

Data-driven artificial neural network formulated multi-factored expression for predicting construction duration in government projects

Ahmad Kueh, Sim Nee Ting and Yee Yong Lee
*Department of Civil Engineering, Faculty of Engineering,
Universiti Malaysia Sarawak, Kota Samarahan, Malaysia and
Faculty of Engineering, UNIMAS Water Centre (UWC),
Universiti Malaysia Sarawak, Kota Samarahan, Malaysia, and*
Chee Khoon Ng
*Department of Civil Engineering, Faculty of Engineering,
Universiti Malaysia Sarawak, Kota Samarahan, Malaysia*

Abstract

Purpose – Project delays are a considerable challenge in the construction industry, often leading to financial disputes and complications. Traditional methods for estimating construction project duration are error-prone and frequently underpredict the total period due to hastily formulated activity timelines. This study aims to develop a reliable data-driven artificial neural network (ANN) approach and an accurate predictive model for estimating construction durations in government projects.

Design/methodology/approach – This study analyzes 111 government-approved projects to identify key variables such as project locality, project type, project cost, inclement weather, internal issues, external obstructions, unforeseen events and relativity. These variables are statistically analyzed and then trained, tested and validated using an ANN technique. The ANN model is developed using MATLAB, with a training:test:validation ratio of 70:15:15, from which the first-ever practically convenient explicit equation has been formulated to help construction practitioners make a quick and reliable prediction of project duration. ANOVA and Shapley impact analyses have been performed to showcase the significance of the proposed factors including their ranking of importance.

Findings – The study identifies key factors impacting project timelines and utilizes the ANN model to create a multi-variable straightforward yet precise mathematical formula for duration estimation. The model demonstrates a high degree of agreement between predicted and actual project timelines, with correlation coefficients of 0.99396 for training, 0.95618 for validation, 0.98057 for testing and 0.98225 overall. The prediction coefficient of determination is 0.929 and the mean absolute percentage error is 15.66%, indicating the model's accuracy. All factors or their interactions display high significance ($p < 0.05$) towards project duration with relativity, project cost and locality ranked as the top three influencing components.

Originality/value – Differing from standard black-box neural network models, our ANN approach produces a practically convenient single-line equation that can be applied with a basic hand calculator, making it accessible to engineers and project managers. This research highlights the critical importance of evidence-based methods in enhancing construction project management, ensuring that project estimates are dependable and easily applicable in practical situations.

Keywords Artificial neural network, Construction, Duration estimation, Computational simulation, Mathematical expression

Paper type Research paper

1. Introduction

Project delays continue to pose a significant challenge in the construction industry, leading to substantial financial disputes and implications (Abbasi *et al.*, 2020; Danial and Misnan, 2022). Traditional project management methods often struggle to accurately predict project duration,

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thereby complicating matters and increasing uncertainties. Furthermore, current methods for estimating construction duration heavily rely on experiential insights and qualitative judgment, thus potentially failing to fully grasp the intricate dynamics of modern construction projects (Venkat Raman *et al.*, 2019; Vinayagam *et al.*, 2021). The Global Construction Disputes Report (Arcadis, 2021) highlights the severity of this issue, revealing that construction quarrels worldwide amount to an average of approximately \$41m, primarily attributed to delays, change orders and misinterpretations of contracts. Factors that contribute to delays include inadequate project planning, ineffective site management, environmental conditions, mismanagement of contracts and communication issues with stakeholders (Nguyen *et al.*, 2010; Raykar, 2016; Tariq and Gardezi, 2023; Wang *et al.*, 2018).

Although there exists heightened awareness of the challenges of accurately estimating project duration, obtaining trustworthy forecasts continues to be a major obstacle. A significant aspect is the reliance on decisions made from experience. While seasoned professionals offer valuable insights drawn from their wealth of experience, their perspectives can be influenced by past strategies that may not suit different contexts. The assumption that circumstances will remain constant is the foundation of most traditional methods. Yet, those who have experience on a construction site understand that this is rarely the case. Schedules can be easily disrupted by unforeseen issues, including delays in material delivery, last-minute design changes or bad weather. As rigid, traditional models struggle to incorporate unforeseen disruptions, delays continue to jeopardize project execution. Moreover, cognitive biases, such as optimism bias or the tendency to underestimate risks, can skew early-stage planning, resulting in unrealistic timelines. Without a systematic framework to identify and address these biases, project schedules are often grounded on flawed assumptions, leading to large deviations from planned timelines as the project progresses.

While some studies have applied machine learning (ML) approaches in predicting different aspects of construction projects, most focus on black-box models, which lack interpretability and accessibility for practitioners. These models often require sophisticated software and technical expertise (Al-Fasih *et al.*, 2017, 2018, 2020; Kasiman *et al.*, 2022; Kueh *et al.*, 2022, 2023a, b; Kueh and Kho, 2019; Kueh and Siaw, 2021; Mokhtari *et al.*, 2013; Mu *et al.*, 2021a, b; Wang *et al.*, 2022; Yasin *et al.*, 2023), limiting their practical utility in everyday project management tasks. In the current methodologies, simplified breakdowns of activities or heuristic approaches have been favored, which can lead to a substantial underestimation of the time required for project completion due to the absence of adequate consideration of multiple influencing factors (Flyvbjerg *et al.*, 2014; Gransberg and Windel, 2008). Despite the existence of studies in optimizing the scheduling processes within project management, their relevance and applicability to the prediction of project durations continue to be significantly constrained, thus limiting their overall effectiveness in a practical context. Most models prioritize computational sophistication over usability, which can limit their adoption in localized contexts like government-approved projects with specific influencing factors. These limitations fail to completely represent the intricate and complex interplay of factors that include project location, project type, project cost and unforeseen events, all of which can have a profound impact on construction timelines and their management (Agrawal *et al.*, 2024). Understanding various drivers behind project duration estimation is imperative for enhancing the planning processes and the successful delivery of construction projects on time. Our study bridges these gaps by introducing an ANN-based framework specifically tailored to local construction projects. Unlike existing models, our approach produces an interpretable, explicit multi-variable equation that integrates the main critical factors, enabling quick, practical application by engineers without requiring advanced computational tools.

