REPUBLIC OF TURKEY

YILDIZ TECHNICAL UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

COUPLED INTELLIGENT PPREDICTIVE MODEL BASED GLOBAL HARMONY SEARCH AND EXTREME LEARNING MACHINE FOR MODELING PROJECT CONSTRUCTION ESTIMATION AT COMPLETION

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DOCTOR OF PHILOSOPHY THESIS

Department of Civil Engineering

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Advisor

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A thesis submitted by Enas Fathi Taher ALHARES in partial fulfillment of the requirements for the degree of **DOCTOR OF PHILOSOPHY** is approved by the committee on 19.10.2020 in Department of Civil Engineering, Civil Engineering (English) Program.

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Enas Fathi Taher ALHARES

Signature

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Consequent to expressing profound gratitude to God for giving me the strength and capacity to finish this research, I might need to show the truthful to fathers and family who have conferred in me the drive and support to complete this work.

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Enas Fathi Taher ALHARES

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LIST OF SYMBOLS

Ai	Activities of Daily Life
b	Bias
M	Dimension of The Feature Space
H	Feature Space
x_i	Inputs
W_i	Input Connection Weights
D	Number of Inputs
Y	Output
h_i	Output of The Hidden Nodes
T	Target Matrix
x	The Input Variables
f	Threshold Function
β_i	Weight of The Output Matrix

LIST OF ABBREVIATIONS

ACWP	Actual Cost of Work Performed
ACWP	Actual Cost of Work Performed
AI	Artificial Intelligence
BAC	Budget at Completion
BCWP	Budgeted Cost of Work Performed
BCWS	Budgeted Cost of Work Performed
BF	Brute Force
CCI	Construction Price Fluctuation
CEAC	Cost Estimate at Completion
CPI	Cost Performance Index
DEA	Data Envelope Analysis
DNN	Deep Neural Network
EAC	Estimates at Completion
ECD	Estimated Completion Date
ECD	estimation completion date
EFHNN	Evolutionary Fuzzy Hybrid Neural Network
ELM	Extreme Learning Method
ES	Earned Schedule
EV	Earned Value
EVMS	Earned Value Management System
FHNN	Fuzzy Hybrid Neural Network
FL	Fuzzy Logic
GHS	Global Harmony Search

GP	Gaussian Process
HNN	Hybrid Neural Network
HONN	High Order Neural Network
IEAC	Independent Estimates at Completion
IPMR	Integrated Program Management Report
MLP	Multi-Layer Perception
MMAE	Multiple Model Adaptive Estimation
MRE	Mean Relative Error
NN	Neural Network
NSE	Nash Sutcliffe Coefficient
PCD	Planned Completion Date
PSO	Swan Optimization Algorithm
RE	Relative Error Percentage
RMSE	Mean Absolute Error
SI	Scatter Index
SLFNs	Single-Layer Feed For Ward Networks
SPI	Schedule Performance Index
SRA	Schedule Risk Assessment
SV	Schedule Variance
SVM	Support Vector Machine
SVM-FMGA	Support Vector Machine with Fast Messy Genetic Algorithm
SVR	Support Vector Regression
WSVM	Weighted Support Vector Machine

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ABSTRACT

Coupled Intelligent Predictive Model Based Global Harmony Search and Extreme Learning Machine for Modeling Project Construction Estimation at Completion

Enas Fathi Taher ALHARES

Department of Civil Engineering

Doctor of Philosophy Thesis

Advisor: Assoc. Prof. Dr. Cenk BUDAYAN

Estimation at completion (EAC) is a manager's projection of a project's total cost at its completion. It is an important tool for monitoring a project's performance and risk. Executives usually make high-level decisions on a project, but they may have gaps in the technical knowledge which may cause errors in their decisions. In this current study, the authors implemented new coupled intelligence models, namely global harmony search (GHS) and brute force (BF) integrated with extreme learning machine (ELM) for modeling the project construction estimation at completion. GHS and BF were used to abstract the substantial influential attributes toward the EAC dependent variable, whereas the effectiveness of ELM as a novel predictive model for the investigated application was demonstrated. As a benchmark model, a classical artificial neural network (ANN) was developed to validate the new ELM model in terms of the prediction accuracy. The predictive models were applied using historical information related to construction projects gathered from the United Arab Emirates (UAE). The study investigated the application of the proposed coupled model in determining the EAC and calculated the tendency of a change in the forecast model monitor. The main goal of the investigated model was to produce a reliable trend of EAC estimates which can aid project managers in improving the effectiveness of project costs control. The results demonstrated a noticeable implementation of the GHS-ELM and BF-ELM over the classical and hybridized ANN models.

Keywords: Construction project monitoring, coupled intelligent model, substantial input section, extreme learning machine

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ÖZET

Birleşik Akıllı Tahmine Dayalı Model Tabanlı Global Uyum Araması ve Modelleme Projesi Tamamlama Simülasyonunda Aşırı Öğrenme Makinesi

Enas Fathi Taher ALHARES

İnşaat Mühendisliği Anabilim Dalı

Doktora Tezi

Doç. Dr. Cenk BUDAYAN

Tahmini tamamlama maliyeti (TTM), bir yöneticinin bir projenin tamamlandığında projenin toplam maliyeti ilgili olarak yaptığı tahmindir. Bu hesap projenin performansını ve riskini izlemek için önemli bir araçtır. Yöneticiler genellikle bir proje hakkında üst düzey kararlar alırlar, ancak kararlarında hatalara neden olabilecek teknik bilgiler konusunda eksiklikler ve boşluklar olabilir. Bu çalışmanın amacı ise inşaat projeleri için TTM'yi hesaplanmasında kullanılabilecek aşırı öğrenme makinesi (ELM), entegre olan küresel uyum araştırması (GHS) ve kaba kuvvet (BF) olarak adlandırılan yeni birleştirilmiş zekâ modellerini uygulamaktır. GHS ve BF, TTM'nin bağımlı değişkenine yönelik olan önemli etkileyici nitelikleri soyutlamak için kullanılmışken, ELM'nin incelenen uygulama için yenilikçi bir model olarak etkinliği gösterilmiştir. Geliştirilen modelin tahmin doğruluğunu onaylamak amacıyla, bu modelin mukayese edilebileceği klasik bir yapay sinir ağı (YSA) geliştirilmiştir. Tahmini modeller, Birleşik Arap Emirlikleri'nden (BAE) toplanan inşaat projeleriyle ilgili tarihsel bilgiler kullanılarak uygulanmıştır.

Çalışma TTM'nin belirlenmesinde önerilen birleştirilmiş modelin uygulanmasını araştırmış ve tahmin modeli monitöründeki bir değişimin eğilimini hesaplamıştır. Araştırılan modelin temel amacı, proje yöneticilerinin proje maliyet kontrolünün etkinliğini artırmasına yardımcı olabilecek güvenilir bir TTM tahminleri eğilimi oluşturmaktı. Sonuçlar, GHS-ELM ve BF-ELM'in klasik ve hibritleştirilmiş ANN modelleri üzerinde gözle görülür bir uygulamasını göstermiştir.

