

DOI: <http://doi.org/10.52716/jprs.v14i2.845>

Energy Saving Via Accurate Computation of Crude Flow Measurement and Calculations

Hisham I. Siddiq

North Oil Company, Ministry Oil, Arafat, Kirkuk, Iraq.

*Corresponding Author E-mail: hisham742004@gmail.com

Received 20/12/2023, Revised 18/02/2024, Accepted 22/02/2024, Published 12/06/2024



This work is licensed under a [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/).

Abstract

Oil industry involves transporting crude oil using pipelines for long distances. One of the major losses factors in this industry is the inaccurate flow calculations. The flow is calculated by pressure differential measurement between two adjacent pumping stations. In addition, there are flow counters at the discharge end of the pipeline. A multi-pumping station oil pipeline, the subject of this case study these two methods seem not to give the same result any more. That's because of the lack of effective flow factors updating, and the very slow or even no response to sudden unexpected changes in pressure differential in pipeline sections.

This paper shows the tremendous effect of these factors and its impact to continuous pumping with proposed empirical formula for updating, for minimal calculation errors and hence related losses.

Keywords: flow Measurement, crude accurate calculations, flow computing, energy saving, process optimization.

ترشيد إستهلاك الطاقة بتقليل الخسائر بواسطة قياسات وحسابات جريان النفط الخام الدقيقة

الخلاصة:

تتضمن الصناعة النفطية نقل النفط الخام بواسطة الأنابيب الى مسافات بعيدة. من أهم العوامل التي تسبب خسائر في هذه الصناعة هي حسابات الجريان الغير دقيقة. بحسب معدل الجريان عن طريق قياس فرق الضغط بين محطتي ضخ متتابعين وأيضاً عن طريق وجود عدادات جريان في نهايات خطوط الأنابيب. بخصوص محطات الضخ المتعددة لخط من الأنابيب النفطية موضوع بحث الدراسة فان هاتين الطريقتين لم تعد نتائجهما متطابقة. وهذا الاختلاف هو بسبب قلة أو عدم تحديث بيانات معاملات الجريان المؤثرة، وبطء أو عدم الإستجابة للتغيرات المفاجئة وغير المتوقعة في فرق الضغط في مقاطع أنبوب الضخ.

تبين هذه الورقة البحثية التأثير الكبير لهذه العوامل وأثرها على الضخ المستمر مع مقترح بصيغة معادلة وضعية لغرض تحديثها للتقليل من أخطاء الحسابات وبالتالي الخسائر المترتبة.

1. Introduction:

Factors affecting oil flow can be divided into three groups. The first are pipeline material-dependent factors like inner diameter, wall thickness, and inside roughness. The second group is for pumping liquid properties such as viscosity in terms of API (American Petroleum Institute) number and liquid temperature. And the third and last group is environmental effects like elevation from sea level in terms of head loss, earth gravity force, and temperature of the pipe surrounding the environment [1].

2. Theory

Depending on the standard mathematical relations showing the effect of each factor on the calculations the following equations help to understand the sources of calculation errors and, hence, the suggested solutions for the problem. Taking into account the effect of each variable on other, linear or nonlinear effects regarding the rate of change of each one.

First, the following are the main relations governing the flow of oil in the pipeline:

$$\Delta P = Hf_{bar} - \Delta e \quad (1)$$

Where ΔP is the pressure difference, Hf_{bar} is the head losses, and Δe is elevation difference all in bar units.

In Bernoulli's equation, Hf represents the head loss in meters due to friction between fluid and internal surface of constant diameter pipe as well as friction between the adjacent fluid layers.

$$P_1/\rho g + V_1^2/2g = P_2/\rho g + V_2^2/2g + Hf_m \quad (2)$$

Where: P_1 and P_2 are the inlet, outlet pressures in bar units, V_1 and V_2 are the inlet, outlet fluid velocities in m/s, ρ is the specific gravity in kg/m³, and g is the earth gravity m/s

This will result in continuous change of energy from a valuable mechanical form to less valuable thermal form. This change of energy is usually referred to as frictional head loss which represents the amount of energy converted into heat per unit weight of fluid.

The head loss Hf_m can be determined by **Darcy-Weisbach** equation, which gives friction factor if head loss is already known [2]:

$$Hf_m = fLv^2/(2gD) \quad (3)$$

Where: f represents the friction factor, L for pipe length in meters, v oil velocity in m/s, g earth gravity m/s^2 , and D pipe size diameter in meters.

