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Original Article

Predictive Approach of Cost and Time Optimization for Enhancing Scaffold Management through AWP

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Abstract *- Scaffolding in the oil and gas sector is a very important operation, but its operations are mostly influenced by some inefficiencies that add cost and project time. The systematic methods aimed at enhancing planning and implementation are increasingly in demand. This paper examines how Advanced Work Packaging (AWP) can be implemented in scaffold management to streamline the cost and time performance. Multi-Expression Programming X (MEPx) was used to estimate Adjusted Scaffolding Cost (AC) and Adjusted Scaffolding Hours (AH) as affected by Unit Rate (UR), Quantities (Q), Weather Impact (WI), Equipment Downtime (EQ), and Labour Fatigue (LF). The models were tested by standard training, testing, and validation. The outcomes demonstrated a moderate accuracy in terms of cost prediction with Mean Absolute Error (MAE) = 5.85; Root Mean Square Error (RMSE) = 7.93; coefficient of determination (R^2) = 0.76, and a greater reliability in terms of time prediction with MAE = 0.49; RMSE = 1.02; R^2 = 0.86. The results show that data-driven predictive modeling, applied in conjunction with AWP principles, would provide a more realistic and data-driven approach to decision-making, resulting in more effective scaffold management in oil and gas projects.*

Keywords *- Advanced Work Packaging, Multi Expression Programming, Multi Expression Programming X, Optimization.*

1. Introduction

The oil and Gas industry is one of the most complicated, capital and safety-intensive ones, which is acknowledged around the globe [1]. The control of temporary works like scaffolding takes center stage in the access provision of construction, maintenance, and turnarounds [2]. Scaffolding is a repetitive and mandatory aspect of upstream, midstream, and downstream activities and tends to consume an extensive labor cost and materials duration in its application [3]. Nevertheless, scaffold management is often littered with inefficiencies associated with re-do installations and dismantling, waste material, and delays in schedules [4]. Such inefficiencies are not just limited to single construction-related activities, but they spill over to larger problems in the delivery of projects, affording more cost and time overruns. That is why scaffold management has become one of the key target areas that require optimization in the spheres of current project execution. Advanced Work Packaging (AWP) is a formalized project-delivery system that was created by the Construction Industry Institute (CII) and the Construction Owners Association of Alberta (COAA) to enhance harmonization between engineering, procurement, and construction operations. It breaks down complex projects into hierarchical work packages, which it calls Engineering Work Packages (EWPs), Construction Work Packages (CWPs), and Installation Work Packages (IWPs), and sequences them on a specified Path of Construction (PoC).

The concept of Advanced Work Packaging (AWP) has been gaining popularity in construction and oil and gas industries as a formalized system of aligning all Engineering, Procurement, and Construction (EPC) activities. Developed by the CII, AWP seeks to simplify massive and complicated projects into manageable work packages, thus leading to improved integration, planning, and execution [5]. AWP lowers risks, which ensures the uncertainty is reduced and makes it more economical as far as productivity across project life cycles is concerned [6]. Its use in its application to scaffold management is especially relevant since the nature of scaffolding operations is by definition cross-functional: it serves various trades, needs to be installed and dismantled at a specific time, and uses significant project resources to accomplish the said work. Incorporating this would allow AWP into scaffolding planning and implementation, hence affording the chance to eliminate redundancies, match the work-front readiness to the real construction requirements, and eventually eliminate the costs and the time.

Whereas AWP provides a systematic approach to the enhancement of project implementation practices, the dynamics of scaffolding work processes require more than improvement in the processes [7]. As per the experts who have vast field experience, it is found that about 25% of the project productivity improved, and there was a 10% cost reduction from the stipulated cost [8]. The requirements of the scaffolding are usually conditional upon the site conditions, changes in work scope, and concurring activities in a confined area [9]. Such uncertainties make it difficult to estimate the actual resource demand for scaffolding work. Conventional planning methods are mostly deterministic methods that are used with past average estimates, judgments, or average productivity levels. Such approaches tend to oversimplify project-specific variations and lead to scaffolding costs and time being underestimated or overestimated. In this sense, one of the most important steps in scaffold management would be the incorporation of predictive modeling. Computational modeling techniques, such as predictive models, based on historical projects and statistical methods, enable analysis of more precise forecasts based on project-specific parameters.

Even though the importance of scaffolding as far as the implementation of a project is concerned is obvious. The combination of the AWP principles with the predictive modeling techniques, which examine the inefficiencies in the scaffold management, has not been specifically addressed by sufficient research. The literature on AWP has been devoted to the general project planning and integration. Scaffolding peculiarities, since it has a repetitive nature, its cross-functionality, and its vulnerability to various unpredictable situations, have not been studied appropriately through AWP. Such a discrepancy proves the need for the method, which is oriented on the usage of both the Structured Work Packages (SWPs) and advanced predictive techniques to improve the quality of costs and time estimations of the scaffold operations.

AWP scaffolding projects that incorporate the use of predictive models in cost and time estimates can help the decision-makers in predicting projects with more accuracy. It can provide an estimation of not only direct costs but also indirect constraints such as delays, rework, and inefficiencies in resource use by training the models on such variables as scaffolding elements, hours per activity, amounts of materials, cost per activity, and complexity of the project. Predictive analytics can therefore act as a decision support tool that connects the two ends, namely, structured planning offered by AWP and data-informed understanding offered by computational modelling. The integration has facilitated proactive management because interventions are countered early to allow resource allocation optimization and enhance project performance indicators.

This study aims to test predictive models of scaffolding cost and labour hours using AWP methods with Multi Expression Programming (MEP). Several factors are considered critical and are cumulated in the construction of equations using Multi-Expression Programming X (MEPx). The research is important because it adds to the available data in making decisions regarding scaffold management. The study will minimise uncertainty, remove inefficiencies, and improve the cost and time performance of oil and gas projects by enhancing the accuracy of forecasts and the alignment of the scaffold operations with the AWP principles.

Although AWP has been widely used in enhancing reliability in planning, there still exists a deficit of specific use in temporary works like scaffolds, where rework, idle time, and safety risk are very common. The current project delivery processes are unable to consider the dynamic and repetitive nature of scaffolding processes, resulting in poor forecasts of cost and duration. Thus, the paper bridges the gap by creating a predictive model of cost optimization and time optimization with AWP principles, as well as allowing the use of data to make decisions regarding scaffolding management in the oil and gas project.

2. Literature Review

Scaffolding is an essential part of industrial construction and maintenance works, especially in the oil and gas industry, where temporary scaffolding construction is the key to accessibility, safety, and productivity [10]. However, in spite of its significance, scaffolding has been traditionally a lump of inefficiencies and reactive styles of management. Research documented that a huge percentage of the project delays and cost overruns are attributed to scaffolding-related activities due to re-erections, frequent adjustments, and a lack of liaison with other trades [11]. Productivity in turnaround projects decreases, such as where more than one-third of the total labor hours may be spent on scaffolding erection and late design updates, nonconcurrent operations [12]. The findings support the fact that there is a necessity for more comprehensive planning strategies with an attempt to align scaffolding and the scope of project execution, rather than continuing the approach that treats it as a secondary process.

