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A STUDY ASSESSING THE APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR PRELIMINARY ESTIMATION IN SRI LANKAN BUILDING PROJECTS

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ABSTRACT

Preliminary estimations are prepared at the early stages of every construction project to determine the project's financial feasibility. The Artificial Neural Network (ANN) method is a machine learning method that could also be utilised in preliminary estimation for forecasting and predicting the cost with higher accuracy at a very early project stage. A mixed research approach was used for this research. In the first stage, an ANN model with 11 input attributes was developed, with an obtained accuracy of 89.56% in the validation process. In the second stage, the suitability and applicability of the ANN method for preliminary estimation within the Sri Lankan context were investigated through 10 semi-structured interviews. The frequent use of traditional methods for preliminary estimation practice is widespread. Furthermore, the preferred accuracy is more than 80% in the context. The increased accuracy, time efficiency and usability of the ANN model emphasise the suitability of ANN in the construction industry. However, the insufficiency of the databases within the firms, the lack of programming knowledge, and people's reluctance to change were identified as challenges. Conversely, initiating a centralised database system within the context, outsourcing the resource requirement to develop the ANN model, and reducing the knowledge gap in the industry regarding modern methods were identified as remedies. Adding location, price fluctuation, and risk uncertainty as input attributes are suggested improvements and modifications for the ANN model, which is the first model with almost 90% accuracy.

Keywords: *Artificial Neural Network (ANN); Cost Estimation Model; Computer-based Estimation; Preliminary Estimation.*

1. INTRODUCTION

Innovative thinking drove society to a modern era where basic human needs and wants are sophisticated (Moses, 2022). Modern civilisation demands more complex, reliable, and aesthetically pleasing buildings and infrastructure to fulfil basic human needs and wants (Ubayi et al., 2024). Preliminary cost estimates are prepared to counsel on the feasibility and profitability of the project. Past project data is used to prepare preliminary estimates with necessary adjustments (Elhegazy et al., 2022). Several methods are

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followed in the industry for early-stage preliminary estimation of projects, such as the gross floor area, functional unit method, cube method, and story enclosure method. These methods are usually quicker to perform but less accurate in most scenarios due to insufficient and unavailability of project information. Meharie et al. (2019) note that, even though there are methods to increase the reliability of conventional methods, the accuracy highly depends on the indices used. It emphasises the requirement and the importance of advanced cost forecasting and estimation methods suited for the current practice in the construction industry.

According to Abiodun et al. (2018), Elmousalami (2019) and Doroshenko (2020) Artificial Neural Network (ANN) could be used as a deep learning method for preliminary estimation in construction projects to overcome the drawbacks of the conventional estimating methods. Further, Hakami and Hassan (2019) mention that this method showed high effectiveness and accuracy with less than 1% error in the preliminary estimation of Yemen Projects. Supporting that, Elmousalami (2019), Kim et al. (2005), and Mohamed (2021) explain that the ANN-based preliminary estimation models have obtained a higher accuracy than conventional methods. Moreover, Hakami and Hassan (2019) and Kim et al. (2005) mentioned that ANN models have a higher accuracy when compared to regression analysis and support vector machine techniques, which have been used with project historical data for preliminary cost estimating. ANN models can be configured to have more accurate results with fewer inputs (Shehatto, 2013). Furthermore, the effects of seasonal changes and trends could be identified by an ANN model, which is more beneficial for increasing the accuracy of the estimate (Karaca et al., 2020; Sanni-Anibire et al., 2021; Tabtabai et al., 1999).

According to Akinradewo et al. (2020) and Jassim et al. (2025), industrial practice for preliminary estimation in Sri Lanka is to use conventional methods. In most scenarios, it causes a less accurate estimate and consumes a significant amount of time to prepare. Gupta & Debnath (2022) declared that existing estimation software in the international market is incompatible with the Sri Lankan context due to limited usage policies and availability. However, ANN-based preliminary estimation has provided promising results in the global context (Al-Tawal et al., 2021; Matel et al., 2022). Therefore, adopting the ANN method for preliminary estimation can be recognised as suitable for the Sri Lankan context. Further, it will assist the parties involved in the project to determine future project decisions more accurately with less information available. The study aims to investigate the applicability of artificial neural network-based methods to enhance the preliminary estimation in Sri Lankan building construction projects. An ANN model is developed, and necessary improvements and modifications relevant to the cost attributes are suggested to enhance the practical implementation of the ANN method within Sri Lanka.