Therefore, this study proposes a suitably designed data-driven prediction model that incorporates an explicit mathematical expression (Drahman *et al.*, 2024; Kueh, 2012, 2013, 2014, 2025; Rasin *et al.*, 2016; Kueh, 2023b; Kueh *et al.*, 2020) that adopts ANN to advance the field of project duration estimation. Through an extensive analysis of a total of 111 government-approved projects, our research not only consolidates the identified influencing

variables but also plays a crucial role in uncovering the ranking of importance among them — project type, locality, cost, weather conditions, internal challenges, external obstructions, unforeseen events and a relativity factor—ensuring a holistic representation of project complexities that have not been sufficiently addressed or captured by existing methodologies (Agrawal *et al.*, 2024; Jie and Wei, 2022). To address this matter, we propose the use of a practically useful equation derived from the data-driven ANN to enhance the accuracy and reliability of estimating project durations. The ANN-based approach utilizes the identified variables to comprehensively train, test, validate and then formulate a single-line predictive model, thereby permitting engineers and project managers to efficiently estimate project durations utilizing a simple hand calculator without the need for complex software and time-consuming computational efforts (Kueh, 2023a). Such a data-driven, formulated and statistically validated, easy-to-apply multi-factor equation is new and unavailable from existing scholarly works. Our method is devised to promote the easy-to-use, accuracy and reliability of project duration estimation, thereby solving inaccuracies, delays and budget overruns that affect the construction industry in the present practice.

2. Relevant scholarly works

In tackling the pressing issue of project delays in construction, it is crucial to leverage insights from existing research while recognizing their contributions and constraints. Akinosho *et al.* (2020) offered valuable insights into the utilization of ML in construction projects, emphasizing its ability to enhance project delivery, reduce cost overruns and improve safety and sustainability. Similarly, Sanni-Anibire *et al.* (2021) employed various ML techniques to mitigate delays in building projects, including k-nearest neighbors, support vector machines and ANN but relied heavily on black-box models that are challenging for practitioners to interpret and apply directly in the field. Uddin *et al.* (2023) integrated ML, network science and project management to assess project performance, gathering data through an online survey and utilizing five ML methods to explore the interactions among project attributes and networks, as well as cost, time and quality, without addressing the specific factors influencing project delays. Tayefeh Hashemi *et al.* (2020) categorized ML techniques for estimating construction project costs into statistical, analog and analytical models, elucidating their characteristics and applications. Adamu and Aromolaran (2018) examined specific ML heuristics for solving multi-mode resource-constrained project scheduling problems, where the output of the ML heuristic proved to be a valuable starting point for metaheuristic procedures. Aytug *et al.* (1994) carried out a comprehensive examination of ML approaches in project scheduling, emphasizing the significance of integrating AI-based techniques in intricate scheduling issues. The cost index and time index for 20 finished Private Property Venture Tasks were predicted using multiple linear regression (MLR) and ANN from the Directorate of Lodging's data. ANN outperformed MLR in terms of accuracy and correlation coefficients. The accuracy of MLR was 78.48% and 66.6%, respectively, whereas ANN achieved 90.31% for the Time Index model and 90.21% for the Cost Index model (Aldhamad *et al.*, 2024). ANN outperformed the American Concrete Institute technique in forecasting the time-dependent deflection of concrete beams, with a variability of -30 around the mean (Al-Zwainy *et al.*, 2018a, b). ANN models were used to predict the residual strength of self-compacting concrete (SCC) in the presence of temperature change employing the Garson Algorithm for sensitivity analysis and Neuframe v.4 software for modeling and estimating the cost of sustainable building projects. The SCC model achieved an R^2 of 96.73% and a mean absolute percentage error (MAPE) of 12.82%, while the cost estimation model achieved 87% accuracy and a strong R coefficient of 93.33% (Al-Somaydai *et al.*, 2024; Al-Zwainy *et al.*, 2021). Multifactor linear regression technique (MLRT) and support vector machine (SVM) were applied to predict earned value (EAC) and time/cost indices in construction projects. Five key factors in predictions are recognized: Actual cost (AC), earned value (EV), planned value (PV), budget at completion (BAC) and duration. Additionally, a lack of earned value

application in Iraqi bridge projects was noted. MLRT achieved a correlation coefficient of 93.91% and an average model accuracy of 93.86%, while SVM effectively predicted indices with cost ranging from 0.12 to 17.14 and time varying from 35 to 309 days (Al-Zwainy *et al.*, 2018a, b; Jaber *et al.*, 2019). In terms of bridge projects, another study employing ANN models accurately predicted schedule performance index (SPI), cost performance index (CPI) and cost-schedule index, showing strong correlations with actual data, with average accuracies of 89.91%, 69.83% and 83.79%, respectively (Al-Zwainy *et al.*, 2024). ML regression techniques and ANN models were used to forecast EAC indices. The ANN models showed high accuracy and reliability with correlation coefficients for SPI (85.5), CPI (89.2) and To Complete Cost Performance Indicator (86.3) and R^2 values of 73.2, 79.6 and 74.4, respectively (Aidan *et al.*, 2020; Jaber *et al.*, 2020; Jasim *et al.*, 2020). When theoretical surveys and ANN models were used to predict the CPI in tunnel projects, the results showed an accuracy assessment (AA) of 90.37% and a MAPE of 9.6%. The report emphasizes the need for improved data recording in the construction industry (Hammoody *et al.*, 2022). In another investigation, irrigation and drainage construction project indices were forecasted using the ANN framework's design, modeling and validation. To assess the implications of the variables, sensitivity analysis was carried out on numerous historical data sets — training, testing and validation. In many applications, the ANN models showcased exceptional accuracy and reliability, with installation and maintenance models achieving up to 99.17% and 89.34% AA, respectively (Hameed and Al-Zwainy, 2022).

Despite attaining favorable predictive performance, existing efforts display two key limitations. First, ML models often lack practical accessibility, as they do not offer simplified, explicit equations that practitioners can readily apply. Second, they fail to identify context-specific or site-relevant factors, along with their relative importance in influencing project duration. This study aims to address both gaps.

3. Project data collection

The research method employed here involves a study of multiple cases. This method allows a comprehensive view of the research problem to gather rich and detailed data from multiple sources, thereby developing a holistic and deep understanding of the patterns, themes and underlying relationships and mechanisms that contribute to the problem (Flyvbjerg, 2011).

The studied samples are all governmental contracts related to public infrastructure, obtained from the Sarawak Public Works Department (PWD), Malaysia, documenting a total of 111 completed projects spanning from 2014 to 2019. Specific criteria, such as the project start and finish dates, the original and final construction durations and the existence of contract duration extensions, which indicate delay events and the corresponding periods, were used to choose which projects would serve as case studies. Project correspondences, applications for extensions of time and their results, on-site instructions and meeting minutes were among the supplemental paperwork and project files that provided the data for these case studies.

Conversations were held with the authorized personnel to ensure the suggested influencing variables matched actual project delays. These discussions assisted in determining the main causes of time extensions, which were backed by findings from previous research that showed a clear correlation with delays in the completion of construction projects. These suggested criteria will be further evaluated and proven via ANOVA and ANN modeling. The significance map generated from the ANN analysis will unveil the relative significance of each factor, providing a robust foundation for their inclusion in the predictive framework.