Scaffolding management has been widely known as one of the most labour-intensive, as well as cost-sensitive, elements of the industrial and infrastructure projects. Despite being temporary work, it has a direct influence on productivity, safety, and the whole duration of the project. The scaffolding tasks can use up to 15-40 % of total indirect labor hours in the shutdown and turnaround projects [13]. The management of scaffolds is critical to ensuring the safety of oil and gas construction projects, efficiency, and costeffectiveness. The complex working environments and the risky operation of the sector mean that scaffold planning and management are essential in order to support the various building and maintenance processes. Several professionals identify scaffold management as a vital performance indicator in project undertakings in the oil and gas sector. Various research studies have shown that poor scaffold planning is one of the major causes of time and cost overruns in projects [14]. Scaffold management is an important factor that affects the outcome of projects in the oil and gas industry. AWP is offered as a potential remedy to the challenges within the industry because various researchers confirm the perks of the approach. The key advantages are a maximum 25 % schedule decrease and 4-10 % overall installed cost reduction, as well as enhanced quality and morale of the workers. These results have seen widespread use of AWP practices by contractors and increased interest of owners in requiring AWP on capital projects [15]. As the CII industry infographic shows, projects that applied AWP in scaffolding and in access management have claimed a reduction of up to 20 percent of the site labor hours and costs. Although these figures are not based on the general empirical data, but rather on specific project examples, they show how substantial the benefits can be in the cases of the structured planning methods [16]. Nonetheless, these numbers are to be viewed as case-related demonstrations instead of general standards, as the extensive empirical data is not available yet.

2.1. AWP in Construction Projects

AWP is one of the efforts that has been gathering momentum in trying to remedy project inefficiencies [17]. AWP was designed as an orderly project delivery system that focuses on decomposing megaprojects into CWPs, IWPs, and EWPs, thus coordinating engineering, procurement, and construction efforts [18]. CII [5] provides an example of AWP improving workface planning that consists of better constraint management, sequencing, and flow of information. Measurable gains of AWP in the form of enhanced predictability, better direct-work rates, and minimal rework have been documented in several studies [19, 20]. Studies consistently show that AWP enhances project efficiency by improving workflow standardization, reducing rework, and strengthening coordination across engineering and construction stages [21]. The technique has been effective, especially in projects where there is much complicated work that requires a series of trades and subcontractors to work together in limited spaces. In the case of scaffolding, AWP integration would help eliminate duplicate scaffolding installations and align access with specific construction requirements, as well as align scaffolding erection and dismantling to enhance execution preparedness.

Halala and Fayek [22] highlight that although AWP is presented as a best practice in building industrial work, much evidence has been presented in qualitative or case-study forms. The absence of an effective and systematic framework to measure the costs and benefits of implementing AWP is one of the prohibiting factors to the wider adoption. The framework offered allows practitioners to determine AWP maturity, supplementary expenses, and the performance of the project. The recent research highlights the role of data-driven approaches in construction management, which is on the rise. Wu et al. [23] explore that Machine Learning (ML) can be successfully used to find the non-linear, intricate connections between factors and the outcomes of any project and provide more confident predictions compared to traditional estimates. Their contribution proves that meaningful use of predictive analytics as a part of construction processes allows them to make proactive decisions, minimize uncertainties, and enhance the overall project performance. A study by Calabrese, Camaioni, and Piervincenzi [18] highlighted that nearly 70% of industrial projects exceeded expected cost and schedule targets due to poor planning reliability. The authors proposed AWP as a standardized methodology that integrates engineering, procurement, and construction through structured work packages. Their findings indicated that AWP improves project predictability, reduces rework, enhances labor productivity, and strengthens stakeholder alignment across the project life cycle.

The research on AWP that has been published has concentrated considerably on overall project delivery, as opposed to a particular temporary work, such as scaffolding. Flores, Ramos, and Rey [24] highlighted that although the use of AWP for structural steel, piping, and equipment installation has become common, there is limited empirical evidence of using AWP for temporary works. This is a vital fact since the use of scaffolding is what may constitute the root of access and safety in any industrial activities [25]. However, there is still little quantitative research associating AWP with real scaffolding-associated costs and time savings, indicating a potentially important research gap.

Although numerous studies report productivity improvements of 10–25% through AWP adoption Musarat et al., most focus on core engineering and construction activities. Typically, about 20% of cost overruns and schedule overruns are seen in the literature. Flores, Ramos, and Rey emphasized that while AWP standardizes planning and enhances labor productivity, its use remains rare in temporary works such as scaffolding, formwork, or shoring [24]. These tasks are typically managed reactively, leading to duplicated installations and increased idle time. Hence, there exists a lack of empirical frameworks quantifying how AWP principles can directly enhance scaffold planning efficiency, cost, and schedule reliability.

2.2. Predictive Modeling in Construction Cost and Time Estimation

In construction management, the cost and time prediction has always been a problem [26]. Conventional estimation approaches have generally depended on expert opinion, past averages, and deterministic productivity rates [27]. The approaches may give us a minimum, but they have a tendency not to reflect variations unique to projects in the form of site density, geographical conditions, and worker experience. According to Ahiaga-Dagbui and Smith [28], traditional approaches often give rise to cost and time underestimation, thus augmenting the project overrun threat. Deterministic estimates may be especially misleading in the context of scaffolding, since the requirements in scaffolding are strongly dependent on changes in design and access requirements when multiple operations are being undertaken.

To avoid the weaknesses of conventional methods, predictive modeling and ML have gained more attention among researchers [29, 30]. The construction forecasting made use of regression analysis, decision trees, support vector regression, and artificial neural networks in some form or other, with some level of success [31-33]. As an illustration, Meharie et al. [34] Applied ensemble learning techniques by predicting construction durations, where the best results were achieved when random forests and gradient boosting were employed, with linear models taken as a benchmark.

Correspondingly, Alqahtani and Whyte [35] utilised neural networks in the cost estimation task and concluded that they outperformed regular regression. Such studies indicate that ML may be able to discover multidimensional and non-linear associations between project aspects and outputs, and thus, it can be useful when dealing with dynamic processes such as scaffolding.

One of the issues with many ML models is the fact that they are black-box. Although these models could be very accurate in predicting events, they are not transparent and interpretable, which may not help them in adoption by project managers and practitioners who need to understand them and derive meaningful insights. The symbolic regression algorithms that build on evolutionary algorithms have a lot of potential [36]. Symbolic regression attempts to identify symbolic statements of the relationships between inputs and outputs as a way to cope with these issues. Genetic programming (GP) has already been explored widely in this regard, although recently, more efficient and more interpretable progress, such as MEP, has been made in this area [37]. The MEPx tool offers an intuitive system of symbolic regression, classification, and time-series prediction that allows users to train predictive models with the project data [38]. In case of the scaffolding projects, the options to come up with clear formulas of correlating variables like scaffolding cost, the number of bays, time taken, and task complexity to costs and time output will be highly beneficial.

MEPx is a development of evolutionary symbolic regression that is employed to formulate mathematical correlations between input variables and project responses. It builds on the traditional MEP model by automatically producing interpretable, closed-form equations as opposed to the use of black-box numerical prediction. MEPx is a genetic algorithm that works by successfully breeding populations of candidate equations via genetic operations, crossover, and mutation until the best symbolic expression with the least error on the data is discovered.