2. LITERATURE REVIEW

2.1 PRELIMINARY COST ESTIMATION FOR BUILDING PROJECTS

Preliminary cost estimates should provide a credible and accurate prediction of the cost at an early stage of a construction project (Kim et al., 2005; Phaobunjong, 2002; Sanni-Anibire et al., 2021; Seeley, 1996; Shehatto, 2013). Gould (2005) explains the preliminary cost estimation as an appraisal, opinion, or approximation of the cost done before the actual construction. Further, Ofori-Boadu (2015) explains preliminary cost estimation as one of the cost estimates prepared in the initial step of developing the budget for a construction project. Therefore, the task becomes more challenging, especially when a higher accuracy level is required for the estimate at the initial stage of the project (Shehatto, 2013). Holm et al. (2005) describe that preliminary estimations are required to select alternative investment options and design options to determine the funding requirements, conduct feasibility studies, and present bids and tenders. Furthermore, Cheung et al. (2012) note that the employer's requirements for the project must be assessed when preparing a preliminary estimate to perform a reliable estimate based on appropriate data.

According to Phaobunjong (2002) and Oberlender (2000), a specific format or industrial standard is not defined for preparing the preliminary estimate. The required accuracy level is determined according to the stage of the project (Gunaydin & Doğan, 2004).

2.2 ARTIFICIAL NEURAL NETWORK (ANN) FOR PRELIMINARY ESTIMATION

An ANN is a computing technique in computational intelligence that can be used for information processing (Gupta & Debnath, 2022; Kukreja et al., 2016; Rojas, 1996). ANN is inspired by the ideology of the human brain neurons. ANN was developed to easily incorporate human intelligence into computers to perform complicated tasks (Abiodun et al., 2018; Goel et al., 2023). Abiodun et al. (2018) describe that ANN models are compatible with mathematically expressing a real-world phenomenon since an ANN model is a simplified mechanism of brain function. System control, pattern recognition, forecasting, and detection are the main areas where the application of ANN is mainly identified (Kukreja et al., 2016). Matel et al. (2022) stated that ANN can be used in parametric cost estimation as an alternative to statistical methods. Moreover, the same article noted that using ANN models in preliminary estimation is more straightforward than using other evolving methods in computational intelligence.

Elmousalami (2019) was able to represent the use of simulation modelling methods for preliminary estimating in building construction projects by considering 47 studies. The use of ANN and hybrid models was emphasised in the study.

Studies conducted by Arafa and Alqedra (2011), Bayram et al. (2015), Bode (2000), Cheng et al. (2013), Elmousalami (2019), El-Sawah and Moselhi (2014), Emsley et al. (2002), Gunaydin and Doğan (2004), Hakami and Hassan (2019), Kim et al. (2005), Pesko et al. (2013), Petroutsatou et al. (2012), Shehatto (2013) and Wilmot and Mei (2005) signify the applicability of ANN method for preliminary estimation process in the construction industry which results to acquire a higher accuracy than traditional methods.

2.3 IDENTIFYING INPUT VARIABLES FOR THE ANN-BASED PRELIMINARY ESTIMATION MODEL

Identification of the most significant cost parameters of the building is vital when developing the ANN model. The cost relationship between the input variable and the output must be substantial to have more dynamic output from the ANN model and to improve the accuracy with reduced redundancy and noisiness (Arafa & Alqedra, 2011; Elmousalami, 2019; Gunaydin & Doğan, 2004; Shehatto, 2013). Further, Hakami and Hassan (2019) denote that the input variables of the ANN model should expose the client's requirements to increase the model's reliability. Table 1 represents key building parameters that could be used as input variables for the ANN model, as identified by various authors.

Table 1: Building parameters used as input variables for ANN models in previous research studies

Building Parameter	References
Floor area	(Arafa & Alqedra, 2011; Chandraratne et al., 2019; Geekiyanage & Ramachandra, 2019; Gunaydin & Doğan, 2004; Kim et al., 2005; Shehatto, 2013; Sonmez, 2011; Wang et al., 2012)
Type of the foundation	(Arafa & Alqedra, 2011; Chandraratne et al., 2019; Gunaydin & Doğan, 2004; Kim et al., 2005; Shehatto, 2013; Wang et al., 2012)
Number of floors	(Arafa & Alqedra, 2011; Chandraratne et al., 2019; Geekiyanage & Ramachandra, 2019; Gunaydin & Doğan, 2004; Hakami & Hassan, 2019; Kim et al., 2005; Shehatto, 2013; Sonmez, 2011; Wang et al., 2012)
Number of elevators	(Arafa & Alqedra, 2011; Shehatto, 2013; Sonmez, 2011; Wang et al., 2012)
Building height	(Chandraratne et al., 2019; Geekiyanage & Ramachandra, 2019)
Building type	(Chandraratne et al., 2019; Hakami & Hassan, 2019; Shehatto, 2013)
Project location	(Chandraratne et al., 2019; Gunaydin & Doğan, 2004; Hakami & Hassan, 2019)
Project duration	(Chandraratne et al., 2019)
Type of HVAC	(Hakami & Hassan, 2019; Shehatto, 2013)
Type of electricity	(Shehatto, 2013)
Mechanical services type	(Shehatto, 2013)
Type of external finish	(Hakami & Hassan, 2019; Shehatto, 2013; Sonmez, 2011; Wang et al., 2012)

