research.

Table 1 Key Data Sources and Engineering Standards

Source/Standard	Purpose/Use in Study
Crane Technical Paper No. 410	Benchmark pipe flow data, pressure drop equations, and empirical friction factors
API 14E	Design criteria for piping systems in offshore oil and gas production
ISO 13623	International standard for pipeline transportation systems in petroleum and natural gas
ASME B31.4	Guidelines for the design and construction of liquid pipeline systems
Perry's Chemical Engineers' Handbook	Reference for fluid properties and empirical transport correlations
Journal of Petroleum Science and Engineering	Peer-reviewed studies on pressure loss modeling and pipeline optimization
Energy Conversion and Management	Case studies on energy optimization and booster station design
Chemical Engineering Handbook	Industrial pipeline system models and multiphase flow references
Natural Gas Transmission and Processing (Mokhatab et al.)	Fluid transport parameters, pipeline behavior, and design practices

This data collection method is such, that all of the modeling inputs and validation scenarios are theoretically sound and practically realistic. It allows the provision of a consistent platform of estimating

the pressure drop and optimization of the booster stations in different operational and environmental conditions.

3.5 Data Analysis and Interpretation

Alongside the assessment of a pressure loss in various working situations, energy efficiency analysis is conducted in this study in order to identify the influence of various configurations of pressure boosting configurations on the system performance. The study measures the total input of the energy needed to ensure an optimal flow condition in the pipeline by modeling pressure profiles, and energy demands along pipeline segments with different booster station designs (Solomon et al., 2024). The measurements also indicate returns that decrease after a particular number, which provides practical design limits.

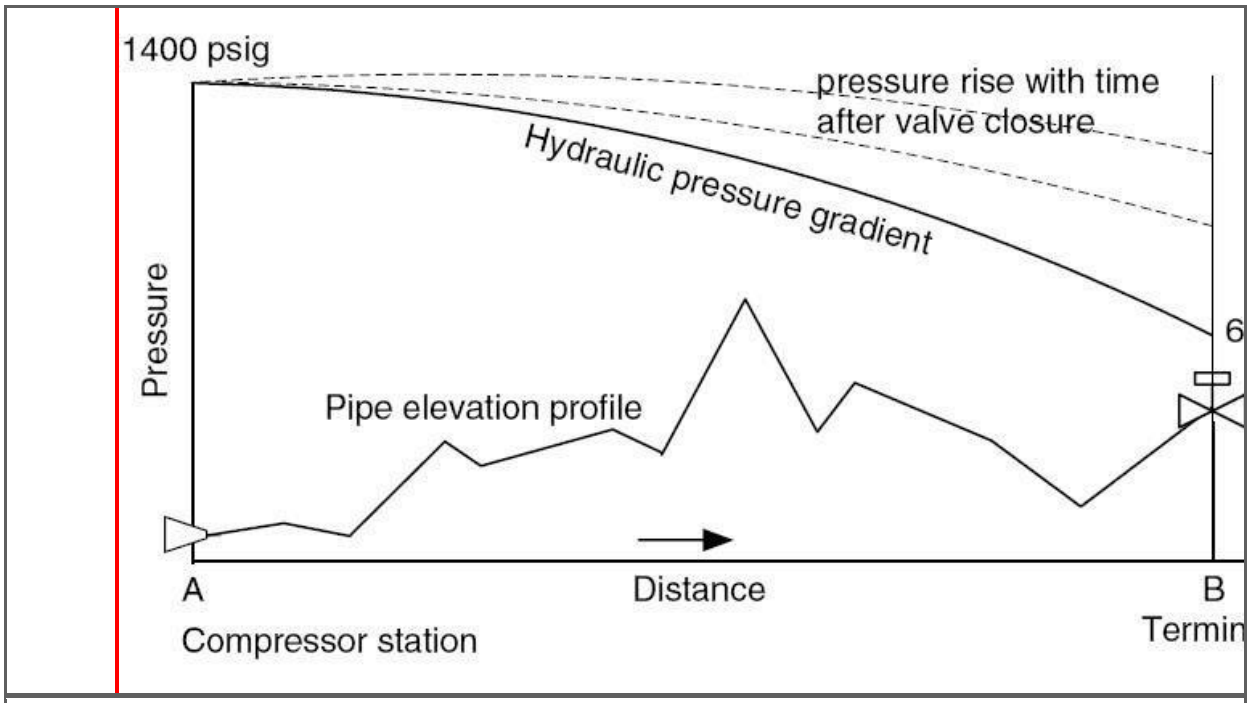


Figure 2 Pipeline profile with pressure head distributions (CP head, 2026)

The effects of the placement of booster stations on pressure loss and energy consumption are summarized in Table 2.