A study by Tian et al shows that MEPx has been used in various engineering fields to perform various tasks, including assessment of consolidation, geotechnical prediction, estimation of material strength, and optimizations [39, 40]. Its strong side is that it merges the predictive ability of evolutionary computation with transparency, meaning that users can easily view the interaction of variables in the resulting equations. MEPx offers a definite and verifiable connection between factors and results when compared to neural networks or ensemble learning procedures, which are generally hard to interpret.

This is especially useful with construction-management applications in which the logic of the decisions can be traced. MEPx will be used in the current investigation to determine the nonlinear correlations between variables, including unit rate, quantity, weather influence, equipment downtime, and labor fatigue, and their impact on the adjusted scaffolding cost and labor hours.

Such a literature review, therefore, leaves an evident research gap, whereas AWP does offer a process framework towards better scaffolding planning and execution; however, little focus has been made on integrating predictive modeling methods that can effectively generate accurate and interpretable cost and time estimates of scaffolding activities. The innovative chance at fulfilling this gap is through the adoption of MEPx, which can generate transparent mathematical models. The proposed study, utilizing the combined powers of AWP and scaffolding work in a highly structured manner, and MEPx as a means of predictive modeling, can help increase the accuracy and usability of scaffolding cost and time estimations.

Contrary to the previous research, which used AWP for general EPC coordination or project productivity but did not combine them, the study adopts both areas of work, connecting AWP-oriented planning with MEPx-based symbolic regression modeling. This two-fold integration provides an equation-based predictive framework of scaffolding cost and time prediction, a focus that has not been previously considered in the literature.

2.3. Comparative Review of Related Studies

The analysis of the current literature indicates that AWP and predictive modeling have developed along dissimilar lines. Table 1 lists the representative studies and their methodological weakness compared to the current study.

Table 1. Comparative summary of key studies on AWP, constraint management, and predictive modeling

Study	Focus Area	Method Used	Key Limitation
Halala and Fayek [22]	AWP cost–benefit evaluation in industrial construction	Analytical framework	No predictive or quantitative modeling
Wu, et al. [23]	Constraint modeling in AWP	Hybrid deep-learning model	Focused on design constraints only
Calabrese, Camaioni and Piervincenzi [18]	Standardized AWP framework for EPC projects	Conceptual modeling	Lacked quantitative validation
Meharie, et al. [34]	Highway construction cost prediction	Ensemble machine-learning	No integration with structured planning
Alqahtani and Whyte [35]	Building life-cycle cost estimation	Neural-network regression	Non-interpretable black-box outputs
This study	Scaffold management under AWP	MEPx symbolic regression	Integrates structured planning and transparent prediction

The comparative analysis in Table 1 shows that there is a tendency of consistency in existing studies since most research studies focus on either process standardization using AWP or predictive modeling using computational methods, yet only a few research studies integrate both views. Other articles, including Halala and Fayek and Calabrese, Camaioni and Piervincenzi, should be looked into as valuable conceptual frameworks formalizing AWP procedures, but they are still more descriptive and have not been quantitatively validated as regards their performance [22, 18]. Conversely, papers that used more sophisticated analytical or machine-learning methods (Meharie et al.; Alqahtani and Whyte) were able to achieve higher predictive accuracy but did not provide much information on how these models can be operationally implemented into organized project-delivery systems [34, 35].

Moreover, earlier computational strategies are likely to be based on non-transparent (e.g., neural networks or ensemble learners) black-box models, which are often strong, but not transparent and understandable to practitioners. The lack of interpretable predictive tools that are based on equations limits their application in project planning environments where verifiable logic and traceability are required. At the same time, AWP-based studies rarely lead to the temporary works, including scaffolding, which have a major impact on the project time and cost performance, but are not in the core interest of engineering-construction alignment.

In comparison, the current research paper seals this gap in the methodology by introducing an explicit symbolic-regression framework (MEPx) into the AWP process framework. This integration allows the derivation of explicit mathematical equations to imply critical parameters to adjust the cost and time results of scaffolding operations. Therefore, it is not only that the study contributes to the field of predictive modeling with enhanced interpretability, but also that it expands the scope of operation of AWP to temporary works. This twofold contribution directly serves the identified gap in the research and offers a reproducible, data-driven basis for future optimization studies of AWP.

3. Methodology

The research methodology employed in the study is the creation of a predictive model, as illustrated in Figure 1. The model provides optimization of the scaffolding processes in the oil and gas projects with the help of AWP and MEPx. To begin with, the rich data set was built upon the industrial projects which applied the principles of the AWP, not only the quantitative (e.g., the cost of one scaffolding element, time to perform a task, amount of material) but also the contextual (e.g., project complexity) data. Data were then pre-processed and modeled.

MEPx was implemented using evolutionary algorithms and in a coded environment to produce the mathematical equations that modeled the relationship between the input variables and the project's significant outputs, Adjusted Scaffolding Cost (AC), and Adjusted Scaffolding Hours (AH). These were later tested and used in the cost and estimated time performance of the scaffold in new project situations based on these equations. The general construction incorporates the AWP-based structured planning and data-based predictive models that offer a systematic approach to enhancing the accuracy of planning, resource utilization, and schedule regularity in scaffold operations. The parameters used in the MEPx modeling Unit Rate (UR), Quantity (Q), Weather Impact (WI), Equipment downtime (EQ), and Labor Fatigue (LF) were selected based on an extensive review of literature, project data, and expert consultations. These variables collectively represent the major determinants of scaffolding cost and time performance within oil and gas projects.