4. Artificial neural network (ANN) method

4.1 Formulated parameters

From the collected data as explained in Section 3, customized checklists were created based on project types (buildings, roadworks/bridges, etc.). Two sections were included in each checklist: Section I collected project details (such as title, tender number, timeline and budget),

whereas Section II dealt with delay factors, each featuring checkboxes and space for comments. After consultations with various stakeholders, numerous factors influencing the duration of projects are first summarized. Its detailed description is not repeated here, as it is readily available in our preliminary work (Ting *et al.*, 2021). Based on the findings when exploring the parameters that influence construction duration and the ability to meet project time expectations, as also gathered from project closing justifications from all parties (contractors, designers and PWD) as well as matching with the literature observations, seven factors can be further classified, namely project type, project locality, project cost, inclement weather, internal issues, external obstructions, as well as unforeseen events as depicted in Figure 1. Additionally, a relativity factor is created. The justification for selecting these factors will be elaborated in the results section, where an in-depth analysis of data collected from PWD will be presented.

4.2 Multi-factored ANN mathematical expression

The MATLAB (2020) toolbox is used to build the proposed ANN model. All simulations are conducted on a computer with an Intel I5-7400 CPU running at 3 GHz and 8 GB of RAM. The computation tasks are organized as follows: training:test:validation = 70:15:15 due to the limited fluctuation noticed in trials.

Figure 2 depicts the ANN framework used for the current work. There are four computation blocks: input, hidden layer, response layer and response (Tang *et al.*, 2022). The model gets a collection of inputs and expresses them vectorially. In the vectorized response block, the anticipated output, in this case, the project duration is produced. It has been verified that a multi-layer network can provide strong global predictability with a minimum of one hidden layer (Hornik *et al.*, 1989; Kueh, 2021). Moreover, various numbers of hidden layers have been tested, resulting in insignificant differences in the outcomes. To simplify the process and save time, the current research employs just one hidden layer. Furthermore, $q = 8$ input terms (project type, project locality, project cost, inclement weather, internal issues, external obstructions, unforeseen events and relativity), $f_{q \times 1}$ and one response output, $CD_{1 \times 1}$, for project duration ANN model is developed. $r = 10$ neurons are preset in the hidden layer, thus, resulting in an input weighted matrix, iw , of $r \times q$ and hidden layer bias matrix, β_1 , of $r \times 1$ dimension. The output layer has an output layer bias matrix and a layer weight matrix after such configuration, indicated, respectively, as $\beta_{2(1 \times 1)}$ and $lw_{1 \times r}$. Furthermore,

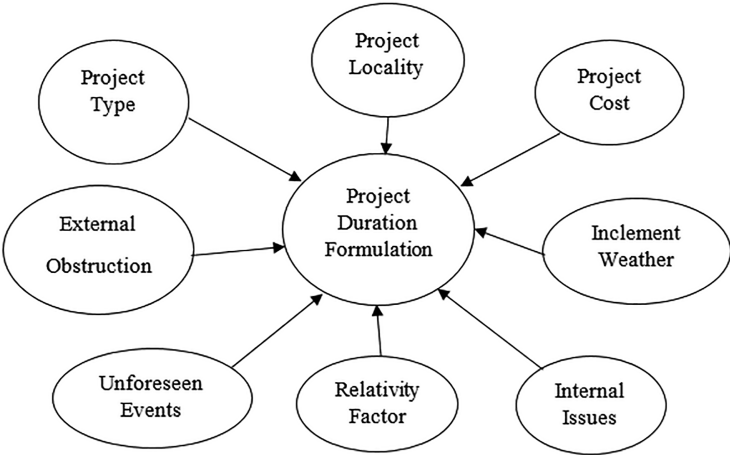


Figure 1. Factors affecting construction project duration. Source: Authors' own work

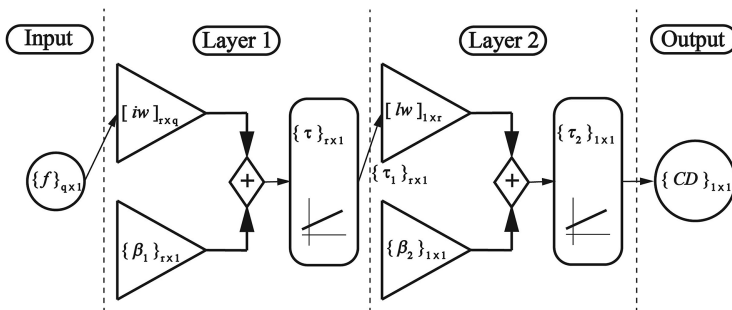


Figure 2. General framework of the employed neural network. Source: Authors' own work

backpropagation (BP) is the training strategy chosen for the multilayered ANN model. The following is an explicit representation of the mathematical connection between input terms and response (Kueh, 2021; Yakub *et al.*, 2022):

$$CD = A_i f_i + B \quad (1)$$

where CD and f_i are the response (project duration) and factor vector, respectively, A_i is the responsiveness weight vector and B is the weight bias. A_i and B take, respectively, the forms below (Kueh, 2021):

$$A_i = \sum_{i=1}^q \frac{\widehat{D}_2}{\widehat{f}} w_i \quad (2)$$

$$B = \frac{\widehat{D}_1 + \widehat{D}_2 G}{2} - \sum_{i=1}^q \left\{ \frac{\widehat{D}_2}{\widehat{f}} w_i f_{i \min} + \frac{\widehat{D}_2}{2} w_i \right\} \quad (3)$$

from which

$$\widehat{D}_{1,2} = D_{\max} \pm D_{\min}, \widehat{f} = f_{i \max} - f_{i \min} \quad (4)$$

where

$$G = lw \beta_1 + \beta_2 \quad (5)$$

while w_i is determined with

$$w_i = lw \times iw \quad (6)$$

iw , lw , β_1 and β_2 matrices are produced by the neural network as weighted results. The transitional matrices are expressed by τ , τ_1 and τ_2 , using the pure linear function of transfer, *purelin*.

$$\tau = iw f + \beta_1 \text{ or } \tau_j = \sum_{j=1}^r \sum_{i=1}^q iw_{ji} f_i + \beta_{1j} \quad (7)$$

$$\tau_1 = \text{purelin}(\tau) = \tau \quad (8)$$

$$\tau_2 = lw\tau_1 + \beta_2 \text{ or } \tau_2 = \sum_{j=1}^r lw_j\tau_{1j} + \beta_2 \tag{9}$$

$$CD = \text{purelin}(\tau_2) = \tau_2 \tag{10}$$

where $q = 8$ and $r = 10$ in the present study. By stating input factors, $f_i = \{f_1, f_2, f_3, \dots, f_8\}^T$, the resultant output, CD as project duration can be calculated. The Levenberg-Marquardt approach is the employed training method.