According to Table 1, floor area, type of foundation and number of floors are significant building parameters for the ANN model. Moreover, the studies conducted by Chandraratne et al. (2019) and Geekiyanage and Ramachandra (2019) additionally, emphasise the significance of building parameters, namely building height, building type, location and project duration, concerning the Sri Lankan context.

3. MATERIAL AND METHODS

This research intends to investigate the suitability and applicability of ANN-based preliminary estimation in Sri Lanka through design science research methodology. Specifically, the suitability and relevance of ANN within the Sri Lankan context were evaluated using a qualitative method. The ANN model development and validation were approached using a quantitative method since it should be performed using numerical figures generated from performance measures as identified in the literature review. This research consisted of two main stages, and the required activities and the sequences of activities for this research study at each stage were identified in Figure 1.

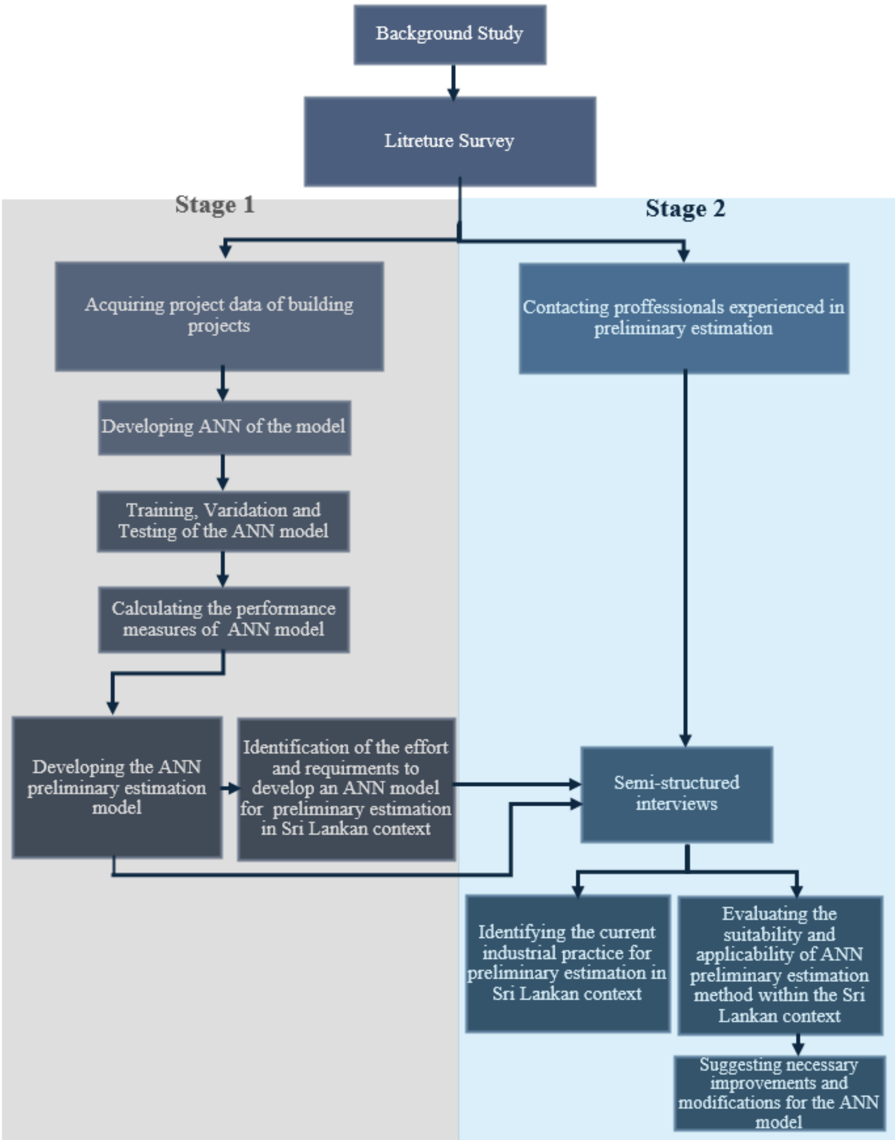


Figure 1: Research process

Fellows and Liu (2015) explain that expert interviews are more beneficial for effective data collection, as they gather data for a relevant matter from someone experienced. Therefore, 10 semi-structured interviews with the building construction sector (Quantity surveyors, Cost consultants, and Project managers) were conducted, since this study should elaborate on the suitability and applicability of ANN for preliminary estimation, which would be a new subject matter for the interviewees. Since the number of experts is unknown in this study area sample size is determined based on the saturation of the information. Snowball sampling is adopted for this study to select suitable experts for the study data collection. Accordingly, data were collected from 10 experts in the building construction sector.