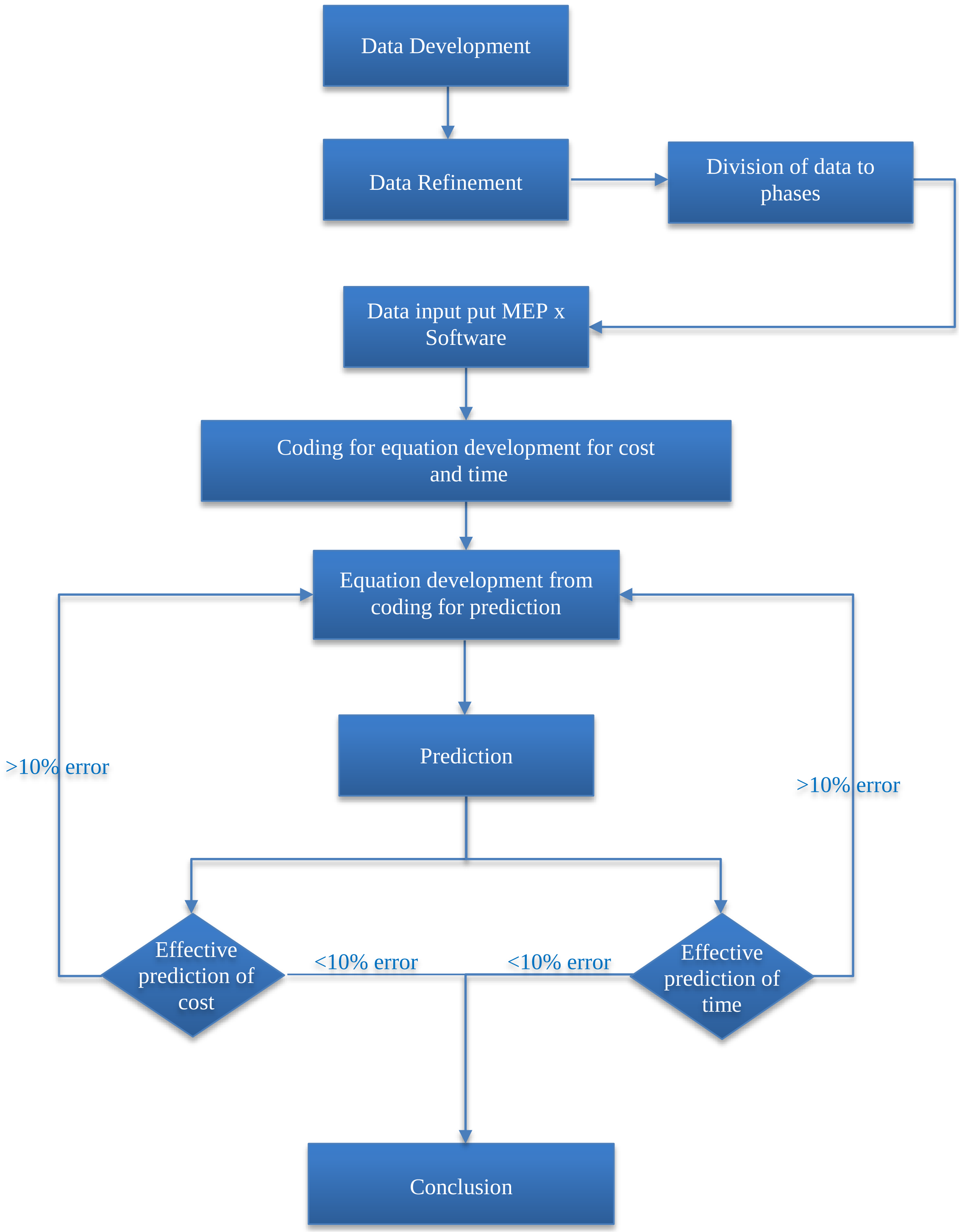

Fig. 1 Methodology of study integrating Advanced Work Packaging (AWP) and Multi-Expression Programming X (MEPx) for scaffold management optimization

The raw dataset utilized in this research was obtained from industrial partners under strict confidentiality agreements. Due to the proprietary nature of the data, detailed project identifiers and complete datasets cannot be disclosed. However, the presented results and aggregated outputs fully reflect the underlying patterns and relationships derived from the confidential data. The analysis focuses on statistically validated results that are scientifically reproducible and beneficial to the research community without compromising industrial confidentiality.

3.1. Dataset Development

The initial stage of the research methodology is the creation of a complete dataset since it forms the basis of the following modeling and analysis. The choice of such projects was precise in the sense that they had been initiated with the use of the AWP principles in scaffolding operations. To be certain that the data were recorded was a matter of planned and executed practices. The data set included the historical data of assembling and removal processes of scaffolding, expense reports, resource allocation registers, and schedules. Key factors that were considered comprised the cost per scaffolding element, the number of bays, the task length, and total materials required. In addition to these, contextual parameters were also factored in, such as the complexity of the project, the magnitude of work packages, and access constraints to denote the real-life situation that influences the performance of the scaffolding in the labor business. The preprocessing and data cleaning were done to remove inconsistency, form sharing units, and offer reliability before analysis.

3.2. Computational Framework for Equation Development

The integrated coding environment was used to develop the equations in MEPx to ensure precision. Where MEPx provides a graphical interface to execute the symbolic regression, the research prescribed the input parameters, evolutionary settings, and testing processes in a systematic way with the help of the code-based configuration. The process of coding the execution process facilitated the possibility of automating the data import, the definition of the independent variables, the definition of the dependent outputs AC and AH, and multiple generations of the evolutionary algorithm can be calculated without human intervention. Such methodology might render the experiment standardized, able to give precise results, and capable of saving and replicating the evolved equations to be tested further. The execution of code during MEPx not only provides resiliency to the modeling process but also provides an eloquent way in which the analysis can be performed in the future using a different dataset.

3.3. Evolutionary Equation Development

After setting up the dataset and coding, the third stage is mathematical equations that depict the connection between input variables and outcomes of interest, which are the cost and time. To this end, the MEPx tool is used. MEPx is an evolutionary algorithm-based package that is used to create explicit mathematical models based on empirical data. The data set was loaded into the MEPx, and the program was patterned to run a number of generations of evolutionary search to enable the algorithm to iteratively develop expressions that fit the relationships between scaffolding parameters and the resultant cost and time. The result of this process was that MEPx generated interpretable, closed-form equations that related the attributes of the scaffoldings, the factors that made up the workforce, and the contextual factors to the outcomes of projects. Contrary to the conventional black-box models, these equations were easily interpretable, verifiable, and applicable by practitioners, hence leading to their own increased accuracy and practical use.

3.4. Predictive Modeling of Cost and Time

The final stage of the methodology was to generate scaffolding cost and time predictions relying on the equations created in MEPx. Upon selecting the most favorable equations, based on their precision in the forecasting efficiency, they served as forecasting instruments for the data. MEPx operates based on equation development, and thus, based on these equations, cost and time predictions were derived. This practice was a high level of estimation of scaffolding demand in a project where the use of AWP was already integrated, and assisted the planners and decision-makers in predicting the demands of resources more accurately, such as establishing the potential schedule implications.

The predictiveness of the equations is also verified by comparing the results to those of actual projects in order to ensure that the models not only fulfil the intention of interpolating the past, but also can be useful in making unseen instances. In that direction, the methodology positions AWP and data-driven predictive modeling, where the management of scaffolding can be optimized in oil and gas projects, which offers a viable and scientifically grounded platform.

4. Results and Discussion

4.1. Algorithm for the Equation Development of Cost

The actual implementation of the MEPx tool yielded a collection of developed equations that could give the potential forecast of AC when it comes to scaffolding work. The legibility of the program presents the symbolic regression process whereby a transformation of combinations between the input parameters, which could be UR, Q, Unit Hours (UH), WI, EQ, and LF, in addition to arithmetic and mathematical operators, is performed into a prediction output as shown. The fact that nonlinear transformation features in the evolved equation shows that MEPx was able to detect complex nonlinearities between variables, which would not have been possible to identify through the linear estimation technique.

4.1.1. Algorithm 1

Given:

UR: Unit Rate
Q: Quantity
UH: Unit Hours
WI: Weather Impact
EQ: Equipment Downtime
LF: Labour Fatigue

Output AC:

AC: Adjusted Scaffolding Cost

Process :
1. Load project dataset including UR, Q, UH, WI, EQ, and LF.
2. Initialize intermediate variables temp1 … temp12.
3. Set prediction output AC = 0
4. Compute multiplication term: temp1 = UR × Q.
5. Apply square root: temp2 = √(temp1).
6. Apply non-linear transformation: temp3 = sin(UH).
7. Compute interaction: temp4 = UR × UH.
8. Adjust with weather impact: temp5 = WI × temp2.
9. Combine with sine effect: temp6 = temp3 × temp4.
10. Subtract weather effect: temp7 = temp4 – WI.
11. Aggregate non-linear terms: temp8 = temp7 + temp6.
12. Add multiplication base: temp9 = temp8 + temp1.
13. Refine subtraction: temp10 = temp7 – WI.
14. Combine weather adjustment: temp11 = temp9 + temp5.
15. Aggregate totals: temp12 = temp10 + temp11.
16. Compute Adjusted Cost: AC = temp12 – WI.