5. Result and discussion

5.1 Characterization of projects

Figure 3 displays the distribution of project categories by percentage. Projects that are categorized under “other projects” include agriculture sub-station (2 projects), airport (2 projects), earthwork (1 project), electrical system (1 project), gate (1 project), jetty (3 projects), playground (2 projects), RC pontoon (2 projects), riverine terminal (1 project) and seashore works (1 project). Other projects ranked third with 16 projects in total representing 14.4%, followed by the roadwork and bridge project category with 15 projects (13.5%), while 8 projects under the bridge-only category (7.2%) and 7 projects (6.3%) under the waterworks category.

Figure 4 presents the number of projects that failed to meet their time objective in the respective years of 2014–2019. The majority of projects that failed to meet their time objective, that is 34 projects or 30.6%, occurred in the year 2016. This is followed by the projects in the year 2017, with 25 projects representing 25.6% of the total. Projects in 2015 are ranked third with 21 projects that failed to meet the original construction duration (18.9%). This is followed by the year 2018 with 16.2% (18 projects), 2014 with 9.9% (11 projects) and 2019 with 1.8% (2 projects). During the data-collection phase, it was observed that only a limited number of projects in 2019 failed to meet the predetermined time objective. This can be attributed to a majority of the projects were either still in progress or had just commenced construction work at the time of data collection. These statistics offer the significance of widespread delays across the considered projects.

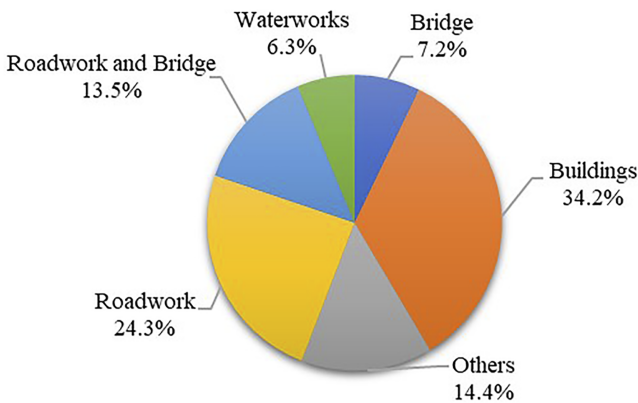


Figure 3. Distribution of project categories by percentage. Source: Authors’ own work

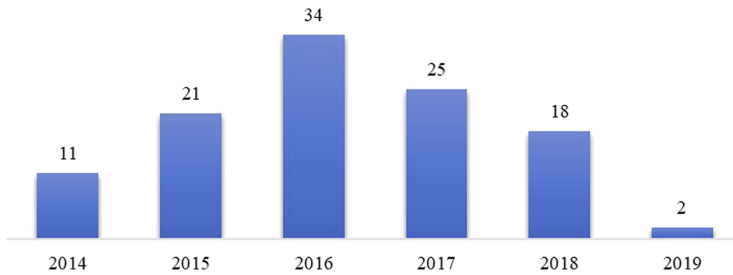


Figure 4. Distribution of projects that fail to meet time objective by year. Source: Authors' own work

5.2 Total extension of time (EoT)

Figure 5 unveils that 41 (36.9%) out of 111 projects have a total EoT of less than 50 days. This suggests that the majority of the total EoT of projects did not exceed 50 days. This was followed by 101–200 days of EoT, with about 26 projects or 23.4% and the third rank is 51–100 days of EoT, with about 20 projects or 18%. Projects that have EoT between 201 and 300 days and more than 300 days share an equal amount of 12 projects (10.8%) each. The longest EoT period observed is 671 days.

The study of qualitative data from structured checklists prompts the formulation of explanations for these projects' EoT. Several variables influence the actual project length. Among them are low water levels, site conditions, client delays in making decisions, bad weather, site ownership, third-party obstructions, air quality, design changes, contractor selection techniques, suspension of work, authority inspection and approval, superintendent officers' (S.O.) instructions, delays caused by electrical authorities, unforeseen reasons, pre-existing utilities, land blockages, flooding and other factors.

5.3 Project profile analysis

In formulating the main factors that contribute to the project duration in **Figure 1**, a project profile analysis has been conducted. A summary of factors affecting the construction duration is presented in **Table 1**. Analyzing these elements facilitates the extraction of key factors in the ANN model for formulating the mathematical expression used in predicting project duration. Through observations, survey insights and alignment with relevant literature as described in **Sections 3** and **4**, we identified and categorized those presented in **Figure 1** as the primary

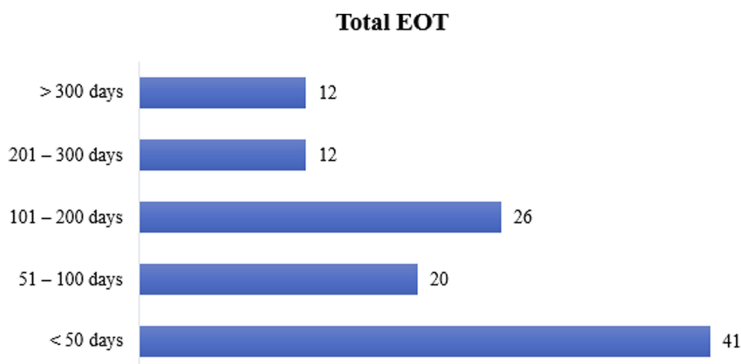


Figure 5. Total EoT quantitative analysis. Source: Authors' own work

Table 1. Project duration affecting factors from the case study

Project duration affecting factor		No. of the affected project
1	Inclement weather	92
2	Site possession	17
3	Contractor-related issues – lack of performance, reworks, repair and misalignment	13
4	Changes and errors in design	8
5	Late site instructions by the engineer	8
6	Client-related issues such as changes in design, schedule and material requirements	4
7	Suspension of work due to disputes	6
8	Regulatory requirements and coordination with other authorities/agencies	14
9	Obstructions by the third party	3
10	Relocation of existing facilities	4
11	Land blocked by other structures/properties	3
12	Unforeseen circumstances such as flooding	3
13	Environmental issues such as haze, air pollution, soil erosion and extremely low/high water level	17
14	Unforeseen site conditions	9
15	Late material delivery	4

Source(s): Authors' own work

influencing factors. Next, we discuss the number of projects linked to these factors, thereby justifying the relevance of these considerations in affecting project duration.

Project type can significantly affect project scope, complexity and construction time. [Hamzah et al. \(2011\)](#) discussed how different project types, such as infrastructure versus residential projects, exhibit varying complexities that directly influence their duration. For instance, infrastructure projects such as roadways, bridges and tunnels are generally more complex and have a larger scope than building projects such as office buildings or residential homes. Based on the data collected as shown in [Figure 6](#), there are 61 (55%) projects with a budget range of RM 1mil – RM 25mil, followed by 24 projects (21.6%) with a budget range of RM 50mil – RM 100mil. Within the range of RM 25mil– RM 50mil, there is a total of 11 projects (9.9%). Falling under the two extremes of more than RM 100 mil and less than RM 1 mil, there are 5 projects (4.5%) and 10 projects (9.0%), respectively.