With given flow Q in m^3/s :

$$v = Q/A \quad \text{and}; \quad A = \pi(D/2)^2 \quad (4)$$

For pipe section circular area A in meter square, in order to calculate the pressure difference Hf_m in bar units and oil specific gravity ρ in kg/m^3 we should use:

$$Hf_{bar} = \frac{\rho g Hf_m}{10000} \quad (5)$$

Together equations 3, 4 and equation 5 can be combined to yield:

$$Hf_{bar} = \frac{\left(\frac{0.08}{\pi^2}\right) \rho f L Q^2}{D^5} \quad (6)$$

Where:

L represents the pipe section length measured in km. As shown above L , desired Q , and D of oil pipe will not change during the normal operation and even if they did, their changes can be neglected. While calculated friction factor f and oil specific gravity ρ are the most effective factors.

One way to find the friction factor of flow through a pipe is the approximation by professor S.E. Haaland first proposed in 1983[3]. It is used to derive the friction factor for a full-flowing circular pipe. It was constructed using experimental results of both laminar and turbulent flow studies.

The Haaland equation is appropriate for both liquid and gaseous flows through pipes, through the formula shown is most appropriate for liquid flows for friction factor calculations:

$$\frac{1}{\sqrt{f}} = -1.8 \log \left[\left(\frac{\varepsilon/D}{3.7} \right)^{1.11} + \frac{6.9}{Re} \right] \quad (7)$$

Where: f represents the friction factor (unit less), Re = Reynolds Number (unit less) and, ε / D = pipe's relative roughness (unit less)

3. Calculations and Results

For this case a new *empirical formula* was suggested and successfully tested with Moody diagram [4] for accurate friction factor calculations, hence accurate flow measurement suitable for the worked case study:

$$\frac{1}{\sqrt{f}} = -4 \log_{10} \left(\frac{k}{3.707} - \frac{5.045}{Re} \log_{10} \left(\frac{k^{1.1093}}{2.828} + \left(\frac{7.1488}{Re} \right)^{0.8962} \right) \right) \quad (8)$$

Where: Re is Reynold number a function of oil viscosity, diameter of pipe and oil velocity. And k is the ratio of pipe inside roughness, to pipe diameter both in meters (where: $k = \epsilon/D$), Table (1) gives an appropriate comparison method for these factors variations.

Table (1) Pressure Differential Effective Factors Variations

Oil Factors		Typical Values				
		Minimum	Maximum	Average	Unit	
f	Friction factor	0.005	0.029	0.017	unit less	
L	Pipe length	17.5	445	231.25	km	
Q	Flow rate	1000	8000	3500	m ³ /hr.	
ρ	Specific gravity	838.6	850.2	844.4	kg/m ³	
D	40"	Pipe diameter	39.86	39.98	39.92	inch
	46"	Pipe diameter	45.89	45.98	45.935	inch

The variations in the friction factor can be shown for different pressure differences as illustrated in Figures (1) and (2) below:

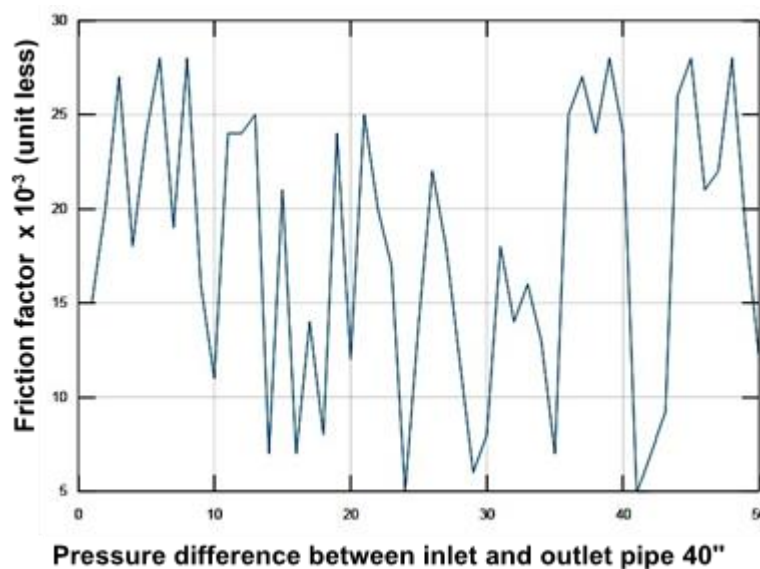


Fig. (1): Simulated Friction factor versus Pressure Differential Link X over 40” line

New detailed tables of pressure differential and flow were calculated based on equation 6 above for 40” and 46” pipelines by writing Matlab v. R13 code software. Two pipeline links designated as X

and Y are selected between two random stations to be curve fitted with second order model as shown in Figures (3) and (4) below.