4.2. Algorithm for the Equation Development of Time

The MEPx tool has also developed predictive equations of AH, which reflect the total time of scaffolding work on AWP conditions. The resulting evolved structure was traded out as a C program, which exemplifies the symbolic regression procedure to obtain nonlinear correlation among the input parameters, i.e., UR, Q, UH, WI, EQ, and LF.

The equation produced involves many different mathematical expressions, such as trigonometrical functions (sine, cosine), square terms, combinations of multiplication, etc. These nonlinear operators show that there is a lot more connectivity and interactivity between the scaffolding activity duration and influencing factors than initially assumed in classic deterministic scheduling.

The developed framework is considerate of the compounded effects of downtime, due to weather conditions, and labor exhaustion, all of which usually result in a heavier extension of the project time in unexpected but severe ways.

4.2.1. Algorithm 2

Given:

UR: Unit Rate
Q: Quantity
UH: Unit Hours
WI: Weather Impact
EQ: Equipment Downtime
LF: Labour Fatigue

Output:

AH: Adjusted Scaffolding Hours (Labour Hours)

Process:
1. Load project dataset including UR, Q, UH, WI, EQ, and LF.
2. Initialize intermediate variables temp1 … temp24.
3. Set prediction output AH = 0.
4. temp1 = UR
5. temp2 = UH
6. temp3 = sin(UR)
7. temp4 = Q
8. temp5 = cos(UH)
9. temp6 = UR + UR
10. temp7 = UR / Q
11. temp8 = temp7 + temp5
12. temp9 = temp8 × temp8
13. temp10 = temp6 + temp3
14. temp11 = UR – temp9
15. temp12 = temp10 + temp10
16. temp13 = cos(temp9)
17. temp14 = temp9 – temp11
18. temp15 = temp14 × temp5
19. temp16 = temp13 – temp3
20. temp17 = temp16 × temp15
21. temp18 = temp12 – temp17
22. temp19 = temp15 × temp15
23. temp20 = Q × UH
24. temp21 = temp18 – temp20
25. temp22 = LF
26. temp23 = temp19 – temp21
27. temp24 = temp17 + temp23
28. Compute Adjusted Hours (AH) = LF + temp24

4.3. Analytical Framework for Cost Prediction

In an attempt to develop a predictive model of scaffolding expenses in AWP-incorporated projects, the proposed study employed the MEPx framework to develop mathematical equations that connect the input variables and the outcome of interest.

The cost modeling dataset captured quantitative data as well as contextual information that generally affects scaffold-related expenditure. The core variables were solved in matrix form, where X0 = UR, X1 = Q, X2 = UH, X3 = WI, X4 = EQ, and X5 = LF. The AC expresses the real cost used as the dependent variable, which was adjusted to the direct and indirect hypothetical factors that influence it, as shown in Equation 1.

$$AC = ((Q \times UH) \times (WI)) - (WI) + (((Sin(UH)) \times (Q \times UH)) + ((Q \times UH) \times (WI)) + (Q \times UR) + (WI) \times (\sqrt{(Q \times UR)}) - WI \quad (1)$$

4.4. Analytical Framework for Time Prediction

This research was also aimed at predicting scaffolding time, as time is one of the most severe parameters, having a great impact on the performance of delivering the projects. This prediction was conceptualized in terms of the dependent variable AH, as shown in Equation 2, defined as a measure of the realistic working hours needed to perform scaffolding actions that would be under AWP implementation. The explanatory variables, just as the cost model, have been taken as datasets of the projects and further written in matrix form, which deals with consistency. In this instance, X0 will be given the meaning UR, X1 will be known as Q, X2 is the UH, X3 is WI, X4 is the EQ, and X5 represents LF.

The variables chosen were so due to their impact on the productivity of scaffolding erection and dismantling in the oil and gas projects.

$$AH = (cos[\,(\frac{UR}{Q}) + cos(UH)] \times [(\frac{UR}{Q}) + cos(UH)] + cos(UH) - sin(UR)) \times ([(\frac{UR}{Q}) + cos(UH)] \times [(\frac{UR}{Q}) + cos(UH)]) - ((UR) - [(\frac{UR}{Q}) + cos(UH)] \times [(\frac{UR}{Q}) + cos(UH)]) \times (cos(UH)) + LF \quad (2)$$

Industry professionals (those having experience in the field of 8-15 years) were consulted on the preliminary predictive model, AWP-based workflow, and the choice of scaffold management parameters. Their response provided feedback on the refinement of model input variables, category of constraints, and sequence logic. Even though project-level data remains confidential, the predictive results of the model (cost, duration, quantity of materials, and cycle efficiency) were compared with the aggregated historical trends in the past scaffolding projects. This was to guarantee that the forecasted patterns matched the actual operational behavior in real life without revealing sensitive figures.

Several what-if simulations were performed with different scaffold geometries, types of material used, erection-dismantling cycles, and AWP readiness level. The predictive model was found to be internally stable by the consistency of repeated situations. Outputs of the model were analyzed with the logic of AWP that is set to achieve, especially alignment with constraint management, PoC, and better sequencing. The model's theoretical validity was reflected in the predictive trends compared to documented AWP benefits (reduced rework, smoother flow, and improved workface readiness), supporting the theoretical aspects of the model.

4.5. *Predictive Analytics for Cost*

Standard training, validation, and testing split was used to assess the predictive power of the MEPx-evolved cost equation. Figure 3 shows the comparison of the predicted outputs (blue) with the target values (red), at the three phases. The cost projections presented in the training stage (n = 3,800 samples) showed a high accuracy rate in their outputs compared to the modeled values, an indicator that the model was able to measure nonlinear couplings among the sources of influence, including UR, Q, UH, WI, EQ, and LF.