Combining with data on the original contract duration, a similar pattern is observed in [Figure 7](#). When project cost is higher, a longer original contract duration is observed. Based on the data collected, the study finds that projects with a budget of less than 1 million to 25 million typically have a construction duration ranging from less than 12–24 months. In contrast, projects with a budget exceeding 25 million to over 100 million have a construction duration of 25–36 months, with 2 even exceeding 36 months.

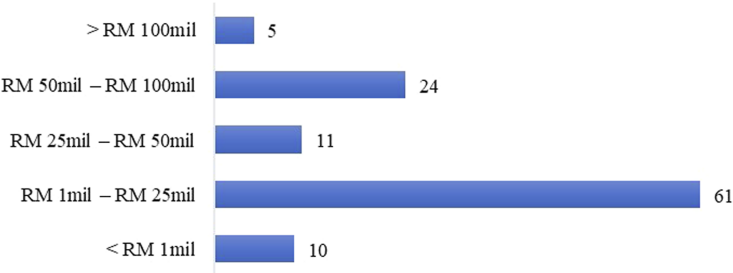


Figure 6. Distribution of projects by cost group. Source: Authors' own work

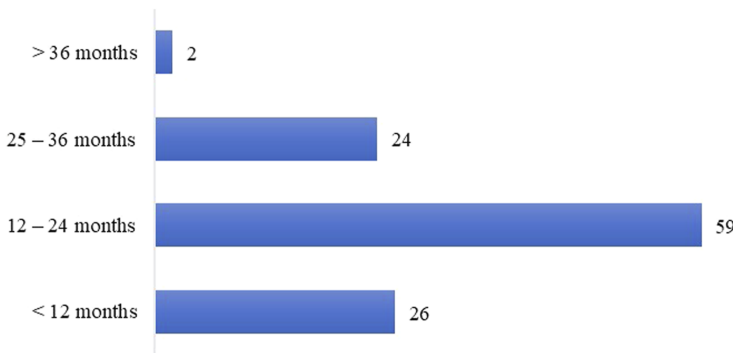


Figure 7. Breakdown of projects according to total contract duration. Source: Authors' own work

In light of the relationship between project cost and the original contract duration, it can be inferred that project scope and complexity are related to project cost. Therefore, it is reasonable to consider project cost as a factor to be taken into account in determining the project contract duration (Doloi *et al.*, 2012).

Another factor under consideration is the project locality. Project locality refers to the geographical location of a construction project and its proximity to necessary resources such as labor, equipment and materials. Project location and distance in this study are concerned with the nearest urban center. There are a total of 41 (37%) projects in this study that are located less than 25 km away from its nearest hub, 19 (17%) projects that are located between 25 and 50 km, 16 (14%) projects that are located between 50 and 75 km, 3 (3%) projects that are located between 75 and 100 km and 5 (5%) that are located more than 100 km away from its nearest hub. A total of 27 (24%) of the projects under study are found to have no access to the site via traditional road and highway networks, making waterways the sole means of access. Based on the data, it can be deduced that the occurrence of high numbers of delay days is widespread in projects that are located over 50 km away from the nearest hub, with the highest number of days of delay occurring in projects with no access. These findings suggest that project locality needs to be carefully considered, as it relates to project distance, or the project's location, thereby corresponding to the change in the project duration. Romzi and Doh (2022) highlighted challenges such as slow decision-making and poor site management in geographically remote areas.

Probing further, inclement weather is found to have the highest occurrence rate in the case study projects, affecting 92 projects (82%) of the 111 projects that meet the predetermined construction duration. These projects span various sectors, including RC pontoon, agriculture sub-station, building, playground, fencing, waterworks, bridge, earthwork, airport, jetty, roadwork and electrical system projects. The impact of this factor ranges from 1% to 160% of deviation from the original construction duration. Only 23 projects out of the 111 projects have a less than 10% deviation from their original construction duration. Singh and Kalidindi (2006) noted that environmental conditions, such as heavy rainfall or extreme temperatures, can significantly disrupt construction schedules.

Internal issues such as site possession, site instructions, S.O.'s directives and suspension of work have a significant impact on the timelines of construction projects. Alaghbari *et al.* (2007) found that factors like poor site management and supervision, along with external challenges such as regulatory approvals, can cause severe project delays. Site possession, which affects 15% of projects, often results in considerable delays, particularly in projects involving roads and bridges. The complexities involved in securing access to construction sites can hinder progress and prolong project timelines substantially. Contractor performance-related issues, accounting for 12% of projects, highlight challenges such as inadequate

resource management and ineffective communication, which can disrupt project processes and lead to inefficiencies. [Vidhyasri and Sivagamasundari \(2018\)](#) suggested that changes in design have a scale of 4 in severity to cause schedule overruns in a project. Altercations in design, impacting 7% of projects, can lead to delays ranging from 5% to 160% of the original timeframe. This is chiefly attributed to modifications in design often demanding changes to construction plans and procedures, resulting in additional time and resources. Delayed site instructions contribute to setbacks in 8% of projects, with extensions varying from 10% to 180%. Delays caused by late instructions are credited to the time and resources necessary to carry out modifications and adjust project schedules accordingly. Client-initiated design changes result in delays of 16%–32% in 4% of projects. These delays arise from the necessity to revise plans and acquire approvals, significantly extending project timelines. Work suspension, impacting 5.5% of projects, results in delays of 21%–106%, often due to conflicts over delayed payments and work quality. The estimated project cost of the projects influenced by late authority inspection and approval ranges from RM 932.8k to RM 133.3mil. Suspension of work is not mentioned as a factor affecting the overall project duration. However, data from PWD shows that five projects were influenced by this issue. Suspension of work is a factor that will be taken into account when awarding contractors the EoT. The EoT approval form will be awarded for reasons such as occurrences of stoppage under clause 50 of PWD 203A. These results emphasize the crucial requirement for efficient management and communication to address internal challenges and ensure timely project finalization, thus emphasizing the significance of proactive strategies to mitigate issues promptly and prevent disruptions to project schedules.

External obstructions, such as regulatory requirements, approval processes and coordination with authorities, significantly obstruct the advancement of projects. For example, delays were encountered by 14 projects, accounting for 13% of the total, due to slow responses from local authorities in issuing essential approvals and licenses, resulting in deviations in project duration ranging from 20 days to almost a year, equating to 16%–160% of the original project timeline. Also, issues such as uncertainty regarding the status of existing facilities and the complexities of relocation protocols further added to the delays, with four projects, constituting 4% of the total. These projects experienced setbacks of 20–90 days caused by utility relocation, resulting in deviations from the initial schedule. Moreover, obstruction by third parties, such as local communities or environmental organizations, led to substantial postponements in three projects, varying from 54 to 137 days, reflecting deviations of 21%–93% from the overall project timetable. Additionally, delays inflicted by inspections and approvals by authorities affected six projects, with one project encountering a delay of 352 days, whereas issues related to land access and unauthorized constructions influenced three projects, resulting in deviations of 11%–50% from the original construction timeframe. These bureaucratic inefficiencies and external obstacles emphasize the necessity of comprehensive planning, proactive risk mitigation and efficient communication and cooperation among project teams and regulatory bodies to ensure the successful delivery of projects.