The quantitative analysis report comprises performance measures of the developed ANN preliminary estimation model. The measures can be identified during the ANN model validation process and used for the performance evaluation of the ANN model. An efficient analysis was conducted by adopting qualitative data analysis. Therefore, content analysis is preferred in this research to perform Stage 2 of this research. As the preliminary estimation model development platform Google Colaboratory platform is used, and its selection has been justified in Subtopic 4.1.3.

4. RESULTS

4.1 STAGE 1: ANN ESTIMATION MODEL DEVELOPMENT

4.1.1 Identification of Input Attributes and Encoding

In this study, categorisation and data encoding were carried out according to the availability of the dataset. The qualitative attributes of the buildings were encoded, and the quantitative attributes were inserted as numerical values. The relation of each input attribute to the cost was identified through Figure 2, generated using Python coding libraries in the Google Colaboratory platform, where the calculation is processed statistically within the model.

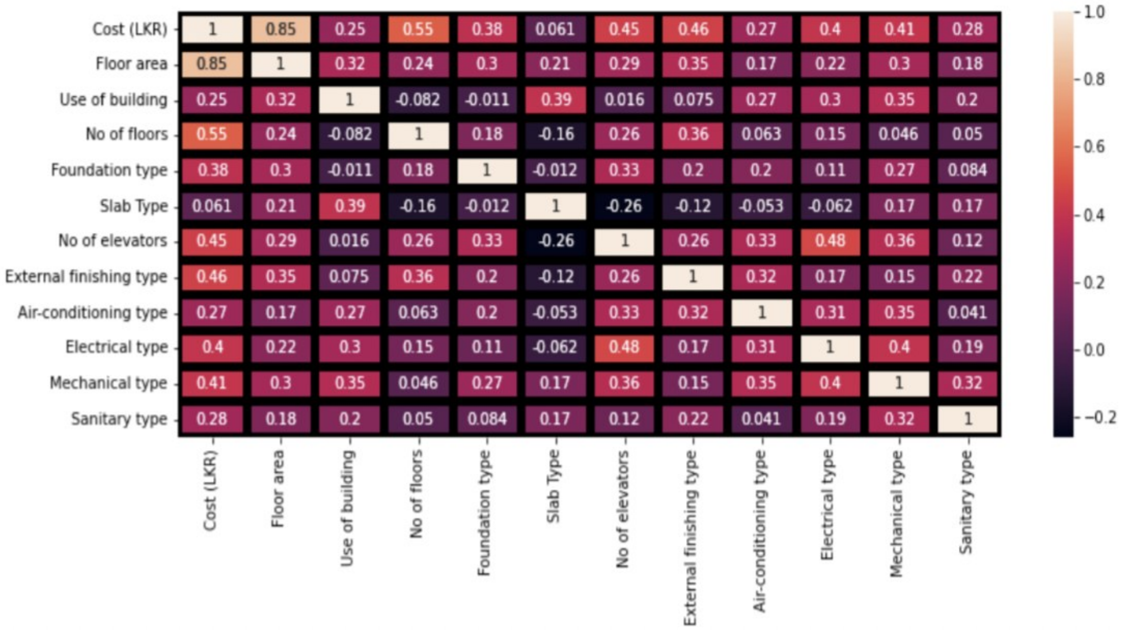


Figure 2: Correlation of cost to each input attribute

Figure 2 shows that the floor area is the most significant input attribute to the cost, and the slab type is the least affecting input attribute. Therefore, it can be stated that various input attributes can be considered when preparing the database as per the ANN model developer's desire. The correlation figure could be generated from Google Colaboratory to identify the model's most significant and suitable input attributes. Then the ANN model was developed using a database related to the UAE with 169 building projects.