The relationship between the friction factor and Reynold number is complex such that the empirical formula fits for certain constrains or limitations.

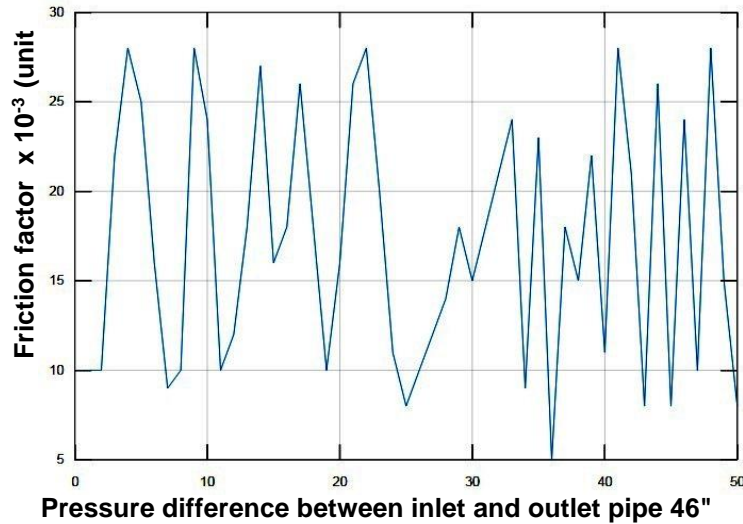


Fig. (2): Simulated Friction factor versus Pressure Differential link X over 46” line

Proposed friction factor is suitable only for the case study taken for this work and any other similar cases should be handled with care and the worst case analysis may show the differences between the proposed and simulated curves with that actually measured from the process itself.

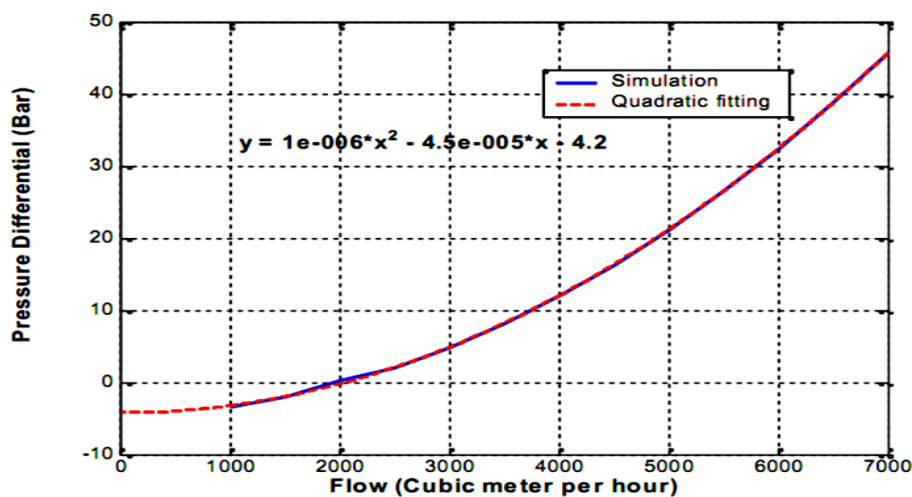


Fig. (3): Simulated Flow versus Pressure Differential Link X over 40” line with Quadratic Fitting Equations