Project durations are also often affected by unforeseen events, which are usually sudden and unexpected ([Romzi and Doh, 2022](#)). Natural disasters or force majeure events are caused by natural phenomena, such as floods, storms, earthquakes and tsunamis. Based on the collected data, it is observed that natural disasters have affected a total of three projects, which represents 3% of the total 111 projects examined. Among these projects, all three are impacted by site flooding, with the highest recorded delay being 28 days. In addition, the effects of such natural disasters often require post-event site clean-up and salvaging works, materials and equipment before construction work can resume, thus adding to the overall delay. Out of the total 111 projects, 17 (15%) are affected by environmental factors including air pollution, soil erosion, haze, drought leading to extremely low water levels and a rise in sea level resulting in extremely high water levels or king tide ([Lee et al., 2021](#); [Tay et al., 2022](#)). The projects involving roads with bridges are found to be the most affected as they are often located near

waterways, making them susceptible to extreme water levels in the river (Zhang *et al.*, 2024). Extreme water levels can cause delays in completing specific tasks that need to be done within a stipulated window of time, transportation of materials, alternative work methods to suit the sudden water level changes and additional protection works to be carried out should the event occur. A total of 10 projects in this study are affected by non-environmental related unforeseen events with 4 projects due to supply chain disruption and transportation issues causing delays in the delivery of materials to the site. Traditional scheduling and monitoring methodologies pose a challenge in achieving supply chain synchronization, leading to prolonged lead times, heightened buffer levels and subsequently, increased expenditure. A total of 12% of the projects are affected by unforeseen events with delays ranging from 3 to 238 days, representing a 1%–93% deviation from the original schedule. All these are grouped under the unforeseen events categorization.

Finally, the introduction of a relativity factor in construction duration formulation aims to address the inherent variability among construction projects stemming from factors like stakeholders, geographical location, project complexity and scope (Flyvbjerg *et al.*, 2004). Acting as a normalization mechanism, the relativity factor adjusts project duration forecasts based on diverse contextual elements. For example, projects led by experienced teams or with efficient management may exhibit shorter durations compared to less experienced counterparts. Similarly, historical data from similar projects can offer valuable insights into potential duration outcomes. By integrating the relativity factor, the model can effectively synthesize all available data and generate more precise forecasts of construction duration by accounting for the specific circumstances and characteristics of each project. This normalization process boosts the reliability and robustness of the model, ensuring that duration predictions are tailored to the unique attributes of individual projects, thereby enhancing overall prediction accuracy.

5.4 Formulated project duration mathematical expression

Having identified the eight chief factors as shown in Figure 1 alongside their rating by reviewing the projection of results for the data presented in Section 5.3, the outcomes obtained from the regression analysis of *CD* through the ANN model are presented in Figure 8, showcasing the outcomes of training, validation, testing and combined fitting. These results have been generated efficiently within merely one second, utilizing the current computational capacity with less than ten iterations. Moreover, the correlation coefficients, *R*, demonstrate a satisfactory performance across all cases, with values of 0.99396, 0.95618, 0.98057 and 0.98225, respectively. Notably, all data effectively converge with the fitted linear curve for each category.

The mathematical expressions derived from weighted and transfer functions through the ANN model simulation by the procedure following Equations (4–10) yield A_i and B as outlined in Equations (1–3). These expressions in explicit form (i.e. containing the considered factors) serve to predict the construction duration (*CD*) as presented further in the text:

$$\begin{aligned} CD = & 69.259f_1 - 26.427f_2 + 4.78 \times 10^{-6}f_3 + 48.273f_4 + 0.737f_5 + 33.448f_6 + 1.141f_7 \\ & + 57.7f_8 + 338.227 \end{aligned} \quad (11)$$

where f_1 = project locality, f_2 = project type, f_3 = project cost, f_4 = inclement weather, f_5 = internal issues, f_6 = external obstructions, f_7 = unforeseen events and f_8 = relativity factor. Equation (11) depends on numeric inputs denoted as f_1 to f_8 , each representing different project factors. These factors will be described and explained in the next section. Containing explicit terms that correspond to the analyzed factors, this formula is new and unavailable in existing literature, thus emphasizing the novelty of this study.

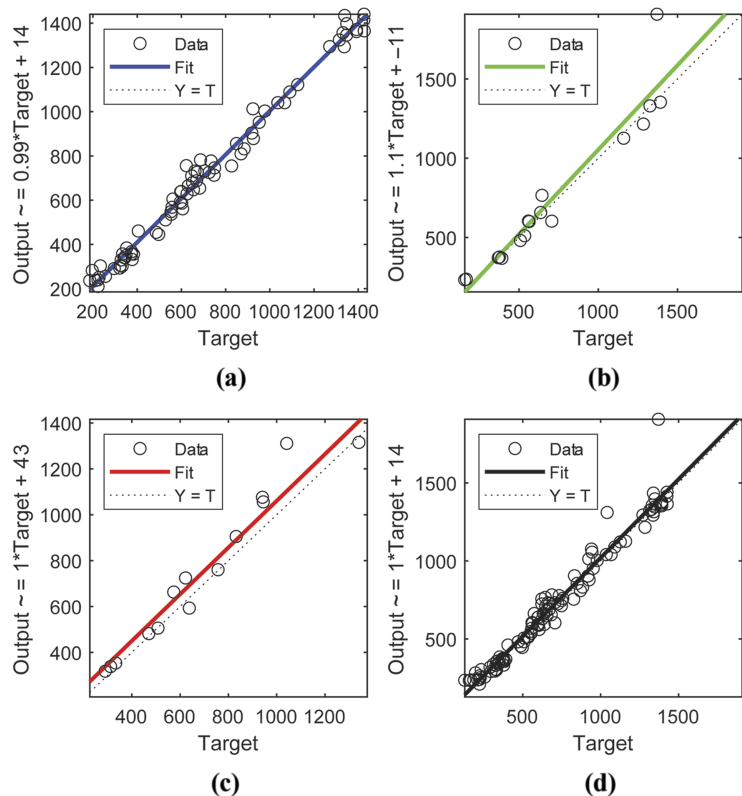


Figure 8. ANN regression for construction duration: (a) Training: $R = 0.99396$ (b) Validation: $R = 0.95618$ (c) Test: $R = 0.98057$ (d) All: $R = 0.98225$. Source: Authors' own work