4.1.2 Evaluation of the Data Distribution of the Database

Evaluation of the data distribution is mandatory to develop a reliable ANN model. The review of the data distribution was conducted through the Google Colaboratory platform. The data is preferred to be generally distributed within the expected range. Therefore, the data distribution of the most significant input attributes identified in Figure 2, and the model output attribute must be studied before the model development. This data set evaluation would be more beneficial in generating a model with higher accuracy. Figure

3 displays the data distribution of the most cost-significant input attribute (floor area) and the output attribute (building cost) specified in this ANN model.

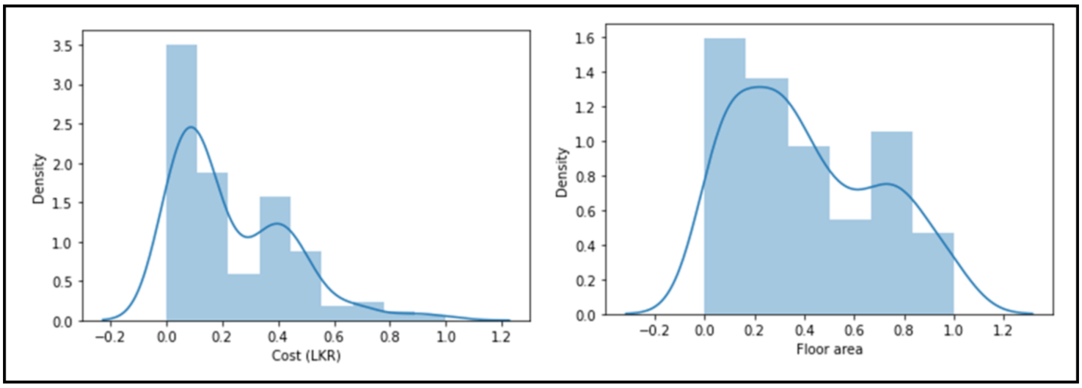


Figure 3: Data distribution of building cost and the floor area in the dataset

According to Figure 3, the selected dataset represents a bimodal distribution of data rather than a normal distribution. It emphasised the need for more mid-range cost data within the chosen dataset so that the ANN model could be more accurate in estimation.

4.1.3 Developing the ANN Preliminary Estimation Model

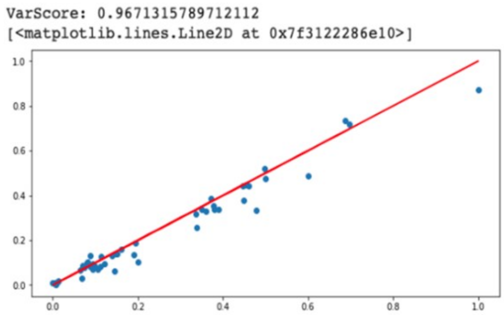
Three ANN preliminary estimation models were developed using the Google Colaboratory platform, MATLAB Software and Neural Designer Software. The Google Colaboratory platform enabled the development of models from scratch with Python coding online. At the same time, MATLAB and Neural Designer software were capable of developing ANN models without coding knowledge.

The models' ANN architecture, training, and testing processes were substantially similar, although the sequential model is significantly different from the Google Colaboratory model. The Google Colaboratory model is highly customisable compared to the MATLAB and Neural Designer models. (Ray et al., 2021; Sukhdeve & Sukhdeve, 2023). The architecture of the ANN model can be changed as the developer desires. The ANN models developed using MATLAB and neural designer software took less time to create, but a cost was incurred for the purchase of the software. In contrast, the Google Collaboratory platform was available free of cost. When considering the performance measures of each model, the correlation and validation performance of the Google Colaboratory and MATLAB models are shown in Figure 4.

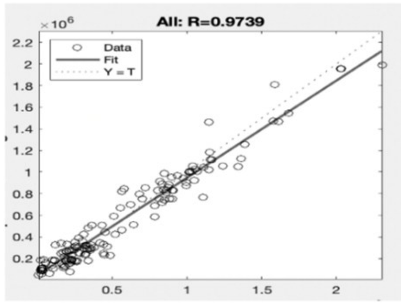
Both models were able to achieve a correlation of more than 0.96 and were able to obtain a validation performance within the respective range of epochs. The ANN model developed in Neural Designer software validated a lower accuracy than the other two ANN models.