Anahtar Kelimeler: Inşaat proje takibi, birleştirilmiş akıllı model, önemli girdi bölümü, aşırı öğrenme makinesi

1
INTRODUCTION

1.1 Literature Review

Due to the risky nature of construction, it has often suffered poor performance. The construction industry has a high impact on the economy of any country [1]. However, the construction industry is getting to be more and more complicated because of the construction process itself and the large number of parties involved in the construction project (i.e. clients, users, designers, regulators, contractors, suppliers, subcontractors, and consultants) [2]. In general, the performance in construction projects is considered to be the indicator for the project management success or failure. In a construction project, four determinants are used to measure the performance, namely: (1) the quality of the work, (2) the delivery of a project on time, (3) project completion within the estimated budget, (4) level of client's satisfaction. A project may be regarded as a successful endeavor when it satisfies the cost, time, and quality limitations. However, the history of the construction industry was filled with construction projects that were completed with a cost overrun, time overrun, and poor quality [3]. As per [4], the constant environmental changes urge to reduce cost and maintain schedules, as well as the ever-increasing complex construction techniques associated with the construction industry make it difficult to evade risks. For efficient and profitable operations, construction companies must ensure frequent project cost performance monitoring to take appropriate action in times of deviations. Being that construction firms normally concentrate on budget planning at the early stages of projects, they normally ignore the real influence of changes in engineering costs and information updates during the project [5]. The obvious result of this neglect is that project cost cannot be effectively controlled, and potential problems may not be detected earlier. Upon the commencement of any project, there is bound that project conditions must change, thereby necessitating regular budget reviews for effective project cost management. Project managers have often depended on the Earned Value Management (EVM) as a managerial &

monitoring method for project control of all the three critical elements (i.e., scope, time, and cost) of project management [6]. They also depend on the EVM for estimation at completion (EAC) computation which is an automatic approach to the evaluation of the costs of pre-scheduled project activities completion [7]. The manager can depend on the estimated EAC to detect cost-related problems by calculating the deviation between the actual & planned project costs.

The earned value has evolved all around the world in the last couple of decades as an acquisition process from a hot topic to managerial best practice [8]. Earned Value Management (EVM) is a collection of business management practices that provide a structured method of performance measurement and analysis [9]. A properly applied and interpreted EVM measure can help project managers predict the status of their projects in terms of schedule, cost, and performance. This can be attained by measuring the project management process. Further, the EVM helps in proper project organization concerning its scheduling, budgeting, and planning the components that can predict the projects' status [10]. With the EVMS, program managers can predict the outcome of their decisions; project alterations are mainly necessary when there is a need to meet set objectives after comparing the current state of a program to the expected status. The accuracy of forecasted estimations is heavily reliant on efficient decision-making processes. The EVM methodology highlights the measured EAC which serves as the inputs for these forecasts.

In practical implementation, poor decision making, and inaccurate predictions have often resulted in cost overruns, schedule delays, and cancellations. For instance, a case study by Calcut in 1993 reported over budgeting in about 20 to 50 % of completed contracts based on phase and type [11]. A project with an overrun of about 15 to 20 % is not likely to be completed with a decreased cost overrun [12]. The Department of Defence (DOD) deemed it necessary to spearhead the for better estimation methods after the failure of the Navy's A-12 Avenger program which added to the list of growing management disasters [13]. In Nigeria, 70% of the projects suffered delays in their execution, according to the survey performed by Odeyinka and Yusif [14]. Hundred percentage of road construction projects in Palestine suffered from delay and cost diverge [15,16]. Omoregie and Radford [17] conducted a study in Nigeria to investigate the size of cost and time overrun. They found that the minimum average percentage cost overrun of projects in Nigeria to be 14%, and the minimum average delay was found to be 188%. Battaineh [18] investigated the delay size in 164 buildings and 28 highway projects constructed during the period 1996–1999 in Jordan. He found that the percentage of time overrun to be 160% for road construction projects and 120% for building projects. Flyvbjerg, Holm, and Buhl [19] addressed the cost increase in 258 transportation infrastructure projects executed in both developed and developing nations. The main study conclusions were: (1) 90% of transport infrastructure projects suffered from cost overrun, (2) The average cost overrun is 28%, (3) Cost overrun is a global phenomenon, (4) Cost overrun is more pronounced in developing nations than in North America and Europe, (5) Cost overrun has not decreased over the past 70 years.

When acquiring new systems, cost control is a major challenge, especially in today's world of rapidly changing technology and steadily declining project budgets [20]. The main objective of cost control of a project is to gain the maximum profit within the designated period within the budget and satisfactory quality of work. To monitor and control actual expenditure against the estimated project budget. The tender price/contract sum represents the project budget. According to Nunnally [21], cost control of a project involves measuring and collecting the cost record of a project, and the work progress. It also involves the comparison of actual progress with the planning. A systematic procedure of cost control will give a good result in collecting important data in estimating and controlling the cost of the coming projects in the future. The cost control techniques generally used in construction projects are: Cost Value Reconciliation, Control of Project Cash flow, Break, Even Analysis, Budgetary Control, and Contractors cost Control, Cost Comparison, Schedule Control, and Asset Register. There has in recent years been a great need for an understanding of construction economics and cost control, particularly during the design stage of projects. The importance of this due largely to the following: (1) the increased pace of development, in general, has resulted in clients being less likely to tolerate delays caused by redesigning buildings when tenders are too high. (2) The clients' requirements today are more complex than those of their Victorian counterparts. The most effective system of control is therefore desirable for inception up to the completion of the final account, after that during cost-in-use.

(3) The clients of the industry often represent large organizations and financial institutions. This is a result of takeovers, mergers, and some public ownership. De-nationalization has often meant that these large organizations remain intact as a single entity. There has thus been an increased emphasis on accountability in both the public and the private sectors of industry. The efficiency of these organizations at construction work is only as good as their advisers [22]. At the end of the 20th century, and due to sank the Southeast-Asia economy into recession. The control of the project cost was becoming an essential issue for construction companies and developers for managing construction projects. For example, in Thailand, many projects within this period had overrun the cost significantly [23]. Therefore, the use of good and new technologies and procedures to control the project cost is becoming a concern for construction companies and project investors around the world [24]. Project developers and managers are worried about the failure of a project due to a poor cost control system [25]. Hence, the techniques for controlling the project cost required improvement to ensure that contractors and owners manage the project costs and meeting project goals within budget and on time. The study highlighted systematically biased downward cost estimates in the system which resulted in cost growth [26]. Moreover, many researches identified the causes of overrun the time and cost in such construction projects. The analysis data demonstrated that the plans and project's modifications cause about 39% of the overruns reasons for projects' cost. As well as the errors or modifications in the plans caused about 29% of the projects' time overruns. While the changes in the conditions caused approximately 34% of the project's cost overruns. Weather damages and utility delays were other reasons for cost and time overruns in these projects [27].

Cost control is not only important for construction companies but also it is an important case for other projects conducted by other sectors, such as defense projects. The Navy's A-12 program (terminated in Jan 1991) and the Air Force's C-l 7 program (constantly criticized at the Congress) are some of the recent examples of project failure to control costs [28]. Where the Navy's A-12 program had been canceled due to not providing a well-estimating for the expected final cost of a defense contract, termed "Estimate at Completion" (EAC). Moreover, popular electronic spreadsheets and software packages allow users to rapidly compute a range of EACS. Managers and analysts are left with the task of deciding which EAC or range of EACs is most accurate.

On the other hand, a case study method was selected to obtain a depth understanding of the challenges based on cost management. The case company is a global power solution provider for the marine and energy markets with more than €4.5 billion in annual revenue. For this paper, we shall call it Power Co. Power Co has more than 15,000 employees in more than 70 countries around the world and is divided into three business units. Cases were selected based on theoretical sampling [29]. In this analysis, the focus is on the marine power solutions business unit. The projects studied included two standard delivery projects with low complexity and two projects with high complexity. The selection of the projects enabled us to identify management challenges that are specifically related to the complexity of the project as they were implemented in a similar context.

The empirical data were collected by reviewing the cost management performance reports for the four projects and gathering further information through eight interviews with key persons involved in the projects. The cost management performance reports were reviewed three times during different phases of the project. Interviewees included a general manager of project management, three project managers, two project engineers, one project controller, and the director of business control and administration. All had worked on the case projects, and the project managers and engineers had a deep understanding of the specific case project in which they were involved. In contrast, the general manager, project controller, and business control and administration director had a wide knowledge of all the case projects and provided valuable information when we compared the characteristics of different projects.