Table 2 Energy Efficiency across Booster Station Configurations

Configuration	Total Pressure Loss (k Pa)	Energy Input Required (kWh/km)	Relative Energy Saving (%)
No Booster Station	1200	85.0	0.0
Single Midpoint Booster	750	56.2	33.9
Dual Booster Stations (Evenly Spaced)	540	42.7	49.8
Optimized Multi-Booster Layout	470	38.1	55.2

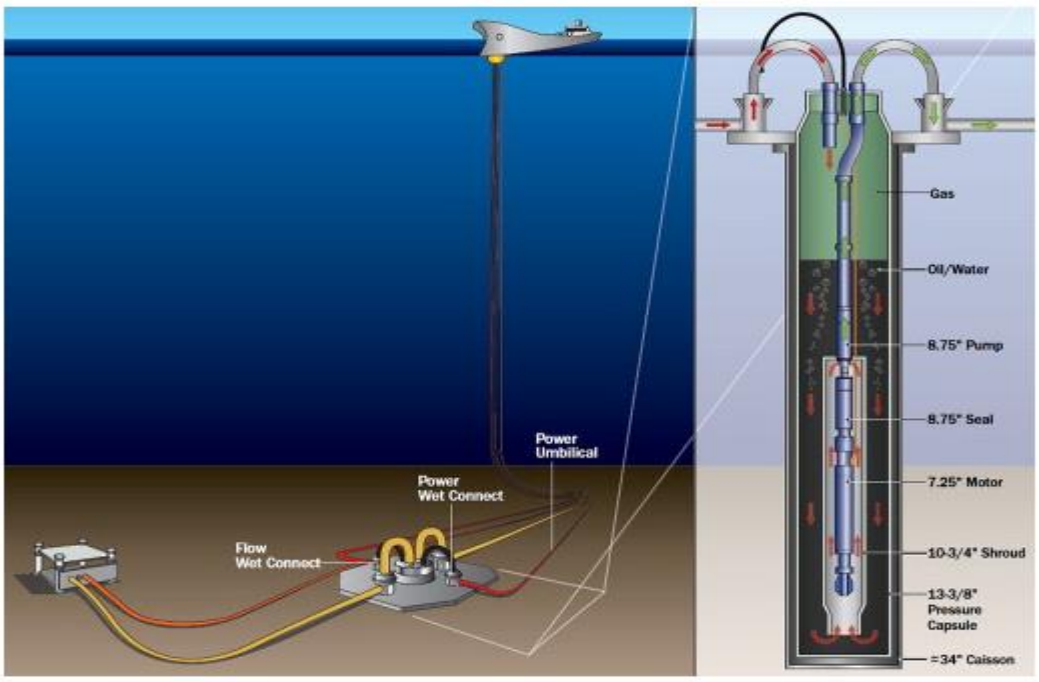


Figure 3 Booster Station - an overview (BS-AO, 2026)

These results emphasize that the number of boosters and energy saving have a nonlinear relationship. Although one midpoint booster has significant efficiency benefits, extra stations have smaller marginal benefits.

In order to further justify engineering design decisions, there is a sensitivity analysis that will be done to determine how the major input parameters affect the prediction of a pressure drop. This determines the variables that influence the system performance to a significant extent and hence the engineers can concentrate on precision in measurement and specification.