4.1.4 Validation of the ANN Models

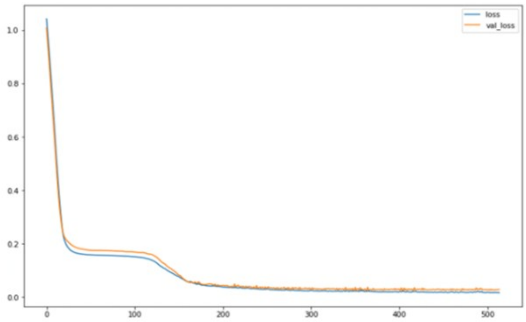
The ANN model was developed using three methods to identify the resource requirement critically. The best ANN model was the Google Colaboratory model, developed using Python. It showed an accuracy of 89.56% and was prioritised for presentation in the interviews. The higher accuracy of the ANN model supports the sound examination with a minimised margin for errors. It benefits the contractor to obtain higher profits and gain customer satisfaction and trust. Meanwhile, accurate estimation avoids the requirements of price adjustments for the client, creating price certainty in the projects.



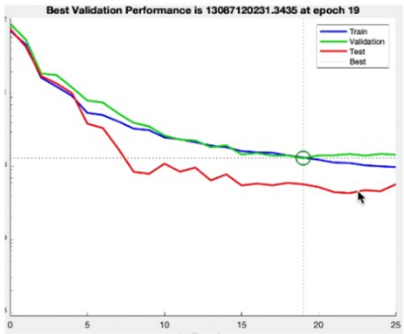
Correlation of google colaborotary model



Correlation of MATLAB model



Validation performance of google colaborotary model



Validation performance of MATLAB model

Figure 4: The correlation and validation performance of ANN models

4.2 Stage 2: Semi-Structured Interviews

4.2.1 SWOT Analysis of ANN Model Applicability within a Firm

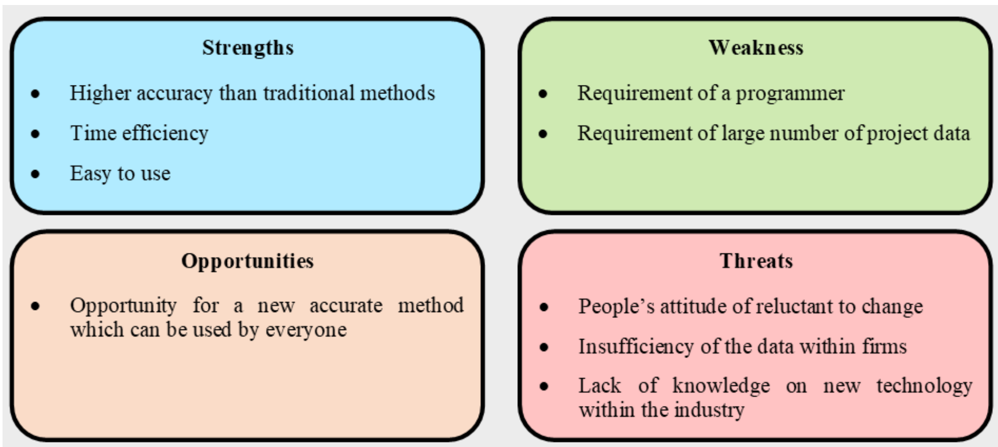


Figure 5: SWOT analysis of ANN model applicability within a firm

Figure 5 demonstrates the SWOT analysis by referring to the interviewees' responses regarding using an ANN model for preliminary estimation within the Sri Lankan context.

4.2.2 Driving and Resisting Factors for ANN-based Preliminary Estimation Model

Figure 6: Identified driving and resisting factors in ANN model applicability

Further, according to the interviewees' responses, Figure 6 was developed to identify the driving and resisting factors for applying the ANN-based preliminary estimation model in the Sri Lankan context.

The interviewees strongly identified the time efficiency and the accuracy of the ANN preliminary estimation model, which will be more advantageous in overcoming the issues of the existing industrial practice of using traditional methods for preliminary estimation.

4.2.3 Suggested Improvements and Modifications for the ANN Model to Optimise its Use in the Sri Lankan Context

According to the research objectives, necessary improvements and modifications for the ANN model have been suggested to optimise the practical application within the industry. Interviewees A1, A4, A7, and A8 have identified that the model should be competent in estimating the different site conditions and settings, and interviewees A9 and A10 identified it as considering the location factor for estimation. Further, the interviewees A2, A6, A7, A9, and A10 emphasised that the model should be capable of being used for a preliminary analysis of the price fluctuations in the industry. Specifically, the interviewees A2, A6 and A7 questioned how the use of CIDA indices could be performed when using the model.

The next improvement identified was having a user interface for the model, where the efficient and effective interaction between the model and the user can be improved. The interviewees A1, A3, A5 and A6 denoted the need for a user interface for the model.