5.5 Description of factors

It is worthwhile to next characterize the formulated equation, Equation (11). To assign value to the factors influencing construction project duration, a categorization scheme has been devised for each factor. The details of these factors, along with their respective categorizations, are summarized in Table 2. Project's locality (f_1) in the ANN estimation model is defined as the distance of the project's location from the nearest working city (Romzi and Doh, 2022). The project type category (f_2) in the ANN estimation model is defined based on its complexity (Brockmann and Kähkönen, 2012; Hamzah et al., 2011). The cost of the project (f_3) in the ANN estimation model is described as the full amount of RM required to finish the project, including any expenditures made, anticipated to be spent, financial commitments assumed or anticipated to be assumed (Doloi et al., 2012). Inclement weather (f_4) is one of the reasons that causes EoT in projects, which is defined as any occurrence of precipitation or rainfall that is more than 10 mm. Once the rainfall exceeds 10 mm, it is considered a non-workable day, such that construction activities are unable to proceed (Singh and Kalidindi, 2006). The internal issue term (f_5) in the ANN estimation model is a combination of a few relevant reasons for EoT, which include design changes, site possession, contractor selection technique, S.O. instructions, suspension of work and incautious contractors. The external obstruction term (f_6) in the ANN estimation model is a combination of a few related reasons for EoT, which include postponement by authority inspection and approval, electricity authority, existing utilities and land blockade (Alaghbari et al., 2007). The unforeseen events term (f_7) consists of

Table 2. Factors and their associated description of values

Factor	Category
Project locality (f_1)	1 Less than 25 km 2 26–50 km 3 51–75 km 4 76–100 km 5 More than 100 km 6 No access (EoT due to “low water level”)
Project type (f_2)	0 Most complex: Military and high complexity infrastructure, e.g. airports, dams 1 More complex: Marine and coastal structures (pontoon, jetty, riverine terminal and structure along coastline) 2 Complex: Civil works of over RM 30,000, bridgeworks or combination of bridge and civil works and structure with state-of-the-art design 3 Mid complexity: Building of more than one block, housing specialized facilities, high rise and civil works including roadworks, waterworks and drainage works with certain length (6–30 km) and high-rise structure 4 Less complex: Buildings (3 stories and above), more than one block in the compound, and have medium complex facilities. Civil works of less than 5 km 5 Least complex: Single block with 1–3 stories, gates, playground, parks, upgrading and small-scale renovation
Project cost (f_3)	The full amount of RM required to finish the project
Inclement weather (f_4)	0 No effect 1 Potential effects of 1–30 days 2 Potential effects of 31–60 days 3 Potential effects of 61–90 days 4 Potential effects of 91–120 days 5 Potential effects of 121–150 days 6 Potential effects of 151–181 days Higher numbers can be applied if the projects are expected to go more than 24 months
Internal issues (f_5)	0 No effect 1 Low chance of occurrence and effects of 1–30 days 2 Low – mid chance of occurrence and creating effects of 31–60 days 3 Mid chance of occurrence and creating effects of 61–90 days 4 Mid – high chance of occurrence and creating effects of 91–120 days 5 High chance of occurrence and effects of 121–150 days Higher numbers can be applied if the projects are expected to go more than 24 months
External obstruction (f_6)	Analogous to f_5
Unforeseen events (f_7)	Analogous to f_5
Relativity factor (f_8)	0 To turn off the term 1 Difference of 16–20% 2 Difference of 21–25% 3 Difference of 26–30% 4 Difference of 31–35% 5 Difference of 36–40% 6 Difference of more than 40%

Source(s): Authors’ own work

site condition, air quality, flooding events, unforeseen and other reasons (Romzi and Doh, 2022). f_8 is created to allow the user to benchmark against previous projects or similar projects completed or ongoing (Flyvbjerg *et al.*, 2004). Users may key in $f_1 - f_7$ first, after which a benchmark against other projects can be made. If the difference is as per the following %, they can opt to adjust their timeline with the code displayed in the table.

Employing Equation (11) and based on enumerated conditions for the 111 projects studied, Figure 9 showcases the ANN-predicted project durations against those of the gathered data. It

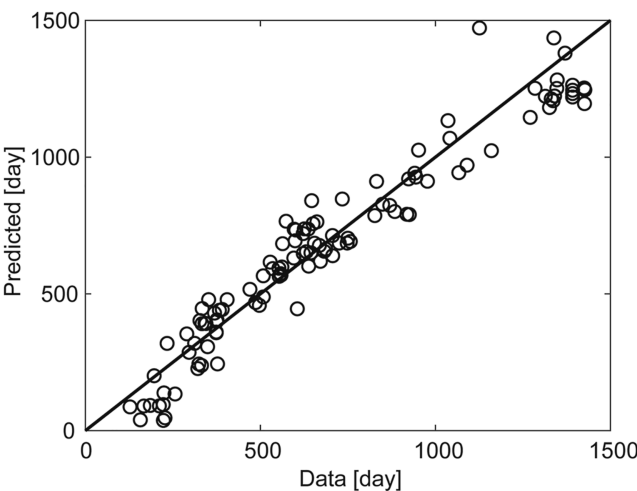


Figure 9. Predicted construction duration vs. input data. Source: Authors’ own work

can be witnessed that the data points are strongly clustered along the accuracy line, signifying the good accuracy of the currently formulated equation.

Furthermore, the evaluation of the agreement between the data and prediction is conducted using a range of statistical metrics, which are outlined in Table 3. The root mean square error (RMSE), normalized root mean square error (NRMSE) and peak signal-to-noise ratio (PSNR) are determined to be acceptably low, which serve as an indication of the accuracy of the ANN model in forecasting project duration. Additionally, a high coefficient of determination (R^2) is indicative of a high degree of precision, as it signifies a strong agreement between the predicted outcomes and the data. A commonly used regression method for ML, known as mean absolute percentage error (MAPE), displays a low percentage of 15.66%, indicating that the model performs well at predicting the data. Consequently, the predictability of Equation (11) is deemed to be robust based on the various statistical evaluations that have been presented.