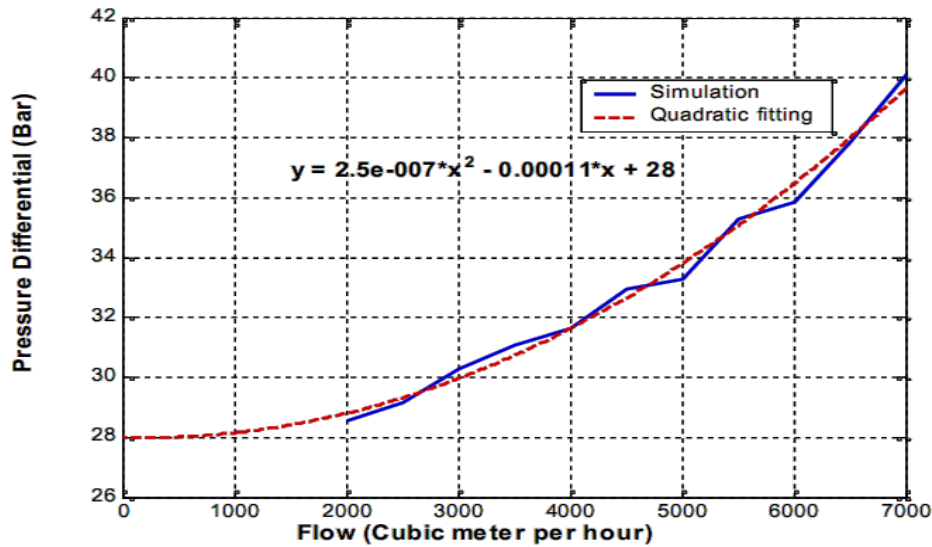


Fig. (4) Simulated Flow versus Pressure Differential Link Y over 46" line with Quadratic Fitting

4. Simulation

The simulation process depends on the retrieved data from actual pumping station running conditions recorded for each station. The recorded variables include the pressure difference between two adjacent pumping stations and the flow rate in cubic meters per hour achieved by the predetermined pressure difference.

But these records are 25 to 30 years old, according to the earlier case of the stations and pumps. The variables used to create the operation tables are no longer fit for the current situation. The need for updated, actual tables is crucial.

The main reason that the tables are made for is the precise pressure difference applied to ensure the related flow rate. These old tables can guide the operator to select the operation conditions as the desired flow, but only prescribed fixed values are calculated. So if any new operating condition is to be considered, a new manipulation should be accomplished with updated factors for maximum efficiency.

The new tables containing new values were updated to meet the new changes and requirements. The new values are fed into the Matlab code such that the flow rate can be figured out through the simulated data and quadratic fitting for the actual data from the historical working conditions. Contradictory, the pressure differential of each station can be given in terms of the designated flow

rate. The accuracy of the process depends on how accurately the factors are measured and fed into the code. Flow chart is illustrated in Figure (5).