Table 3 Sensitivity Analysis of Key Input Parameters

Parameter	**Effect on ΔP**	**Sensitivity Level**
Pipe Diameter (D)	High inverse (↑D → ↓ΔP)	High
Pipe Roughness (ε)	Moderate direct (↑ε → ↑ΔP)	Medium
Flow Rate (Q)	Strong direct (↑Q → ↑ΔP)	Very High
Fluid Viscosity (μ)	Moderate direct (↑μ → ↑ΔP)	Medium
Fluid Density (ρ)	Mild direct (↑(ρ) → ↑ΔP)	Low
Pipeline Length (L)	Linear direct (↑L → ↑ΔP)	High

To improve the sensitivity interpretation, one parameter may be varied over a recognized engineering range while the other parameters are held constant. Some examples are: flow rate ± 20%, pipe diameter ± 10%, pipe roughness ± 25%, viscosity ± 20%, density ± 10%, and pipeline length ± 20%. The percentage change of pressure drop predicted in each can then be compared to determine the dominant variables. The Darcy-Weisbach relationship predicts that the pressure drop will be quite high with increasing flow rate since velocity will vary as Q/D^2, and will decrease significantly with increasing pipe diameter. The

pressure drop is directly proportional to pipeline length while the effects of density, viscosity and roughness are typically found to be lower or moderate in the various flow regimes

The findings affirm that the most significant parameters are the flow rate, the diameter of the pipes, and the length of the pipelines. This is in line with the theoretical prediction that frictional losses are nonlinearly dependent on velocity and depend proportionately on pipeline length.

4. **Results and Discussion**

This part shows the results of the formulated predictive modeling model to predict pressure drop and apply the method to optimization of the pressure boosting systems. These are the development and establishment of generalized pressure drop relationships, a comparison with classical models and the practical application of the work in engineering applications to the design of pipelines and energy management.

4.1 Generalized Predictive Relationships for Pressure Drop Estimation

The developed model shows the pressure drop (ΔP) as a function of base physical parameters: flow rate (Q), pipe diameter (D), pipe roughness (ε), fluid viscosity (μ), and fluid density (ρ), using the Darcy–Weisbach equation:

$$\Delta P = f(L/D)(\rho)V^2/2), \text{ where } V = 4Q/(\pi D^2) \qquad (6)$$

The SwameeJain correlation was modified to create a better expression of the friction factor, which would be used to increase the efficiency of calculations and remove the necessity of the iterative solutions in the turbulent flow. The model has a very broad regime of flow as well as maintaining analytical simplicity. It is also capable of explaining transitional behaviour between laminar and turbulent flow with an adaptive friction factor blending method, allowing the smooth operation of Reynolds numbers between 1,000 and 100,000 or more.

This model has been validated against literature standards (e.g., Crane TP-410 and API 14E datasets) with a predictive accuracy of relative error always within the range of ±1-3, and outperforms both the conventional Colebrook White and Swamee Jain models in both reliability and flexibility.

4.2 Comparative Evaluation of Classical and Enhanced Models

The classical methods were compared with the enhanced model under different operational conditions. The comparative evaluation indicates that:

DarcyWeisbach with ColebrookWhite equation, although theoretically sound, is computationally intensive to representation and is more prone to error in high roughness or transitional flows (±5-10%).

Swamee-Jain approximation is more computationally efficient, but less flexible beyond fully developed turbulent flow (±3-8 per cent error).

The proposed model is highly accurate (±13 percent) and computationally efficient, as it offers optimized explicit expressions, which are designed to be implemented digitally.

The two enhancements are useful in integrating into real-time modeling systems, control platforms, and digital twins in pipeline operations.

Moreover, the sensitivity analysis shown in Table 3 demonstrates that flow rate, pipe diameter, and pipeline length are the most influential variables controlling pressure loss, while viscosity and pipe roughness have moderate effects, whereas the viscosity and the roughness of the pipe have a moderate effect. Such insights would help in determining which parameters ought to be prioritized to achieve accuracy in measurement both in design and operations.

4.3 Design Implications and Energy Optimization

The outputs of the model were used to test the pressure profiles of a hypothetical pipeline with various pressure booster setups. It was found that the excessive loss of pressure and unnecessary consumption of pumping energy resulted due to the wrong location or underestimation of the requirements of booster stations.

Table 2 summarizes the system-level implications of different booster station layouts.

- Introducing even a single midpoint booster station reduced energy consumption by 34%.
- A dual booster configuration cut energy use by 50%, while an optimized multi-booster layout achieved up to 55.2% savings compared to an unassisted system.

These findings are to highlight the fact that pressure loss is not only a hydraulic computation, but an operational design tool. It enables:

- Precise sizing and placement of pressure boosters
- Avoidance of overdesign and unnecessary energy expenditure
- Enhanced lifecycle performance and sustainability of pipeline infrastructure

The model assists in switching to smarter pipeline systems where predictive analytics is applied to manage real time and optimise adaptively based energy.