The existence of numerous methods of EAC calculation contributes to this problem. Among the available methods are simple index-based methods and complex statistical methods. Several reviews have been conducted on the computation of project estimation at completion. For instance, 47 EAC formulas have been listed by McKinney from 18 different sources [30]. In contrast, other complex nonlinear regression-based methods such as Rayleigh probability distribution coupled with Multiple Model Adaptive Estimation (MMAE), Rayleigh probability distribution, and a modified Beta distribution have been suggested [31–34]. The availability of numerous methods makes it difficult to select the right one to perform sufficiently.

Much of the comparative research has regrettably focused on simpler index-based methods and regression methodologies. Despite the advent of the new advanced soft computing models, this problem is yet to be solved due to the existence of several parameters that manipulate the EAC value.

1.2 Objective of the Thesis

Considering the reported complexity associated with the EAC computation, it is imperative to design a fast and effective system that considers the issues of cost control during the project execution for the prediction of project EAC by using AI methods. This research is aiming to improve and solve the effective issues related to the management of project cost through collecting the previous associated data and investigations about managing the cost of a project to detect the effective factors on the project cost. Based on the identified limitations of the existing AI models, it is highly encouraging to explore more reliable, robust, and trustful methodologies to solve the project cost overruns during project execution. Historical data were collected from several construction projects and used to inspect the predictability of the proposed model. The projects' information was used to set up the trend of a project cost flow and the relationship between the project EAC and monthly costs we mapped based on historical knowledge and experience. The research objectives are summarised as follows:

i. A new intelligence model called extreme learning machine was introduced to module the estimation at completion (EAC) for construction projects in the United Arab Emirates.
ii. The predictability performance of the proposed ELM model in computing EAC was validated against the traditional artificial neural network in which it is considered as a predominant AI model conducted for EAC prediction.
iii. The predictive ELM model was improved by input attribute optimization approaches called global harmony search and brute force for the identification of the factors that significantly affect project cost.

iv. Overall, the research explored a new modeling strategy based on the coupled intelligence model, which can assist project managers in making decisions.

1.3 Hypothesis

The ability to prepare an EAC and evaluation of the worst case, best case, and EAC is attracting the industrial practices. Every year, an absolute “bottoms-up” EAC referred to as the comprehensive EAC is needed for the Earned Value Management System necessities [37]. Also, extensive EAC is frequently assembled at the main phage stage beginning, which includes at the commencement of a project or the construction. Moreover, it can show a minimized uncertainty occurring from a design and/or liberated material bills that enhance a project manager in answering the following questions:

- Will the funds that remain execute the project?
- Can previous cost experiences forecast the subsequent cost outcome?
- Can the project that remains be adjusted depending on the performance to date?
- Can project cost performance influence the corporate financial condition?

Hence, a realistic and timely ECD and EAC can be a fundamental portion of both corporate finance and project management applications. Moreover, both need routine differentiation of the ECD and EAC alongside the engage earmarks to foresee a practicable financial performance for stockholders and customers.

1.4 The Concept of the Estimation at the Completion

Due to time constraints, only data sourced from contracts extracted from construction projects in UAE were only used for analysis in this study. The data used in this analysis was considered sufficient due to the nature of the database. İn this study, the scope was mainly on the identification of the overall best performing EAC methods and subject to the previously discussed moderator variables. There was no attempt to implement the proposed predictive model as an actual expert system on a practical project.

Organizations and customers often request the authentication of project costs and schedule goals to be met within the authorized budget, the BAC, as well as the

Planned Completion Date (PCD) from project managers. The response to these demands can only be provided by the project managers using the EAC and ECD. The EAC, as per the EV guidelines, is the sum of the contracts' cumulative Actual Cost of Work Performed (ACWP) plus the managers' best estimate of the required time-phased resources to complete the remaining approved work [35]. This relationship is usually expressed thus:

$$EAC = ACWP + ETC \tag{1.1}$$

Hence, the EAC is used to predict the final cost for a project. The project manager can revise the priorities of work; however, the schedule of the project re-plan does not change and/or reschedule of the technical method to finish up and achieve the aim of the project within the stipulated resources. The aim is purposely to finish up the project within the schedule (Contract Completion Date) and budget (Contract Target Cost).

Based on the calculations, the degree of unpredictability will vary for an EAC depending on the nature of work that remains, perceived risks remaining, and available information. The viability of an EAC should be known for prudent management, mostly if EAC differs greatly from the authorized budget of a project (BAC). Hence, the goals of project management are the establishment of the estimated cost for the work remains, figuring out of uncertainty level relative to the schedule that remains, and controlling the influence pose by uncertainty on goals of the project cost.

Due to these, the Integrated Program Management Report (IPMR) and Contract Performance Report (CPR) need three different EAC to curb the information on the uncertainty cost of the level of risks associated with the project. The report needs EAC which constitutes the lowest potential cost (or best case), highest potential cost (or worst case), and possibly EAC (the best estimation from the project manager) and their respective predicted finish dates, mostly called Estimated Completion Dates (ECDs).

EAC uncertainty depends on the EAC in as much as the real cost to date is known. The ETC is organized through the re-estimation of the needed requirement to finish the prevailing authorized work by utilizing the experience cost to date and using other variables which include overhead rates and direct, root cause analysis, Monte Carlo simulations, and Schedule Risk Assessment (SRA).

Moreover, ETC examines usage and material price, rate and anticipated labor, purchase order commitments, usage performance and other direct cost price, resources by type, opportunities and risk, and other variables through higher management. Besides, the ETC is mostly joined with the existent schedule when it is developed.

For checkmate, the EAC, an independent or mathematical estimation of the EAC is regularly assembled by utilizing the performance indices relative to the schedule and cost experience to date. For instance, the Cumulative Budgeted Cost for Work Performed (ACWP) and Cost Performance Index (CPI) is used to finish the EAC by categorizing the BAC project through the CPI [36]. The emerging EAC is frequently called the Independent EAC (IEAC) to differentiate it from a grass-root or formal EAC. Thus, the IEAC is constructed and utilized to analyze the significance of the present cost estimate and show if an extensive EAC can be initiated. Importantly, these evaluations do not examine any "thinking" on the points as mentioned earlier based on anticipated labor rate and efficiency, SRA, opportunity, and risk. Furthermore, they do not depend on judgment, logic, and sanity. Nevertheless, they are evaluated through a comparative analysis.

1.5 Research Scope and Limitations

This study aims at the use of a hybrid intelligent model to determine the complex nonlinearity/non-stationarity/stochasticity relationship between the related independent variables (i.e., cost variance (CV), schedule variance (SV), cost performance index (CPI), schedule performance index (SPI), subcontractor billed index, owner billed index, change order index, construction price fluctuation (CCI), climate effect index) and the dependent variable (i.e., EAC). The existing literature showed that EAC had been calculated using several versions of artificial intelligence (AI) models, such as an artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM), genetic programming (GP) and decision tree (DT). However, the problem with these models includes local minima entrapment, internal parameters optimization, as well as the need for human interaction for manual network adjustments. With these limitations, there is a need to explore new and reliable intelligence models for accurate and effective EAC problem modeling.