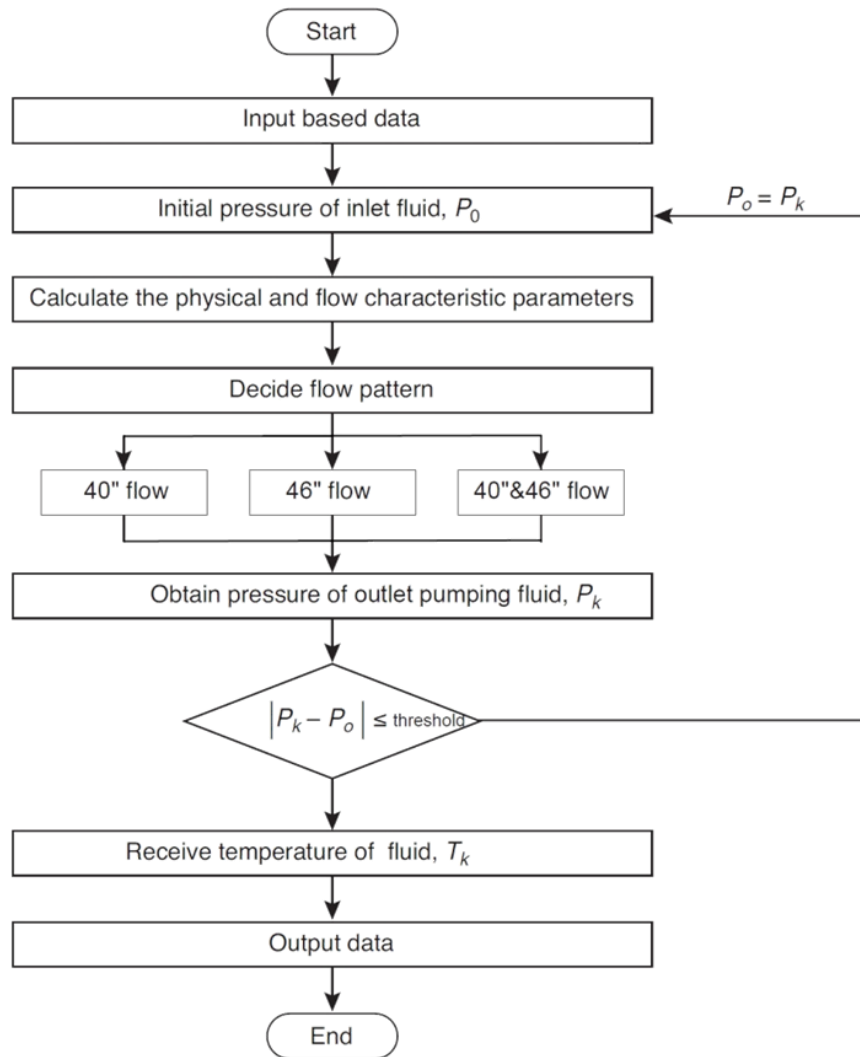


Fig. (5): Flow chart of simulated Matlab code and parameter updating

The new proposed tables are made for the oil lines 40 inches and 46 inches as well. For each station, finding the best difference is a matter of maximizing the flow with respect to minimizing the pressure losses through the pipe.

Giving the precise pressure differences to the main and booster pumps can determine the actual flow rate. This can be done with a newly installed SCADA system where the data flow is smooth and encrypted properly. The need for encryption is very important because a fractional change in the values can make large differences in the total flow.

A worst-case analysis is recommended to take into account the errors in readings and the factors that change with time and environmental changes. Where the flow is always greater than the measured values and should be handled with care, especially when the aging effect takes place.

4.1 Assumptions

Assumptions are made to make the suggested formula acceptable and applicable. The simulation assumptions can be briefed, but not limited to:

- A worst case analysis is considered relating to the calculations of the main factor.
- All collected and historical data supposed to be of normal conditions.
- Any change in the line pumping conditions does not mean in any way stopping the line pumping, because the system has the ability to find a new operating condition with the same flow in no time.
- A part of the processing time is spent applying the industrial encryption algorithm, which should be fast enough to do the job.

4.2 Case Study

The case study dealt with the search for the best path of the many existing paths that ensures the minimum losses in pressure differences between stations, which gives the desired flow rate. The available three modes of operation between each of the two adjacent pipping stations are 40, 46, and both 40 and 46-inch pipe pumping.

An IT oil pipeline has eleven pumping stations; only nine of them are linked with 40- and 46-inch pipes. Thus, the number of links is eight, which can operate in one of the three modes described above.

The first idea was not to be restricted to one mode for all links, and the path will be decided by the state of the desired flow rate for minimum losses of pressure drop at each link or section in terms of getting the optimum pressure difference for all pumping stations. Calculations should be done as fast as the operation is selected to a certain flow rate to give each pumping station its own pump speeds that ensure the desired quantities.

On the other hand, the reverse manner was used to make an update for the system by measuring the actual inlet and outlet pressures of each station (pumping station), and hence the pressure difference comparing these values with the computed ones.

The target of the above is to update and calibrate the speeds of the oil pumps to the desired flow rate. This does not mean to neglect the mounted flow meters along the pipe line, but it gives a low-cost method to compare with.

5. Process Industry Application Prediction of Process Values

Although the factors' main effect is maintained by measurement, the advanced prediction algorithms are making the entire process faster, more accurate, and more reliable to achieve. Using hardware and software solutions, the process industry aims to accomplish industrial processes with the greatest possible economic performance. Keeping in mind the huge amount of data to be collected fetched, and prepared for processing is the job of the whole system. The petroleum industry has historically used a variety of controllers, from proportional controllers to sophisticated predictive-based controllers like Model Predictive Controllers (MPC).

The majority of these systems were created 20–30 years ago, and therefore there is a demand for a detailed examination of the dynamics of the process. And the need for the creation of abstract mathematical models and the construction of a control rule that satisfies specific design requirements

The disadvantages of this tried-and-true technology mainly stem from the complexity of dynamic models and the need for ongoing maintenance to account for supply adjustments, process enhancements, and variations in product needs brought on by the shifting nature of the world economy. By maximizing its assets and using analytics to examine machine and process data that has been collected during operations and productions, the petroleum industry may also create significant value.

Modern machine and deep learning technologies allow for simple process interaction and incremental control behavior improvement. The proposed package's goal is to give process engineers a set of cutting-edge AI tools that allow for the connectivity, validation, and prediction of key KPIs (Key Performance Indicators). Empowering them to make the best operational decisions possible for the maintenance and system improvement leads to an efficient industrial process management system.