As a further improvement, the interviewees A4, A5, A6 and A7 denoted the importance of the model and whether it can be developed to prepare elemental cost planning. Furthermore, interviewees noted that the model would be more useful since the firms are primarily concerned about the elemental cost plan rather than the preliminary estimate.

Concerning the expected modifications, being location-specific, adjustments to price fluctuations and identifying the risk and uncertainty were identified by the interviewees as recommended modifications. Further, improvements in developing a user interface and compatibility with the model in elemental cost planning were emphasised.

5. DISCUSSION

The ANN model developed by Chandraratne et al. (2019), Dissanayake et al. (2015) and Geekiyanage and Ramachandra (2019) was developed using supplementary software, which was made to establish ANN models. Therefore, customizability is low compared to developing an ANN by using Python coding. There should be knowledge regarding ANN to develop an ANN model within a firm. Further, the ANN model developed for this research is a solitary model developed using only ANN, and it was able to perform with an accuracy of 89.56%. Therefore, it can be identified that the ANN is suitable for predicting the costs of building projects at the conceptual stage, as similarly identified in the literature review.

According to the interviews, the Sri Lankan preliminary estimation process still relies on traditional methods. Chandraratne et al. (2019), Dissanayake et al. (2015), Geekiyanage and Ramachandra (2019) and Rathnayake et al. (2018) also mentioned that traditional methods are still in practice in almost all preliminary estimations. According to the interviewees, the reason for using the conventional method in the industry is the simplicity of those methods. People mostly use their experience to prepare estimates (Britto et al., 2013; Dissanayake et al., 2015; Ganeshu et al., 2015). However, traditional and non-traditional methods are being replaced globally by hybrid intelligent models (Elmousalami, 2019; Sanni-Anibire et al., 2021).

Regarding preliminary estimation within the context, it is recognised that the consultant interacts with the client to gather as much information regarding the project as possible. The assumptions are made for the deficiency of information, mostly on building specifications, duration, and price fluctuations. Further, the consultants identify the client's requirements. Bley (1990) and Phaobunjong (2002) also identified the preliminary estimation process similar to the existing practice in Sri Lanka.

With the existing practice, it will take several days to analyse the data and provide a figure to the client. However, using ANN, time consumption can be drastically reduced when providing such a figure to a client. In contrast, Arafa and Alqedra (2011), Hakami and Hassan (2019) and Kim et al. (2005) have also signified the time efficiency of the ANN-based preliminary estimation.

According to the findings, database management within the firms shows a trend to use software-based data collection methods rather than Excel. The use of ERP software could be identified as a trend within the industry, and previous studies have shown a trend to use traditional Excel for data keeping and management (Rathnayake et al., 2018).

Another aspect identified through the interviews was the expected accuracy of a preliminary estimate of more than 80%. Accordingly, ANN preliminary estimation could be identified as a solution where any person within the firm can use the model to get a figure after inserting the project data into the respective input attributes.

In terms of suitability, most interviewees identified that ANN is suitable for preliminary estimation, even though ANN is not familiar to interviewees. The time effectiveness and the increased accuracy were the main advantages identified by the interviewees. It is aligned with the existing research studies of Arafa and Alqedra (2011), Sanni-Anibire et al. (2021) and Shehatto (2013), where the higher accuracy and time efficiency of ANN models were elaborated.

Therefore, according to the findings, even though the ANN is suitable for the preliminary estimation, some challenges should be addressed and rectified. The interviewees noted that the centralised database system will be beneficial in these situations, and the professional bodies related to construction can be initiated to introduce these kinds of methods to the industry to address the issue of resistance to change among people in the industry.

Furthermore, necessary improvements and modifications have been suggested according to the responses of the interviews, which were mainly focused on having a user interface and inserting input parameters to the model regarding the location and site condition of the project, price fluctuations, risk, and uncertainty. These aspects can be inserted into the model as input attributes using the location indices, CIDA price indices and the inflation rate. Along with that, the data set should be updated accurately with each project's relative location indices, CIDA indices and the inflation rate.

Figure 7 elaborates on the cognitive map regarding the applicability of the ANN preliminary estimation model within the Sri Lankan context.