1.6 Research Contribution

Based on the surveyed literature, eight common methods have been implemented based on the utilization of the EVM to predict the EAC for construction projects [10,38]. Every method has been employed at different special projects and accomplished differing EAC error rates. When applied to different special projects, the predictions achieved by the single method are extremely accurate for some and present obvious errors for others. This has generated confusion in the industry as to which kind of prediction method should be chosen for particular project types. Hence, the motivation for exploring a robust methodology is triggered by this concept. Another issue is the EVM, it must be directed to each distinct construction project process, with revisions conducted manually In which creates a complicated EVM that is time-consuming. Consequently, the computerization of the engineering management process is critical if EVM is to be applied effectively to control construction costs. However, for most construction companies in the United Arab Emirates, the implementation of computer systems powerful enough only to analyze initial stage budgets. Systems are not equipped to react to changes at each construction stage or use the EVM method to predict construction project EAC. Thus, intelligent technologies are needed. Due to technological advances, nowadays there is a huge dataset engineering available at an ever-increasing pace, and the size and dimensionality of data sets continue to grow by the day. Therefore, it is important to develop efficient and effective machine learning methods that can be used to analyze this dataset and extract useful knowledge and insights from this wealth of information. In recent years, the feasibility of Extreme Learning Machines (ELMs) has emerged as a popular framework in machine learning. ELMs are a type of feed-forward neural networks characterized by a random initialization of their hidden layer weights, combined with a fast training algorithm. The effectiveness of this random initialization and their fast training makes them very appealing for large data analysis. The theory of ELMs has been proven to be universal approximates, and the random initialization of the hidden neurons are sufficient to solve any approximation problem. Hence, the motivation of the current research is to investigate the capacity of this theoretical model to solve the estimation at completion for construction project management. Besides, even though ELMs have efficient training algorithms due to the model itself merit, ELM can be further enhanced using the potential of input selection procedure that accelerates the learning process with more informative attributes to the prediction matrix. The focus of this thesis, therefore, is on developing an efficient, and effective hybrid ELM methodology that is specifically suited for handling the challenges related to construction engineering problems (i.e., estimation at completion).

1.7 Thesis Outlines

The objectives of this study are met in the following manner. The first chapter of this Ph.D. thesis provides a comprehensive introduction of the research that identifies the research motivations, objectives, and outline of the thesis. Apart from the introduction in chapter 1, the thesis is composed of the following chapters.

Chapter 2 presents an extensive literature review of previous studies conducted on estimation at the completion of various engineering projects. This chapter started with EAC's traditional calculations. Then, the chapter presented an extensive state-of-the-art focus on the researches that have been conducted over the past two decades and covers the latest advances in pure artificial intelligence models as well as an assessment of the surveyed studies.

In chapter 3, the proposed extreme learning machine model is reported. Besides, the benchmark artificial intelligence model is described (i.e., artificial neural network). The input optimization algorithms are also briefly explained. Finally, the case study dataset and modeling development are described.

Chapter 4 showed the results of the modeling applications. There are several performance indicators applied to examine the predictive models. A comprehensive discussion and analysis for the application carried out including the efficiency of the models, the performance of individual and hybrid models, and how much wellness the proposed method in capturing the nonlinearity of the studied problem.

Finally, chapter 5 presents the findings and contributions of this research and proposes several efforts for future research in the domain of project management modeling and particularly on estimation at completion.

2
BACKGROUND

2.1 Introduction

This chapter includes the results of the relevant literature review on Estimation at Completion including history, the overview of the method, the extensions, the drawbacks addressed, and algorithm usage in software projects. Additionally, it presents the review of literature on the parameters that are used to create single and hybrid algorithms and its usage in software projects too.

Poor performances have often been recorded in project management due to its risky nature. The constant environmental changes and other external constraints have made risk management a serious issue in the construction industry [4,39]. Project monitoring must be given adequate attention, (in terms of the close monitoring and detection of deviations and of taking appropriate measures to address any deviations) in order to make a profit. Meanwhile, the initial stage of most construction activities focuses on budget planning, effectively neglecting the impact of changes in the engineering cost and the updating of information during construction [40], and this has prevented an effective detection of the problems associated with project cost control. Owing to the dynamic nature of project conditions upon the commencement of a project, there is a need for a regular revision of the project budget for effective project execution.

One of the managerial and monitoring tools used by project managers is the Earned Value Management [37,41]. The EVM can facilitate the management of the three critical elements of project management (scope, time, and cost) [42]. Most project managers depend on EVM to estimate the project completion time and to make a quick evaluation of the costs of completing scheduled project activities [43]. The estimated EAC can help managers to determine the differences between the actual and planned project costs to resolve any underlying problems. A brief description of the EAC process during the life of a project is displayed in Figure 2.1.

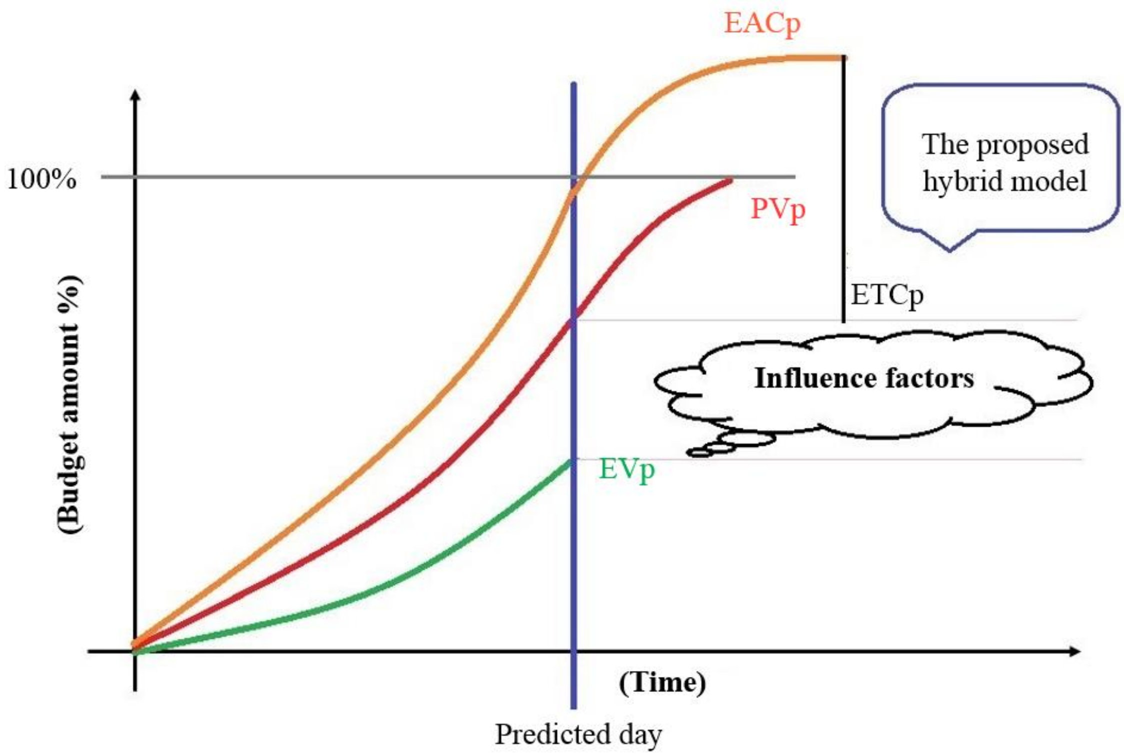

Figure 2.1 A thematic example of the project time and project budget %, and the EAC curve [40]

The practical computation of the EAC demands that managers must first collect data relating to project cost management before using formulas to execute the calculations [12]. The major disadvantage of using formulas for EAC calculation is the numerous available methods for EAC calculations. There are about eight EAC calculation methods in the literature [28]; hence, it is the duty of the managers to judiciously decide the best calculation method that will suit their demands. Project costs are influenced by several factors, and each project has its unique characteristics. Therefore, there is a need to select the best formula that will suit each case. Various regression-based approaches have been developed as an alternative to the index-based approach as advantageous methodologies for performing cost estimation activities [44–46]. The determination of the estimation at completion using soft computing models where the regression problem is introduced and solved and the dependent attribute variables (typically the actual project cost) against an independent variable (a predictor, typically time) configured using nonlinear modeling solution where the respective relationship between the predictor and the response is established.