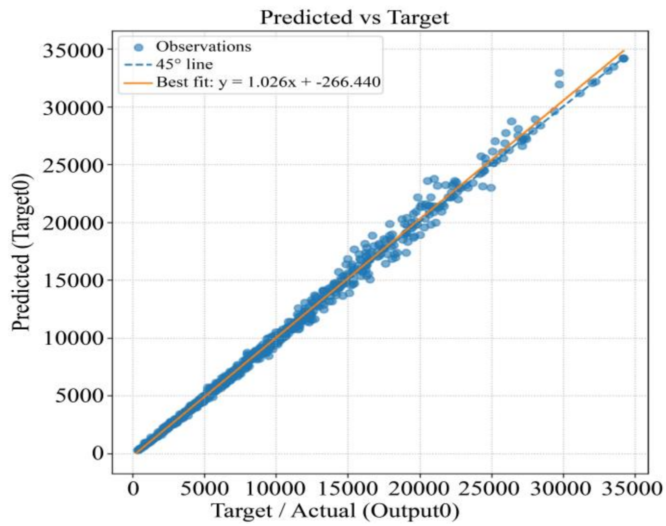

Fig. 2 Comparison of cost model-predicted and actual target values

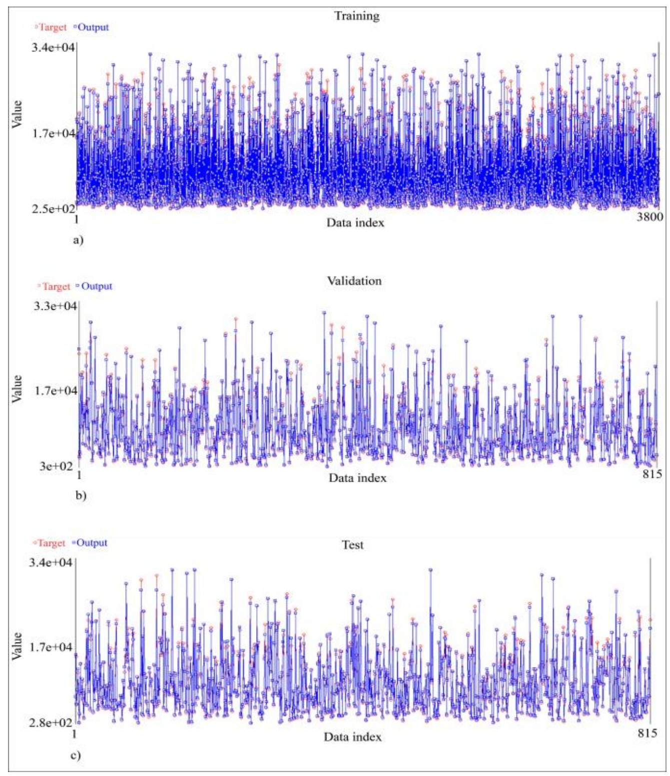

Fig. 3 Predicted vs Actual cost for training, validation, and test in MEPx

During the validation stage (n = 815 samples), the model continued to have high predictive stability with outputs being consistent with the target distribution under different magnitudes of costs. This confirmed that the evolved cost equation was already generalized enough to work well on previously unknown data; thus, it did not overfit. The results of the testing stage (n = 815 samples) proved that the predictive equation showed good predictability; once more, there are few and insignificant differences between estimated and intended cost values. Its repeatability and stability in cost distribution among the various phases confirmed the robustness and increased its credibility in applying the model in the real world. Generally, the MEPx-based modeling paradigm yielded good predictive fits on training databases, on validation databases, and on testing databases. The pattern of correlation between estimated and actual cost values reveals the utility of the developed cost equation as a tool for decision-making on scaffold management. The model offers a more accurate and realistic projection of the AC of projects in the oil and gas construction.

4.6. Predictive Analytics for Time

Through a symbolic regression procedure of the MEPx, a predictive equation of AH in the form that integrates some of the influencing parameters has been established, including UR, Q, UH, WI, EQ, and LF. Figure 4 shows the predictions versus target values in the training (n = 3,800), validation (n = 815), and testing (n = 815) data sets. During training, the model showed good learning ability, predicted outputs (blue) closely moved in line with the target values (red), even in the presence of nonlinear fluctuations in the dataset. This means that the equation developed worked in terms of reflecting the patterns behind the time adjustments as affected by both external and operational parameters.

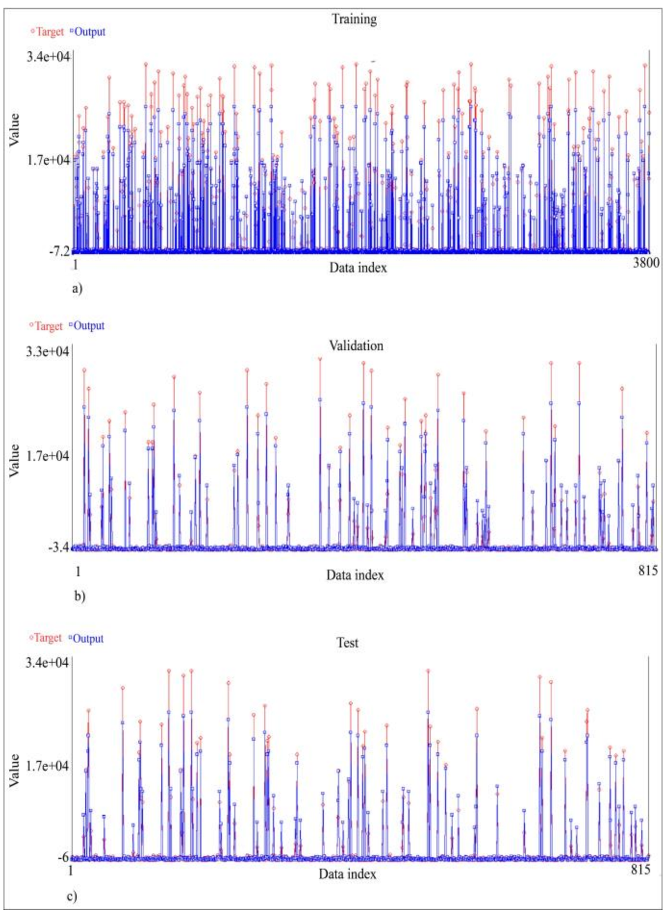

Fig. 4 Predicted vs Actual time for training, validation, and test in MEPx

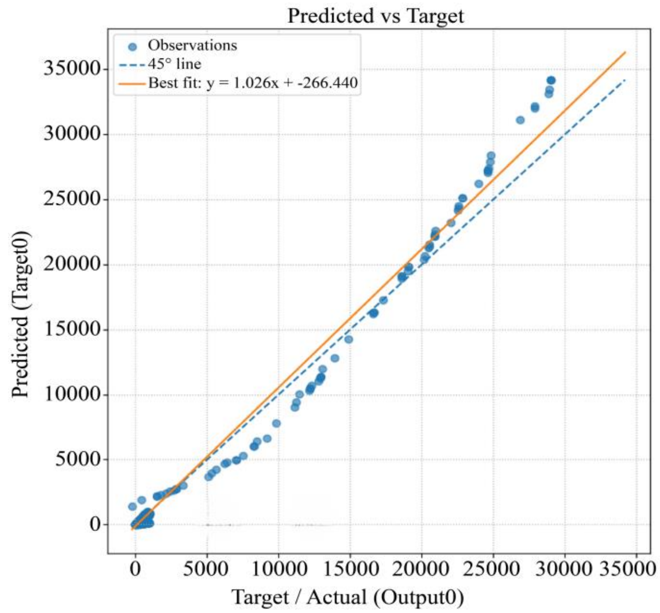

Fig. 5 Comparison of time model-predicted and actual target values

At the stage of validation, the formula demonstrated sound generalization, and the data on predictions closely corresponded with target values at the multiple levels of work hours. The test outcome also helped to establish the strength of the equation derived since the results remained high in terms of accuracy in the prediction of the targets. The very small divergence values justify the stability of the model applied in new circumstances, which suggests its usability in the practical forecasts of work-hour changes in scaffold management projects.