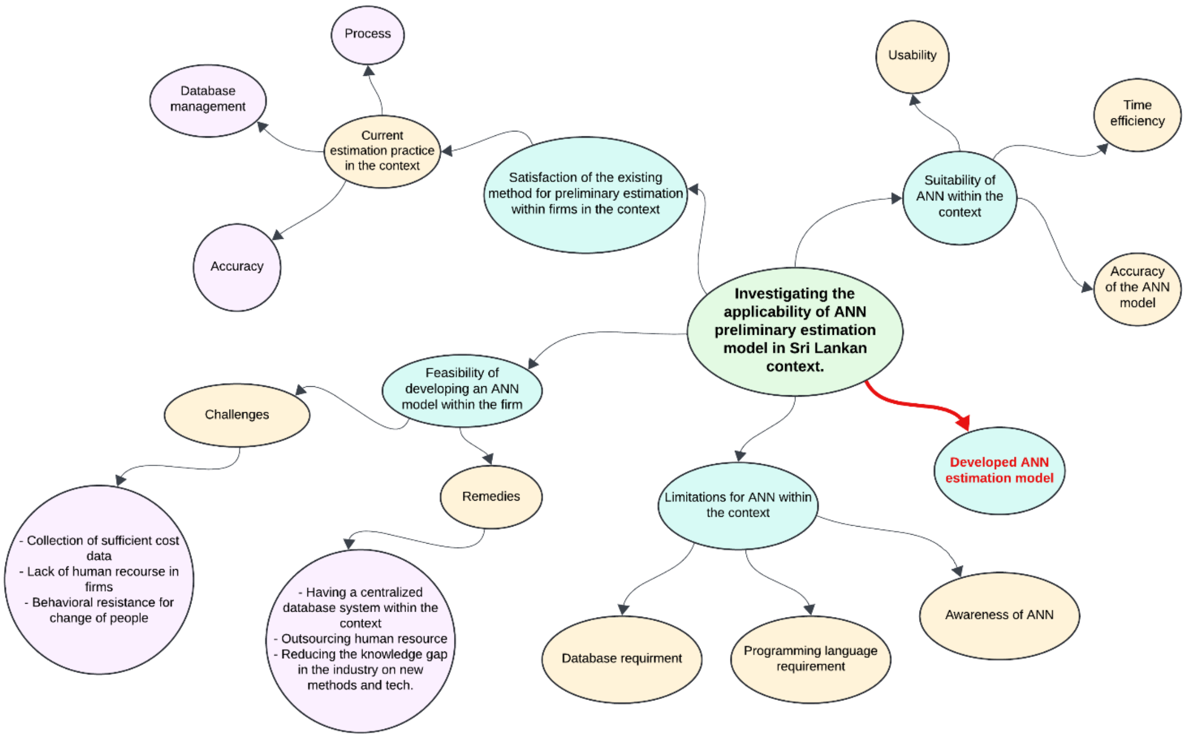


Figure 7: Cognitive map for ANN model applicability in Sri Lanka

The use of ANN for preliminary estimation is identified globally as a more accurate and easier method than the traditional method. The suitability and applicability of the ANN preliminary estimation model were critically analysed within the study. The ANN model was developed, validated, and modified according to the interviewees' responses, which were provided as improvements to the ANN model. The interviewees provided a positive impression of the applicability of ANN within the context while identifying specific challenges which can be overcome with effort within the firm.

6. CONCLUSIONS

Hybrid intelligent models are more advanced than even non-traditional methods such as MRA since hybrid intelligent models may combine several machine learning techniques, namely, evolutionary computing, ANN, SVM, CBR and fuzzy logic. Regarding the Sri Lankan context, the practice uses traditional methods and maintains the required accuracy through the estimator's experience.

Preparing a preliminary estimate within the context includes identifying project characteristics through available drawings, the client’s brief, and discussions with the client. After that, the estimator prepares the estimate using past project data. The experience of the estimator mainly produces the necessary assumptions and adjustments. Further, it can be identified that several experienced estimators are using a combination of traditional methods as a customised method that suits the firm to maintain the accuracy and reliability of the estimate.

The model can be developed within the firm using an appropriate database and the necessary human resources. Further, the investors can make reliable decisions on the project at the initial stage by using ANN models for preliminary estimations. Also, the higher accuracy and time efficiency are the most significant benefits of using ANN for preliminary estimations. A manual validation process was carried out to identify the accuracy of the developed ANN model. The best model was the Google Colaborotary model, which had the highest accuracy of 89.56%. Furthermore, the study used a comprehensive data set along with the expert review on the parameters, ensuring the reliability of the outcome of the study.

The outcome highlighted the requirements for input attributes related to location, price fluctuations, risk, and uncertainty to improve the accuracy of the preliminary estimation model as the limitations of this study. Location and price fluctuation changes can be included in the model using location indices, CIDA indices and inflation rates as the future research direction of this study.

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