Due to the uncertain and context-dependent nature of construction projects, it is usually expensive to develop deterministic models for EAC prediction. In this case, an approximate inference which is cost-effective and fast may be the viable alternative [47]. Inference models are used to formulate new facts from historical data, and its processes adaptively change when the historical data are altered. The human brain is naturally endowed with the capacity of inferring new facts from information previously acquired. Therefore, models that can simulate the inference ability of the human brain can be developed using artificial intelligence (AI). The concept of the AI implies that computer systems can handle complex or ill-structured problems using specialized techniques like Artificial Neural Network (ANN), fuzzy logic, or Support Vector Machine (SVM). Since AI-aided computer systems can operate as humans, it may be viable to deploy AI inference models as a tool for handling EAC problems. While trying to construct AI models to handle EAC problems, EAC forecasting has itself been found to be characterized by several uncertainties, and one of these uncertainties is the huge variable data that characterize construction costs. Besides, there are other factors that influence project costs, such as site productivity, weather, and socioeconomic constraints. The individual prediction of these factors is either tedious or near impractical. Therefore, forecasting models must be able to cope with these influencing factors to achieve a desirable EAC prediction.

Cost overrun is a common problem frequently encountered during the construction phase of a project. Hence, there is a need for proactive monitoring of project costs to identify foreseeable problems. EAC assists project managers in the identification of potential problems and helps them to plan for the appropriate measures to address them.

The earned value management (EVM) is the predominant method applied by the project managers for the construction industry to trail the project status and to measure the performance of the project [48]. The actual mechanism of this method is to configure the actual relationship between the planned resource and the targeted project goals. Even though the EVM method is widely implemented for project control, EVM is associated with several limitations. Numerous studies have been established to enhance the main concept of EVM.

An examination of the likeliness of organizing the data envelope analysis (DEA) approach is conducted for the evaluation of the project performances in a multi-project situation [49]. The investigated modeling approach is performed based on EVM and the multidimensional control system. An attempt on the refinement and improvement of the performance of the conventional EVM through the introduction of statistical control chart techniques has been made by Reference [50]. The authors established a control chart for the monitoring of the project performance through a timely detection system. Another study was performed to improve the ability of project managers to give an informative project decision [51]. Plaza and Turetken (2009) suggested the influence of learning on the performance of a project team through an enhanced version of EVM [40]. Pajares and López-Paredes (2011) integrated risk management techniques with the EVM method to develop two new strategies to identify the project overruns [53]. Despite all these attempts to improve the EVM, there are still drawbacks that require more effort to come up with a better solution. Based on the latest review research on the project cost and earned value management conducted by [54], the authors identified 455 articles on this subject and examined 187 papers in their study. The scholars classified the methodologies applied on the project cost monitoring into (i) observational analysis, (ii) extended EVM analysis, (iii) statistical analysis, (iv) artificial intelligence (AI), and (v) computerized analysis. AI models were recognized as the prevailing reliable implemented control system, yet investigations on the application of these models on project performance control are still in the early stages.

The literature evidenced several benefits of early planning to the final outcomes of projects [39,55] but the issue is that these plans cannot be generally applied wholly as they must be reviewed occasionally during the period of the project. Thus, effective project management requires a constantly reviewed project plan to reflect the actual project condition. The necessary actions must be taken to ensure proper control of the project, otherwise, nothing can be done to remedy any bad situation that is detected late (say at the end of the project). Habitually, construction companies normally focus on the project budget planning during the early phase of projects, thereby neglecting the other aspects that could encounter changes during the project, such as cost, information update, & cost management [40]. Despite the importance of cost control construction projects, it is a time-consuming and tedious task owing to the influence of several factors on the project cost; hence, it is important to assess the influence of these factors individually at each project stage [40]. The EAC remains an important cost control performance indicator [56] that needs an accurate calculation to identify the problems and develop appropriate responses. The EVM is a part of the widely used techniques among the project managers to calculate EAC [6,46,57]. This methodology integrated the scope metrics, schedule, and project cost into a single measurement structure in order to analyze and measure the actual project status over its baseline, as well as to estimate the total project cost & duration at completion [41]. The EVM is gaining broader acceptance owing to the increase in its capacity to reduce the problems of EVM, as well as improving utilities [58]. However, there are certain limitations of the traditional EVM methods; for instance, the calculation of the remaining budget using the index-based EVM methods depends on the use of only past information & performance index [59]. Furthermore, the cost prediction from these models is unreliable at the early project stages due to the limitation of EVM data availability. Despite achieving accurate predictions using the traditional EVM methods in some specialized projects, most of the project cases had obvious errors that led to situations where industries may not know the appropriate approach to be employed for their project prediction. The EVM is also suffering from the need to manually perform reviews owing to its application to each project process. This makes EVM a tedious and time-consuming technique. As such, there is a need to computerize the engineering management process if EVM is to be deployed effectively for project cost control. Powerful computers are normally used by construction companies to analyze the early stages of construction projects. However, such computer systems are not equipped with the capability to respond to changes at each project stage or to predict the EAC of construction projects using the EVM method. Therefore, the development of artificial intelligence (AI) models that can solve this problem is extensively attractive for project engineering scholars.

The cost management results generated from the contractor to Government in the Schedule/Cost Status of Cost Performance Reports can be employed to compute EAC through the formula. The review pieces of literature in this chapter assumed that the results are realistic. The data reliability relies on the level whereby the contractor complies with a powerful structure on the inner controls that involve the contractual effort analysis, budgeting, and scheduling.

2.2 EAC Indexed Formulations

The formulas of EAC depends on the aggregate of different data elements illustrated in the cost management report: Actual Cost of Work Performed (ACWP); Budgeted Cost of Work Performed (BCWP); and Budgeted Cost of Work Scheduled (BCWS). The data elements are reported per month. The average and cumulative data are later evaluated throughout the lifetime contract [28].

The EAC formulas can be grouped into 3 sections such as artificial, regression, and index intelligence modeling methodologies. This Equation 2.1 illustrated the generic index-based formula:

$$EAC = ACWPc + (BAC - BCWPc)/Index \tag{2.1}$$

The cumulative data is indicated by subscript "c" while the aggregate budget for the recognized work is the budget at completion (BAC).

The index (BCWS, BCWP, and ACWP) is utilized in balancing the budgeted cost of the leftover work on the contract (BAC - $BCWPc$). The adjustments of the reflectiveness of future performance, schedule performance, and contract's past cost are regarded as the assumption implicit. The index performances are grouped into 4 classes:

$$\textit{Cost Performance Index: } CPI = BCWP/ACWP \tag{2.2}$$

$$\textit{Schedule Performance Index: } SPI = BCWP/BCWS \tag{2.3}$$

$$\textit{Schedule Cost Index: } SCI = SPI * CPI \tag{2.4}$$

$$\textit{Composite Index: } CI = W_1 * SPI + W_2 * CPI \tag{2.5}$$

The weights (W_1 & W_2) illustrated in Equation 2.5 can be represented by any value from 0 to 1 which are usually added to unity.

These indices depend on average, cumulative, and monthly data. All these labeling conventions are used, and such includes: "CPI_m" demonstrated CPI averaged over x

number of months; “CPI_c” shown as cumulative *CPI*; and “CPI_m” illustrated as a CPI based on the most recent months, starting with the most current moment and moving backward. For instance, CPI_3 showed a 3 months average *CPI* including the recent and past 2 months. *SCI* and *SPI* utilized similar conventions. For instance, “SPI_6” represents 6 months average SPI including the recent and past 5 months.