5.6 Impact analysis

The ANOVA findings corroborate that the selected factors (f_1 – f_8) demonstrate statistical significance and are integral for the prediction of project durations, with the model realizing a substantial R^2 value of 99.07%, thereby confirming its validity (Hasan and Kueh, 2024; Kueh *et al.*, 2023a, b, 2024). Highly influencing factors including project locality (f_1 , $p < 0.000$), project type (f_2 , $p = 0.003$), inclement weather (f_4 , $p < 0.000$), external obstructions (f_6 , $p < 0.000$) and the relativity factor (f_8 , $p < 0.000$) all reveal great significance, with f_8 reflecting

Table 3. Statistical metrics of data vs. ANN prediction

Statistical metric	Value
PSNR	8.156
R^2	0.929
RMSE	99.710
NRMSE	0.077
MAPE	15.66
Source(s): Authors’ own work	

the most substantial influence ($F = 27.40$). Although project cost (f_3) does not display linear significance ($p = 0.530$), its quadratic component (f_3^2 , $p < 0.000$) and its interactions with project locality (f_1f_3 , $p = 0.008$) and project type (f_2f_3 , $p = 0.001$) unveil essential nonlinear and interactive dynamics. Furthermore, internal issues (f_5 , $p < 0.000$) and unforeseen events (f_7 , $p = 0.011$) add substantial value, highlighting the critical role of operational and contingency aspects in project management. These outcomes affirm the necessity of including all identified variables, capturing the intricate relationships that affect project durations and offering a statistically robust and implementable framework for mitigating delays in construction projects (Marini *et al.*, 2024; Kueh *et al.*, 2023a, b).

Figure 10 illustrates the Shapley impact summary plot ranking the importance of all factors in making the prediction. The Shapley plot indicates that the relativity factor (f_8) exerts the most significant influence on the prediction of project duration, as it accounts for variability across projects by utilizing historical benchmarks, thereby enhancing the precision of planning and management. According to studies on financial constraints in high-rise construction projects, larger budgets are often linked to longer durations and broader scopes, therefore project cost (f_3), which is ranked second, has a significant impact on schedules (Alaghbari *et al.*, 2007). Project locality (f_1) comes in third in significance, with logistical challenges like delays in resource accessibility and material delivery (Doloi *et al.*, 2012). Bureaucratic inefficiencies and inadequate stakeholder management are common sources of delays, and both internal and external concerns (f_5 , f_6) receive small scores. This highlights how crucial efficient communication is for teams working on the project (Assaf and Al-Hejji, 2006). Project type (f_2) scores considerably lower by influencing timelines through variations in

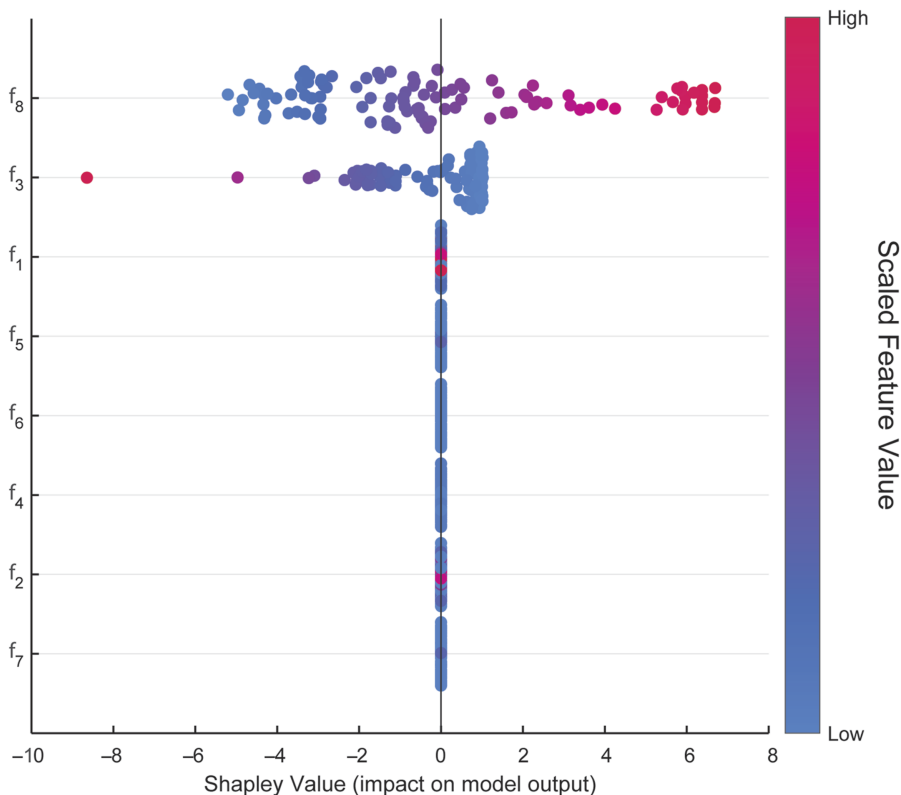


Figure 10. Shapley impact summary plot. Source: Authors' own work

complexity. Infrastructure projects sometimes take longer than residential ones (Sambasivan and Soon, 2007). Environmental variables like weather (f_4) are less significant, but they are nonetheless significant, according to studies on environmental aspects in buildings, particularly in regions that are vulnerable to adverse conditions (Mahamid, 2013). Finally, the least important component is unforeseen events (f_7). These include logistical problems and natural catastrophes, but they are still relevant and highlight the significance of risk management and backup plans in reducing delays (Chan and Kumaraswamy, 1997).

From the impact summary, relativity, project cost and project locality are the main determinants of the governmental project durations, but this ranking also emphasizes the overall effect of these elements. This thorough understanding of factor influence helps practitioners set priorities and improve prediction dependability (Drahman et al., 2018; Omer et al., 2018; Syafiuddin et al., 2019, 2020; Tharima et al., 2019).

6. Conclusions

The present study proposes a comprehensive and holistic approach by estimating an overall construction duration through data-driven formulation that incorporates the main parameters typically responsible for government-authorized construction project timelines. By employing an ANN-based framework trained on data from 111 projects, we identified eight key variables affecting project timelines: project type, locality, cost, weather conditions, internal challenges, external obstacles, unforeseen events and project relativity. The ANOVA analysis justified the importance of these factors ($p < 0.05$). Furthermore, the Shapley impact summary plot identified relativity, project cost and project locality as the top three ranked importance in affecting the government-authorized project duration. The explicitly expressed predictive equation, formulated from the ANN outcomes, offers a useful tool that allows construction professionals to estimate project durations accurately simply by using a hand calculator (Kueh et al., 2020). This equation shows a close agreement with actual existing project durations, as indicated by $R^2 = 0.929$, thereby confirming its effectiveness.

Overall, construction project delays require a transformative approach. By harvesting the abilities of ML-produced predictions, a practical solution can be formulated for enhanced project management that empowers stakeholders to make well-informed decisions. This paper underlines the significance of adopting a scientific and evidence-based perspective in forecasting project timelines, thereby contributing to the ongoing evolution of construction practices and facilitating a more efficient and resilient construction sector.

While our ANN model provides a robust framework for predicting construction project durations, it is important to acknowledge certain limitations. These include the specificity of the data to 111 government-approved projects, potential limitations in generalizability, simplification of complex interactions and the temporal relevance of the data spanning from 2014 to 2019. Future research should consider these factors to enhance the model's applicability and accuracy. By acknowledging these limitations, we aim to provide a balanced view of our study's contributions and areas for future research.

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Corresponding author

Ahmad Kueh can be contacted at: kbhahmad@unimas.my