The best-fit regression, as shown in Figure 2, indicates minimal bias, showing that the model slightly overestimates at higher cost ranges but remains highly consistent overall. This strong linear relationship confirms the robustness and reliability of the predictive model across the full cost spectrum. The regression fit suggests a slight upward bias, indicating mild overestimation at higher cost levels. Overall, the tight clustering of points demonstrates good predictive accuracy and reliable model performance.

The time-prediction model shows a much tighter clustering of points around the 45° line, indicating higher accuracy and lower variance compared to the cost-prediction model, as shown in Figure 5. In contrast, the cost-prediction plot displays greater scatter and deviations from the identity line, especially at higher values, revealing more fluctuations and model uncertainty.

In sum, the time equation developed using MEPx demonstrated high predictive unity in all three stages, which justified its applicability as a decision-supporting instrument in the assurance of more accurate and reliable design of scaffolding-related operations in the oil and gas industry.

Table 2. Performance evaluation of the predictive cost and time models developed using the Multi Expression Programming x (MEPx)

Error Analysis				
Output Parameters	**Phase**	**MAE**	**RMSE**	**R^2**
Cost	Training	7.67	9.65	0.72
	Testing	5.68	8.28	0.79
	Validation	4.21	5.88	0.77
	Average	5.85	7.93	0.76
Time	Training	0.79	1.87	0.91
	Testing	0.49	0.72	0.89
	Validation	0.21	0.48	0.80
	Average	0.49	1.02	0.86

4.7. Statistical Validation of Cost and Time Models

Error analysis of the developed MEPx-based predictive results for cost and time shows that the model has the capability of recording underlying dynamics of a project within acceptable limits, as shown in Table 2. In the case of the cost model, the data set performance, including training, testing, and validation stages, showed reasonably good predictive stability with values of the coefficient of determination (R^2) between 0.72 and 0.79. The Mean Absolute Error (MAE) of 5.85 and the Root Mean Square error (RMSE) of 7.93 indicates that sufficient generalizations of the unseen data could be made, and there were small differences between the actual and the predicted values of the cost. Such a degree of precision can be attributed to the nature of cost estimation, as the processes may involve many variables, including the rates of labor, changes in materials, and site conditions, which may have diverse impacts. The acquired predictive consistency, however, highlights the usefulness of the cost equation as a tool in helping project planners to make more accurate financial estimates of the project.

The outcomes of the time equation were also more encouraging, with even greater similarity between the predicted and intended values, as shown in Table 2. Predictive accuracy of the model was high, with an R^2 range of 0.80 to 0.91 and an overall average of 0.86 in the different phases. The corresponding error levels were highly attractive, with the average of MAE 0.49 and RMSE 1.02, indicating the soundness of the model concerning predictions of labor hours and working hours in the scaffolding. This kind of performance indicates the ability of the symbolic regression to represent nonlinear relationships between the input parameters affecting time, including the productivity of the crew, weather delays, and the task order. Within the framework of scaffold management optimization, the small error margins and high R^2 of the time model affirm the model as a decision-support tool providing accuracy to schedule planning and resource allocation levels throughout oil and gas projects.

In comparing the two models, it is clear that there was better prediction of time when compared with cost prediction. This can be explained by the fact that the relatively direct relations between the task durations and the operational variables can be very high, whereas the cost outcomes can be prone to much broader market uncertainties. However, the intermediate reliability of the cost model (R^2 = 0.76) demonstrates that it can also be a great source of guidance, though it should be applied together with digital project management systems that will make it possible to provide an up-to-date view of the market circumstance. In practical terms, both models contribute to the practical use of the principles of AWP in the scaffolding processes. The models enhance the credibility of planning and facilitate proactive decision-making by providing forecasts of the cost and time. Specifically, the time model will be able to help the project managers to allocate resources more effectively and minimize the schedule risks, whereas the cost model, although at a somewhat lower level of accuracy, can help in financial forecasting and budgeting control. Collectively, they offer a fact-based basis of scaffolding management as it helps to bridge the gap between systematic planning through AWP and predictive analytics through MEP.

Lastly, the more general impact of this study is that symbolic regression methods like MEPx can produce intuitive, closed-form equations, which can be used directly by practitioners. They are more acceptable in industries than black-box models because they add transparency and verifiability. Although the strategy was first applied to scaffolding operations in this case, it can be expanded to other construction support systems, which opens up the possibility of much wider digitization and predictive control of the delivery of oil and other gas projects. The enhanced performance that was gained in this paper can be explained by the compound effect of systematic planning by way of Advanced Work Packaging and the explicit and equation-based characterization of the MEPx symbolic-regression engine. In contrast to most of the state-of-the-art machine-learning methods discussed in the literature, including neural networks, ensemble models, and deep-learning networks, MEPx builds explicit mathematical terms that directly reflect the relationship between variables related to scaffolds. This results in a more specific learning of the nonlinear relationships governing scaffolding cost and labour hours.

The majority of the available predictive research is based on black-box methods that need large datasets to be generalized and do not take into account contextual construction variables like weather influence, equipment offline, or employee exhaustion. Conversely, the current research uses these project-specific variables directly in the equations such that the model captures the operational nature that is usually encountered in oil and gas scaffolding setups. Such coverage of domain-relevant variables further enhances the quality of the model in terms of being able to capture variations that traditional models smooth or overlook, thus leading to better predictive power, especially in time estimates, where the model had an R^2 of 0.86 and low error values. Moreover, the data employed in accordance with the current study represent scaffold works that were performed under the AWP conditions, where the work sequencing and preparation are better organized compared to standard projects. Since AWP to some extent diminishes randomness in field execution, the underlying data will have more evident patterns, which the symbolic-regression process will be able to capture more consistently functional relationships. This is why it should be noted that the time model specifically is highly consistent with actual behaviour: the time of scaffolds in AWP settings is predictable and can be converted into equations by MEPx.

Lastly, symbolic regression models are best suited in situations where the aim is to provide easy-to-understand and practical results. Explicit equations that have been developed during this research provide a firsthand glimpse into the influence of every parameter on the cost and time. This interpretability allows the model to extrapolate with smaller datasets, which neural networks or ensemble models do not do due to the risk of overfitting these models. The structured inputs (AWP) plus the operational variables that are relevant and the learning that is based on equations, hence offers a methodological strength over the approaches that have been reported previously, and eventually give rise to the desired predictive performance.

4.8. Validation Procedure and Dataset Limitations

The predictive equations generated through MEPx were validated using a structured and repeatable process to ensure model reliability and generalization. The full dataset, obtained from multiple oil and gas projects, was randomly divided into training (70 %), validation (15 %), and testing (15 %) subsets. During training, the model parameters were optimized through iterative symbolic regression until convergence. The validation subset was then used to fine-tune model complexity and prevent overfitting, while the testing subset served to evaluate predictive accuracy on unseen data. Standard performance indicators, MAE, RMSE, and R^2, were applied to quantify the goodness of fit. In addition, the model was retrained through three randomized runs to verify the consistency of results across different data partitions, confirming the stability of the derived equations. Dataset limitations are acknowledged. First, the dataset is limited to projects that have implemented AWP practices in scaffolding operations; hence, the models may not fully capture conditions from conventional non-AWP environments. Second, while the dataset includes instances, which are confined to oil and gas facilities in a single geographic region, which is Malaysia, this may restrict wider generalization. Third, owing to industrial confidentiality agreements, detailed project identifiers and raw values cannot be published; only aggregated and normalized data were used for modeling. Despite these constraints, the dataset covers a diverse range of project complexities, weather conditions, and work scopes, offering sufficient variability for robust model training. The policies of the projects did not allow the release of raw numerical data. Thus, aggregated or normalized values are only provided. This does not have any impact on the scientific validity of findings, but restricts the level of numerical description of the results.