The average indices can be classified into 2 ways. Generally, the average index is described as the ratio of the aggregate through x months [60].

$$CPI_x = \sum BCWP_x / ACWP_x \tag{2.6}$$

$$SPI_x = \sum BCWP_x / BCWS_x \tag{2.7}$$

Alternatively, it can be described by dividing the sum of monthly indices by the correct number of months.

$$CPI_x = \frac{\sum CPI_m}{x} \tag{2.8}$$

$$SPI_x = \frac{\sum SPI_m}{x} \tag{2.9}$$

Therefore, this study determines the average index based on Equations 2.6 and 2.7.

The EAC formula of the second and third classes is defined as EAC formulas that are referred to as “regression” and “other.” The regression-dependent formulas are obtained through the use of nonlinear or linear. In this study, nonlinear regression was used to analyze the nonlinear relationship, notwithstanding whether it can be changed to a linear relationship 3. Otherwise, the independent variable (BCWP) and the dependent variable (ACWP) are generally performance time. The formula-based on heuristic is the other group that is present in the first two groups.

Obviously, the EAC formula is possibly infinite numbers. The expert has the choice to decide which group of formula to be utilized. In 1991, a performance analyzer, which is a famous software package that enables the analyzer to choose from the different formula was used. Although, there is no guided instruction concerning any accurate form of a formula. The other part of this study reported the reviewed on EAC for the past sixteen years.

2.3 EAC Computation Using the Empirical Formulation

Modeling methodology is the new formula used in describing Empirical EAC formulations. Mostly, statistic methods are required by each of these studies and they do not lend themselves to comparative analysis.

Base on the weights of the composite index four empirical techniques have been reported [61–64]. The proposed formulation is subjectively assigned based on the weight. Due to the SPI movement to unity, these studies proposed that the SPI could finally lose its content information. As the contract moves forward to completion, the weight given to SPI should be reduced to zero accordingly. However, Haydon obtained a point measured from a range of EACs using the different index-based formula in the fifth study [65].

In 1977, Jakowski (Navy Aviation Systems Command, 1977) suggested that to estimate the weight of the composite index there is a need to use a more difficult heuristic [61]. In the current monthly CPIs, it showed an important reduction. If this occurs an optimal weight of composite index must be utilized. The optimal weighting can be referred to as the weight of the smallest historical standard deviation in the composite index. *CPIc* is utilized after a sixty percentage completion point. Jankowski's heuristic authentic evidence could not be explained and located by [66].

In 1980, Lollar suggested that the cumulative CPI and SPI weight was an absolute value of schedules and relative contribution to the cost variance percentages [62]. Lollar's technique was added as one of their comparative studies by Blythe Cryer (1986) and (1982). Other formulas may not be applicable to it [67,68].

Parker's (Defence Logistics Agency, 1980) technique is made up of composite indices with an estimated range of weight between 0 to 1 and increases by 0.1 [63]. Then, the subjective decision would be made by the specialists to decide which composite index suitable to be used at any given condition of the contract.

Appropriate conversion of variables can be applied to the general linear regression model to inherent linear models. However, a good example is a logistic curve with nonlinear cumulative cost growth patterns that can be changed into a linear pattern before measuring by normal least squares.

Totaro (Defence Logistics Agency 1987) proposed that a function of a complete percentage could be used in estimating the weight of the composite index [64]. The analysts were subjectively allocated proceeding weights for the *CPI* and *SPI* were after due consultations on the program properties including manpower loading forecasted by the contractors.

In 1982, Haydon and Riether (NAVWESA), 1982) reported that a method was established to calculate a computed EACs from a range by applying different formula [65]. Firstly, index-based formulas are used in computing a range of EACs as estimated by [66]. Secondly, to estimate the EAC, the range is increased by 2.5% and then the increased range median is calculated as the estimated. According to an analysis of twenty-one nearly completed contracts (six productions and fifteen development) supervised by the Navy and when the contractor's EAC was smaller than point estimated where 79% of the time accurately forecasted. A specimen worksheet for a numerical and procedure are provided.

2.4 EAC Regression-Based Methodologies

Regression-based technique. On defense contracts, 3 non-comparative studies were conducted with the use of regression analysis to miniature the curvilinear cumulative cost growth profile. The methods revealed in the studies are well complicated, documented, and demand a significant regression analysis and because of this, it will be difficult to execute.

According to Sincavage in 1974 (Army Aviation Systems Command, 1974), a study reported that to forecast the EAC it requires time series [69]. Time Series Analysis for Army Internal Systems Management requires the use of a computer-based model in autoregressive, moving average or union of the two-time series analysis method. Henceforth, it will require enough data for many months before this can be established because of the statistical challenges of autocorrelation. Consistently, at the end of a contract, the only model would be helpful. The authentic documentation has been lost according to the author's discussions.

According to Olsen, et al. in 1976, they used the B-1 system program office to report a time series predicted method technique used by the B-1 System Program Office [70]. General Electric created a computer program that is known as “GETSA” and the B-1 SPO leased it to predict EACs. Exponential and analysis smoothing methods are shortly reported. Several samples are given.

Busse, (1977) suggested that to create a non-linear regression-based model, it requires different methods [71]. But, Busse showed no similarity with the Karsch model [72], and a number of samples were given based on Karsch data. The Karsch model had provided enough of accurate EACs as Busse results were compared with that of Karsch at different contract completion stages.

Weida, (1977) suggested that a normalized S-curve was developed with the help of nonlinear regression analysis to fit the program data [73]. After statistical problems (autocorrelation and heteroscedasticity) and data for inflation have been adjusted. Weida reported on each of the twenty-two development contracts that were supervised as the S-curve of the cumulative cost growth. Then, the normalized S-curve was used predictive and comparative. But, Weida’s methods were very is compelling, cumbersome, and needs careful attention.

Chacko, (1981) recommended the use of time series predicting methods called adaptive forecasting. Chacko reported that about 5 months of data are needed before and possible accurate estimation could be made [74]. Significantly, as the data becomes possible at each month, the data for the forecasting model changes.

Watkins, (1982) reported the use of adaptive technique and linear regression analysis in the form of the Rayleigh-Norden model [31]. Watkins explained that phase-out and pattern of the manpower life cycle of a defense program were described by the Rayleigh-Norden model. This study made use of linear regression analysis of ACWP as against the time. Data collected quarterly from 3 contracts submitted by the C/SSR were utilized in the regression analysis and the inflation data was adjusted and there was no autocorrelation adjustment.

El-Sabban, (1973) established that EAC was measured through the help of Bayesian probability theory [75]. This technique deduced a variance, mean, and daily probability distribution. Bayes’s formula was used to correct the EAC as the recent ACWP data became accessible. This is easily helpful at untimely stages of each contract because the models are not relying on the ancient history of the performance data. Generally, the technique was openly demonstrated but later, its accuracy was questioned by [76]. A sample was given.

Holeman, (1974) suggested that a product improved technique was used in creating the EAC through an established performance factor to detect the subject judgment [77]. Such as the performance factor and performance index were included in a linear combination of variables (cost history, technical risk, overhead fluctuations, schedule variances, inflation, and contract changes). To determine the relative of each contribution belongs to the analyst's decision. Holeman recommended a subjective simulation to evaluate and determine the range of EACs.

EVM index-based techniques used to determine the cost of completion of an ongoing contract are famous for their restriction inherent with early-stage and past EVM unreliability. These constraints were solved by a new suggested CEAC methodology that relied on the model index-based formula to predict the expected cost through a non-linear curve fitting for the Gompertz growth model [46]. Furthermore, cost performance was suggested as a factor affecting the schedule progress of an equation accounts. Conclusively, the exact period of completion was shown by an Earn schedule-based factors. The acclaimed model was demonstrated to have been more precise and accurate in every estimated stage being middle, early, or late than the other four local index-based formulas in their comparison. The project managers need to create practical tools in form of methodology to improve their status by CEAC and spreading EVM research to achieve a better relationship between schedule and cost factors.