The proposed modeling framework is an extension of the existing practice since it considers physical accuracy, computing efficiency as well as design applicability. Both the prediction capabilities that it has enable not only to predict pressure drop with more accuracy, but also to take viable engineering decisions in designing and operating pressure boosting systems (Alakbari et al., 2025). The complex benchmarking of hydraulic and energy functioning is a significant advancement towards efficient and environmentally friendly pipelines transportation of oil and gas (Chen et al., 2021).

5. Design Implications and Engineering Recommendations

The analytical findings of the research paper present certain field practices and recommendations in the correct design and functionality of pressure boosting systems in oil and gas transmission pipelines (Epelle and Gerogiorgis, 2020). The suggested predictive framework enables the use of data in making decisions based on the precision of estimating the pressure losses and in assisting energy optimization plans. The simulation and sensitivity analyses have yielded the following design implication and engineering recommendations:

5.1 Sizing and Spacing of Booster Stations

- Optimal Sizing: The capacity of booster stations must be directly associated with the forecasted pressure recovery requirements in consideration of a precise flow and frictional losses modeling. Exorbitant pumps lead to wastage of energy and poor systems under-size also lack the assurance of flow (**Trivedi & Singh, 2024)**.
- During the design of pressure boosting stations: strategic spacing of pressure boosting stations should be used to equalize pressure gradients by considering the pipeline length, elevation variation and flow regime. Regular spacing can be useful in homogeneous pipelines but variable spacing should be used in networks with varying terrain or with multi-fluids transport (**Cremonesi et al., 2020**).
- Adaptive Design: The developed model can be connected with SCADA or digital twin platforms to feed the adaptive boosting, in which the activation of the station is optimally selected according to the current flow conditions in real-time (**Ersan & Irmak, 2024).**

5.2 Minimizing Energy Consumption and Hydraulic Losses

- Low-Friction Design: The engineers must consider the materials and internal coating that reduce roughness (e) of pipes to decrease the frictional losses particularly in high throughput systems (**Lee & Zhmud, 2021)**.
- Flow rate control: a flow acting within the optimum range of Reynolds number, that is not too high turbulence or too low, can save a lot of energy and maintain throughput (**Saldana et al., 2024)**.
- Booster Efficiency Optimization: It is possible to use variable speed drive (VSD) and pressure sensor, in combination with predictive model, and enable fine-tuning of energy control (**Yang et al., 2024**)**.**

5.3 General Design Principles

- Scalability: The offered framework can be used in the large variety of pipe diameters (4" to 48), lengths (10 km to 1000 km) and types of fluids (crude oil, natural gas, heavy oil) (**Aalsalem et al., 2018**).
- Strength in a Wide Range of Conditions: The model can be used in laminar, transitional, and turbulent conditions, enabling it to be used consistently in varying conditions of operations (**Zore et al/. 2023**).
- To-Integration: The closed-form and explicit expression of the friction factors of the framework causes it to be integrated easily into commercial pipeline simulation software or bespoke tools used in engineering (**Akman & Sadhu, 2024).**

These design suggestions are aimed at filling the gap on the relationship between the theoretical modeling and the actual engineering where energy efficiency, system reliability, and economic viability are taken care of simultaneously.

Conclusions

A coherent analytical framework for pressure drop estimation and optimal design of a pressure boosting station in oil and gas transmission pipelines has been presented. The proposed approach enhances the classical fluid mechanics models by incorporating physically based pressure drop relationships with computationally efficient friction factor estimation and booster station analysis.

The model has been verified against industry standards and has proven to be excellent in many set ups of the flow regime and pipes combination. Its straight use in analysis of its efficiency to the energy also indicates a great potential of optimization in the design and positioning of the booster stations, and the potential energy saved in some of the set-ups is more than 50%.

This research contributes to the provision of a scalable and flexible methodology that helps the engineers and system designers to make effective decisions that are cost-effective. It supports the energy-conscious pipeline processes and the prerequisite to combine it with smart pipeline monitoring systems and digital twins. Further work in the future may be regarded as real-time adjustment using machine learning algorithms and testing on the data of the SCADA system to accommodate predictive care and unassisted control.

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