Table 3. Comparative summary of conventional scaffold management practices and the structured predictive approach developed in this study

Aspect	Conventional Scaffold Management	AWP-Integrated Predictive Approach
Planning Approach	Reactive, based on site requests	Structured planning through work packages
Estimation Method	Deterministic, average-based assumptions	Data-driven equations for cost and time
Cost Prediction Accuracy	Low to moderate; high variability	Demonstrated accuracy with strong model performance
Time Prediction Accuracy	Unreliable due to unknown delays	High accuracy and stable predictions
Consideration of External Factors	Rarely considered	Includes weather, fatigue, equipment downtime, and work intensity
Rework & Idle Time	High due to poor alignment	Reduced through early alignment with structured planning
Data Transparency	Lacks interpretability	Produces interpretable, equation-based predictions
Decision Support Capability	Limited	Enables proactive forecasting for better planning and coordination

The data is a result of a particular project in the industrial setting. Although this is typical of large infrastructure resources and oil-and-gas facilities, the findings might not entirely be representative of smaller resources or non-industrial environments. Table 3 clearly shows the unique predictive approach, which is a breakthrough in the construction management area. Overall, the validation results demonstrate that the MEPx-based models maintain strong predictive accuracy across all phases, with negligible overfitting and consistent error margins. The transparent validation framework and acknowledgment of dataset limitations strengthen the credibility and scientific integrity of the study.

5. Conclusion

The study illustrated that the merger of AWP and equation-based predictive modeling can be implemented to reinforce scaffold management in oil and gas projects. The mathematical equations constructed by the research as a result of the symbolic regression tool provided by MEPx could predict adjusted cost and adjusted labour hours on the basis of key project variables, including unit rate, quantity, unit hours, weather impact, equipment downtime, and labour fatigue. These equations were validated using training, testing, and validation subsets, and the cost model showed moderate accuracy, while the time model was more reliable with fewer error values. Such outcomes capture the possibility of predictive analytics to capture the nonlinear behaviour that is usually found in scaffold operations.

The factor that makes the predictions consistent with the realistic aspects of industries is the fact that the model takes into consideration the actual conditions of the project, including delays due to weather, equipment downtime, and worker fatigue. Consequently, the planners will be able to anticipate resource needs more appropriately, assess potential work schemes, and enhance coordination of field readiness and planned activities. Practically, the created equations can be used as a decision-support tool in estimating the future scaffold requirements more accurately and assist the project managers in that process. The advantage of the interpretability of the mathematical expressions produced by MEPx can provide a benefit over black-box methods since the impact of each variable is clear and can be traced. This renders the model more appropriate in planning talks, scheduling audits, and cost-management procedures in which traceability is a prerequisite. The adjusted cost and adjusted hours predictive outputs can also serve to help the project teams modify the sequence of work, reallocate labour, and identify the most appropriate time to erect and dismantle the scaffold, depending on structured AWP practices.

Despite the high performance of the models, there are other aspects of development as pointed out by the study. The next study might involve further increasing the dataset by incorporating additional AWP-based scaffoldings into it in order to stabilize the predictive equations further. Service variables like work-packaged complexity or finer weather groupings can be additional variables that can be used to reflect more project-specific deviations. Besides, the fact that the developed equations were tested on different types of facilities, or how well they perform compared to traditional scaffolding settings, which is not based on AWP, would give further information about their transferability. The cost model can also be improved by adding market-driven fluctuations, which may increase its predictive power. The steps would increase the generalizability of the approach and lead to the further advancement of predictive scaffold-management strategies in AWP-congruous project settings.

5.1. Recommendations

The research has determined that predictive cost and time models can be utilized effectively as scaffold management instruments in the oil and gas sector to increase the predictability of future costs and aid in making better decisions.

- The value would be further enhanced by the incorporation of MEPx-derived equations into the digital project management systems, where real-time predictive feedback is provided in the project execution process.
- Additional future studies with bigger and more varied data based on diverse project settings should be conducted to enhance the strength, accuracy, and applicability of the models.
- Results showed that the time prediction model performed better than the cost model, but the cost model could be improved with the incorporation of other variables of price fluctuations in materials and uncertainty in the supply chain.
- Although this paper concentrated on scaffolding management, the suggested solution can, in theory, be applied to other construction support systems, providing a gateway to increased digitization in oil and gas project delivery.

5.2. Implications

The research has far-reaching consequences for research and practice in the oil and gas construction industry. Alongside the introduction of AWP predictive modeling through MEP, the research provides a highly organized and evidence-based approach to the management of scaffolds, which is conventionally paired with inefficiencies and uncertainties. The predictive models prepared offer more tested cost and time estimates to the decision-makers and lessen the potential of the overruns, enabling the decision-makers to plan, budget, and allocate resources in a superior manner. Of special interest, the fact that the time prediction model is stronger is indicative of the opportunities of symbolic regression to enhance schedule predictability, which is often a major complication in scaffolding operations. Moreover, the study applies to the general discourse about digital transformation in the construction industry since it demonstrates the possibility of utilizing a symbolic regression to generate interpretable and closed-form equations to which practitioners may be more inclined to agree than black-box models. This avenue boosts scaffold management, in addition to providing a platform where AWP and predictive analytics can be expanded to other construction support systems and speed industry-wide adoption of data-driven project management practices.

5.3. Limitations of the Study

This study is not a perfect means despite its contributions. To start with, the dataset used, although extensive, was restricted to projects where AWP had already been deployed, and this could limit the applicability of the models in projects with other management practices or less organized planning scenarios. Second, predictive models showed great performance, specifically with respect to time estimates, but there was average performance with the cost prediction model, implying that other variables, including market-driven price changes, supply chain disruptions, and inflation pressures, must be added to achieve more robust financial forecasts.

Furthermore, the research was mainly centered on scaffolding operations in the oil and gas industry, and whereas the methodology could be generalized, more empirical studies will be needed in other construction settings in order to ascertain its transferability. Another weakness is the intrinsic weakness of the symbolic regression method as a tool in itself, which, despite being interpretable, does not necessarily identify very complex, non-linear relationships as well as some deep learning methods might. Lastly, the analysis was based on past project figures, which might not have entirely captured real-time dynamic aspects like unexpected changes in weather, manpower, or on-site occupational accidents. Such limitations indicate that research in the future should involve the expansion of datasets, the integration of real-time monitoring, and the experimentation of hybrid models involving the combination of symbolic regression with other ML tools to increase predictive power.

Ethical Considerations

This research was conducted in accordance with ethical requirements related to data confidentiality, responsible use of industrial information, and fair involvement of project stakeholders.

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