Landa-Torres et al., [78] presented a novel hybrid soft-computing approach for evaluating the internationalization success of a company based on existing past data. Specifically, we propose a hybrid algorithm composed of a grouping-based harmony search (HS) approach and an extreme learning machine (ELM) ensemble. The proposed hybrid scheme further incorporates a feature selection method, which is obtained by means of a given group in the HS encoding format, whereas the ELM ensemble renders the final accuracy metric of the model. Practical results for the proposed hybrid technique are obtained in a real application based on the exporting success of Spanish manufacturing companies, which are shown to be satisfactory in comparison with alternative state-of-the-art techniques.

Salcedo, et al., [79] introduced a new hybrid bio-inspired solver which combines elements from the recently proposed Coral Reefs Optimization (CRO) algorithm with operators from the Harmony Search (HS) approach, which gives rise to the coined CRO-HS optimization technique. Specifically, this novel bio-inspired optimizer is utilized in the context of short-term wind speed prediction as a means to obtain the best set of meteorological variables to be input to a neural Extreme Learning Machine (ELM) network. The paper elaborates on the main characteristics of the proposed scheme and discusses its performance when predicting the wind speed based on the measures of two meteorological towers located in the USA and Spain. The good results obtained in these experiments when compared to naïve versions of the CRO and HS algorithms are promising and pave the way towards the utilization of the derived hybrid solver in other optimization problems arising from diverse disciplines.

Manjarres, et al., [80] presented reviews and analyzes the main characteristics and application portfolio of the so-called Harmony Search algorithm, a meta-heuristic approach that has been shown to achieve excellent results in a wide range of optimization problems. As evidenced by a number of studies, this algorithm features several innovative aspects in its operational procedure that foster its utilization in diverse fields such as construction, engineering, robotics, telecommunications, health, and energy. This manuscript will go through the most recent literature on the application of Harmony Search to the aforementioned disciplines towards a three-fold goal: (1) to underline the good behavior of this modern meta-heuristic based on the upsurge of related contributions reported to date; (2) to set a bibliographic basis for future research trends focused on its applicability to other areas; (3) to provide an insightful analysis of future research lines gravitating on this meta-heuristic solver.

Banerjee, et al., [81] proposed opposition-based HS (OHS) of the present work employs opposition-based learning for harmony memory initialization and also for generation jumping. The concept of the opposite number is utilized in OHS to improve the convergence rate of the HS algorithm. The potential of the proposed algorithm is assessed by means of an extensive comparative study of the numerical results on sixteen benchmark test functions. Additionally, the effectiveness of the proposed algorithm is tested for reactive power compensation of an autonomous power system. For real-time reactive power compensation of the studied model, Takagi Sugeno fuzzy logic (TSFL) is employed. Time-domain simulation reveals that the proposed OHS-TSFL yields on-line, off-nominal model parameters, resulting in real-time incremental change in the terminal voltage response profile.

Acebes, et al., [82] describe a new integrated methodology for project control under uncertainty. This proposal is based on Earned Value Methodology and risk analysis and presents several refinements to previous methodologies. More specifically, the approach uses extensive Monte Carlo simulation to obtain information about the expected behavior of the project. This dataset is exploited in several ways using different statistical learning methodologies in a structured fashion. Initially, simulations are used to detect if project deviations are a consequence of the expected variability using Anomaly Detection algorithms. If the project follows this expected variability, probabilities of success in cost and time, and expected cost and the total duration of the project can be estimated using classification and regression approaches.

Lee [83] introduced a software, Stochastic Project Scheduling Simulation (SPSS), developed to measure the probability to complete a project in a certain time specified by the user. To deliver a project by a completion date committed to in a contract, several activities need to be carried out. The time that an entire project takes to complete and the activities that determine total project duration are always questionable because of the randomness and stochastic nature of the activities' durations. Predicting a project completion probability is valuable, particularly at the time of bidding. The SPSS finds the longest path in a network and runs the network the number of times specified by the user and calculates the stochastic probability to complete the project in the specified time. The SPSS can be used by a contractor: (1) to predict the probability to deliver the project in a given time frame and (2) to assess its capabilities to meet the contractual requirement before bidding. The SPSS can also be used by a construction owner to quantify and analyze the risks involved in the schedule. The benefits of the tool to researchers are: (1) to solve program evaluation and review technique problems; (2) to complement Monte Carlo simulation by applying the concept of project network modeling and scheduling with probabilistic and stochastic activities via a web-based Java Simulation which is operatable over the Internet, and (3) to open a way to compare a project network having different distribution functions.

To increase the accuracy of an untimely predicted final cost of completion in ongoing construction projects, CEAC which is the latest regression-based nonlinear was suggested to combine an earned schedule concepts with the growth model [41]. For the construction work at the early and middle stages, CEAC computations were given by this methodology. Lastly, this study would be focusing on three main objectives. (i) To establish the latest formula that would depend on the combination of four candidate growth models (Weibull, Bass, Gompertz, and logistic) and ES technique, (ii) To authenticate the latest methodology via its utilization over past nine projects and (iii) To determine the equation via statistical validity with the most performing growth model and to differentiate the perfection in the CEAC estimates. Based on the differentiation in their CEAC errors and the statistical analysis of the four growth models, the CEAC formula generated perfect final cost estimates more than those analyzed with the help of an index-based technique and three other models and most fitting by relying on the Gompertz model. The methodology that was suggested has a theoretical involvement by integrating regression-based studies with the earn-value metrics. It could also be brought about practicable undertones connected with the perfect predicting method and applications of variables that would be considered the impact of a timetable to be a major factor of cost behavior.

2.5 Artificial Intelligence Models for EAC Computation

Various factors such as cost management, cost budgeting, engineering design, project evaluation, and conceptual cost, play a significant function in the construction work feasibility studies. The expert's instinctive experience was practically relied upon by the construction cost estimates. Knowledge-based techniques must be established and used during the design stage and project planning to enhance the accuracy of the conceptual cost estimate. A latest advancement fuzzy neural network was suggested to have shown improvement in the accuracy of the cost estimation [84]. The basic merits of the neural network, fuzzy logic, and genetic algorithms are integrated to form one union known as an intelligent predictive model. This model was created to provide an optimal solution against any difficult situations. In summary, two different types of estimators were provided by the authors at the early stages of the construction projects to precisely calculate the conceptual construction cost.

The problems faced during construction projects are commonly serious and the project decision-makers must be allowed to work freely in an area that is fraught with unreliable and complex conditions. So many intuitive decisions should be made on the established restricted intuitively information and to make a prosperous decision it relies on 2 factors such as the quality of skills acquired by the expert(s) involved and the quality of past experience and knowledge obtained. Knowledge is affected by different factors that could make its accuracy and cause its value to be destroyed. In using and retaining experiential understanding an alternative inference model method has been developed through the application of a support vector machine an evolutionary fuzzy neural network [85]. This study would suggest two simulations of the hybrid intelligent model as successful to solve different construction management challenges in the construction industry.

The Conceptual cost estimates showed a significant influence on project success and practical studies. This kind of estimations gives important information that could be helpful in cost management, cost budgeting, and project evaluations. The conceptual cost estimate accuracy could be improved using an EFHNN (evolutionary fuzzy hybrid neural network), which was reported by [86]. Firstly, this technique must combine HONN (high-order neural networks) and NN (neural networks) to form HNN (hybrid neural network) which can function by alternating non-linear and linear neuron layer connectors. FL (Fuzzy logistics) was then utilized in the hybrid neural network (HNN) in maintaining an unrealistic approach that could develop the hybrid neural network HNN) into an FHNN (fuzzy hybrid neural network). FHNN is optimized by using a genetic algorithm on the FL and EFHNN was used as the last version. In this study, the category and overall cost for the actual projects were estimated and differentiated. The results have shown that EFHNN could provide an accurate and efficient cost estimator during the course of untimely construction work. Furthermore, in EFHNN the performance of non-linear and linear neuron layer connectors exceeded that of a singular linear neural network (NN).