For various process streams, the software computes and forecasts physical characteristics and chemical compositions and then suggests the necessary process set points to achieve the predicted results. Process analyzers offer online analytical data that is cross-checked and validated against

expected product quality and laboratory findings. The combination of these three technologies will result in a tool that enables the "digital twin" of the simulated process to be updated continually for maximum process efficiency at the lowest cost. [6]

The suggested package offers a thorough picture of how the process units operate based on data on stream quality and safety, security, and environmental factors. A fundamental tool for managers and operators to use to make the right decisions for maintaining and enhancing good industrial process management is the use of contemporary AI technologies powered by precise KPI measurement. The following are the main duties of the suggested package:

- Connectivity to industrial databases using ODBC, OPC, and Modbus TCP/IP
- Interactive HMI for data acquisition and monitoring
- Automatic verification, validation, and correction of measurements results according to international standards and proprietary free tune software
- Statistical evaluation and reporting of validation results
- Prediction of main process KPIs, such as physical properties and chemical compositions for different process streams, using process data from industrial databases and machine learning technologies
- Big data analysis functionality, including multidimensional fusion and distribution of incoming data, abnormality of novel events detection, clustering, decision trees, linear, polynomial, logistic regression, escalation of novelty real-time analysis, etc. using deep learning technologies.

Applying KPIs, which are directly related to the quality of process streams. The chemical and physical properties of the input materials and output products in each process unit are the logical approach to go about this task in the downstream sector. This makes it possible to create a digital twin of a streamlined process that contains an indecision tree with only the KPIs that are most important for process efficiency and explains the process objectives.

The criteria for safety, security, and the environment are additional KPIs that must be taken into account and imposed as limitations. Using principles from linear programming, this approach maximizes overall profit by integrating network input and target KPIs, driving overall process optimization. The following are the key KPIs that will be taken into consideration:

- Physical and chemical properties of different process streams using pressure, flow, level, temperature, vibration, and other measurements by field instrumentation. These predictions shall be authenticated against process analyzers and practical results, including corrections.
- Quick leak detection using pressure, flow, acoustic, seismic, electromagnetic, mechanical, thermal, and other pipeline measurements is affordable. The system detects and analyzes the calculated pipeline status for conditions that suggest a leak and defines their location.
- Advanced corrosion analytics (ACA), using deep learning algorithms supported by process analyzers, pressure differentials, and length of exposure parameters.
- Process safety improvements leverage existing data infrastructure to allow the use of machine-deep learning algorithms.

Process data is retrieved from a real-time data management system for PI that is already in place. Data is protected by unidirectional information flow and is accessible to external devices with an authorized accessibility algorithm.

Enhanced connections to LIMS, IMS, and other databases enable getting data that isn't readily available in PI. Profound support learning (DRL) may be an effective machine learning method that can be successfully utilized to optimize mechanical forms for diverse vital objectives, permitting move-center intelligence and certainty. Reinforcement learning makes utilization of calculations that don't depend as much on authentic information sets to memorize to create a forecast or perform an errand.

6. Discussions

The difference between the fitting and simulated data for link X seems to be very reasonable. While for link Y is not because due to the pipeline section being exposed to severe damage and many repairing processes that definitely with change the pipeline section properties. But the simulated curve still gives the real response because it depends on real field measures. Noting that the difference between simulated and fitted curves does not exceed 0.5 bar.

The software also calculates the flow for any pressure differential of all pumping stations along the oil pipeline. Consequently it can give the optimum pressure differential of all stations for any desired flow. That is done of course, within the limits of normal operational conditions of piping system.

Mixed mode operation defined as selecting 40", 46" or both lines between any two adjacent pumping stations that was done manually. The pipe section links between any two adjacent pumping stations the eleven pumping stations of existing IT oil pipeline are clearly ten links.

But only eight of them consist of both 40" and 46" pipes. This leads to 3^8 possible connections for the overall pipeline [5]. Choosing one mixed mode among $3^8 = 6561$ operational case can be given by the software according to minimal cumulative stations pressure differential.

IT oil pipeline transports the crude between two countries. Along this distance a pipeline of more than 945km need to pump continuously with accurate flow measurement and reliable custody transfer system. All the way from the first pumping station through the substations till the last destination is reached each pipe section may show its own properties like the number of control valves, elbows, restrictions which can be treated separately the then overall effect is the overall behavior of all sections.

Many approaches dealing with the water oil contact level can be combined with this study to give precise rate of crude flow measurements, taking into account the oil water ratio especially in the wet crude facilities [7].

7. Conclusions

If the proposed work is to be applied to the Iraqi-Turkish oil pipeline, the estimated savings in crude oil are between 20 and 40 cubic meters per hour for a flow of 3000 to 7500 cubic meters per hour. In fact, 30 cubic meters per hour was estimated for 6000 cubic meters per hour flow, which is no more than 0.5% change, which is the difference between traditional and accurate measurement of oil flow. Regardless of the saving that can be achieved in the fuel and electricity used for pumping, if an average of 30 cubic meters per hour was wasted by inaccurate flow measurement, that cumulatively equals 3600 cubic meters per week for almost continuous pumping for 20 hours per day and 6 days per week on average, which leads to 1,924,682 (one million nine hundred twenty-four thousand six hundred eighty-two) USD savings per week assuming an average of 85 USD for a barrel. Noting that 1 cubic meter = 6.28981077 barrels (oil), this leads to an annual considerable saving of more than 100 million USD.

Empirical formulae can be used to satisfy predefined limitations to give an acceptable error rate for flow measurement applications such as taxation and custody transfer. Although, further calculations may add other limitations like energy consumption rate [8].

The proposed package carries out data collection, monitoring, verification, validation, statistical evaluation, rectification, and reporting of measurement results using the information from the process. Multivariable data analysis algorithms offer predictions of key process KPIs, such as physical characteristics and chemical compositions for various process streams [9]. To avoid the need for ongoing cloud computing, deep learning and big data analytics can be installed offline. Unprecedented levels of efficiency, productivity, and performance are being achieved by this solution by fusing process expertise, remote analytical technology, and big data analytics capabilities. Good calculations with suitable factors updated would minimize the losses due to bad calculations and increase the savings tremendously.

Acknowledgment

Special thanks go to Dr. Fawzi M. Alnaima, Dr. Raad S. Alfayadh and Dr. Samir S. Algburi for their guidance and support. Also regards are dedicated to engineers, supervisors, and technician's employees of North Oil Company for retrieving historical data and technical support.

References:

- [1] Hisham I. Siddiq, "Internet Based SCADA System for Oil Industry Applications", Ph.D. theses in computer engineering, Alnehrain University Engineering College, Baghdad, 2007.
- [2] Renata T. de A. Minihoni, Francisca F. S. Pereira, Tatiane B. G. da Silva, Evanize R. Castro, and João C. C. Saad, "The Performance Of Explicit Formulas For Determining The Darcy weisbach Friction Factor", Engenharia Agrícola, Jaboticabal, vol. 40, no. 2, pp. 258-265, mar./apr. 2020. <https://doi.org/10.1590/1809-4430-eng.agric.v40n2p258-265/2020>
- [3] S. E. Haaland, "Simple and Explicit Formulas for the Friction Factor in Turbulent Pipe Flow", Journal of Fluids Engineering, vol. 105, pp. 89-90, 1983. <http://dx.doi.org/10.1115/1.3240948>
- [4] T. J. Miller, "Oil Pipes Friction Factors Chart versus Moody Diagram", Foxboro Inc., Technical manual, 2000.
- [5] Olga Moreira, "The Application of Probability Theory", Arcler Press Publishing, 2023.
- [6] Allen S. Walker "Artificial Intelligence in Petroleum Industry", <https://www.modcon-systems.com/products/scada-2/artificial-intelligence/>, 2018.
- [7] W. I. Al-Rubaye, D. S. Ghanem, H. Mohammed Kh, H. Abdulzahra, A. M. Saleem, and A. R. Abbas, "Estimation of Oil-Water Contact Level Using Different Approaches: A Case Study for an Iraqi Carbonate Reservoir", Journal of Petroleum Research and Studies, vol. 10, no. 2, pp. 95-113, Jun. 2020. <https://doi.org/10.52716/jprs.v10i2.354>
- [8] C. J. Greenshields, and H. G. Weller, "Notes on Computational Fluid Dynamics: General Principle", CFD Direct Limited Publishing, 2022.
- [9] Robert B. Hey, "Performance Management for the Oil, Gas, and Process Industries: A Systems Approach", Gulf Professional Publishing, 1st Edition, 2017.