The project managers that determine the total costs of the projects at the point of completion is referred to as the EAC. These tools are significantly employed in monitoring project risk and performance. The executive is well known for taking a high-performance decision but lacks the technical understanding that may bring about decision errors. To calculate EAC, it requires the integration of PSO (swarm optimization algorithm) with GP (Gaussian process) an evolutionary predictive-based model [87]. The suggested model was integrated with the artificial intelligent technique to imitate human decision-making behavior to provide a solution to problems related to management. The GP model was utilized to estimate the relationship between the output and input variables and to optimize the hyper-parameters in the data function using PSO as an optimization tool. This study will examine the functions of the suggested hybrid model to estimate changes in the predictive model and to measure the EAC. This model gives an authentic direction on the EAC estimates that can be of help to the project managers to make project cost controls effectively. The learning results have been validated with real construction project data.

EVM is generally used as a well-organized technique for both EAC prediction and status detection. The local methods used in EAC predictions are generally involved in distributing the recent condition of a project to the future using past performance methods. Feylizadeh et al. (2012) reported that FNN (fuzzy neural network) model can be used to predict the future cost and EAC events [88]. The suggested method included both quantitative and qualitative factors that can affect the EAC forecast. This model was executed on a real-world case study where it provided encouraging initial results.

Most of the time, construction projects are faced with cost overruns. Hence, a dynamic technique is important for examining the costs of projects and identifications of prospective challenges. In construction management, EAC is used to assist the manager of a project in recognizing prospective challenges and generate adequate solutions. The appropriate support vector machine model (WSVM), fast messy genetic algorithm, and fuzzy logic were implemented in this study to curb distinct features for predicting EAC [89]. The WSVM model was utilized as a managed learning method that can treat the characteristics of time series data. Whereas, the fuzzy logic model was focused on improving the capability of a model for an adequate solution and to tackle the uncertainty associated with EAC prediction. The results obtained from the simulation showed that the newly postulated model has attained a noticeable enhancement for EAC modeling.

Using a Bayesian technique depending on the expert opinion elicitation allows the utilization of subjective judgments in a formal and rigorous way; generating an enhanced accuracy in estimating the completion amidst the EVM framework. Caron et al. (2013) used the advantage of this model as an integration of experts' understanding of the project information records to generate more valuable support tools and future-oriented giving room for the enhancement of the forecasting processes [90]. Hence, this estimates adequate development in the process of decision-making regarding project control. The efficiency of a proposed model lies in its strongness in the individual project stage, most especially at the initial stage of the project as the information data are scarcely or scantly reliable. Additionally, it authorizes the evaluation of a confidence range explaining the subsequent phase of the project. The use of the Bayesian method in the project associated with oil and gas industries shows its effectiveness and applicability. Moreover, the obtained results suggested that a similar method could be employed in other establishments to increase the project control processes. The Bayesian model was translated to a software package giving chance for higher user-friendly management of output and input information.

In 2017, new research was developed to establish an automated technique for time for constructing a using the artificial neural network (ANN) [91]. The authors surveyed the literature and expert surveys, the factors that significantly affect the dam construction was recognized. Several data ranges from Iranian dam projects were employed to propose seven ANN models. Various datasets were employed to attain an excellent outcome through the assessment of the correlation values and root mean square errors as the validity and reliability indicators. In the end, a web-based automated prototype was generated and verified to allow the stakeholders to evaluate the time for the dam projects using the ANN technique and the importance of improved infrastructure project management practice.

For better visualization and analysis for the state-of-the-art AI models on cost project management, Table 1 tabulates all the conducted studies over the past decade, with a research remark for each. AI models are presented as a reliable alternative modeling strategy to overcome the problems associated with the indexed procedures to compute the EAC. AI models are distinguished by their capability of solving complex problems by imitating the analytical capability of the human brain. Over the past thirty years, there has been a massive successful utilization of AI models in several areas of science and engineering.

Although there have been several investigations since 2008 on cost project estimation using AI models, the topic is still associated with various limitations and requires more efforts from scholars to figure out new solutions with more robust/concrete modeling strategies. Based on the presented researches in Table 1, a few studies have been explored for EAC prediction. Also, these studies reported several limitations of the AI model, such as the black-box nature, the requirement of a significant amount of data, overfitting, models' interaction, and time consumption [92]. Among several AI models, the artificial neural network, support vector machine, and adaptive neuro-fuzzy inference system have been majorly used.

A new version of ANN called the extreme learning machine (ELM) model was proposed by Reference [93]. Over the past three years, the ELM model has been improved and applied to multiple engineering applications and with more applicability for solving complex problems characterized by non-linear and stochasticity behaviors [94,95]. The massive and solid implementation of the ELM model encouraged the main authors of this current research to develop this model for EAC simulation with the aim of achieving a robust expert system for construction project management sustainability.

In ELM Algorithm Parameters: The results of the experiments are obtained as the average of 30 executions of each algorithm in each dataset, showing also the standard deviation of the results. In the process of initialization of the harmonies, these were initialized randomly between −1 and 1 and the ELM had 50 nodes in the hidden layer, while the activation function is the Sigmoidal. The parameters used for all algorithms are summarized in the Appendix. It is necessary to carry out a detailed parameter tuning process for all the algorithms since at the time the most recommended in the literature were used.

The procedure used to carry out the learning process in a neural network is called the optimization algorithm (or optimizer). There are many different optimization algorithms. All have different characteristics and performance in terms of memory requirements, processing speed, and numerical precision. Some important optimization algorithms are described.

1. Gradient descent.
2. Newton method.
3. Conjugate gradient.
4. Quasi-Newton method.
5. Levenberg-Marquardt algorithm.

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The learning problem is formulated in terms of the minimization of a loss index, f. It is a function that measures the performance of a neural network on a data set. The loss index is, in general, composed of an error and a regularization terms. The error term evaluates how a neural network fits the data set. The regularization term is used to prevent overfitting by controlling the sufficient complexity of the neural network.

2.5.1 Levenberg-Marquardt Algorithm (LM)

The Levenberg-Marquardt algorithm, also known as the damped least-squares method, has been designed to work specifically with loss functions, which take the form of a sum of squared errors. It works without computing the exact Hessian matrix. Instead, it works with the gradient vector and the Jacobian matrix.

The Levenberg-Marquardt algorithm can only be applied when the loss index has the form of a sum of squares (as the sum squared error, the mean squared error, or the normalized squared error). It requires to compute the gradient and the Jacobian matrix of the loss index.

new_parameters=parameters−Jacobian·gradient·damping_parameters

Table 2.1 The surveyed literature of artificial intelligence models' implementation on cost projects over the last decade

Scholars References	Research Remark
[35]	The study was conducted on the usage of the Artificial Neural Network (ANN) model to simulate project cost with the aim to improve the earned value management (EVM) system. The finding evidenced the applicability of the intelligent model to minimize the project cost overruns.
[85]	The integration of a support vector machine with a fast-messy genetic algorithm (SVM-FMGA) was performed for construction management monitoring. The validation of the model approved the estimation of the building cost over the conceptual cost estimation.
[86]	The study inspected a conceptual cost estimation using the evolutionary fuzzy hybrid neural network for industrial project construction. The research outcomes exhibited another optimistic finding for a precise cost estimation at the early stages.
[56]	An independent intelligent based on the weighted support vector machine model and the fuzzy logic set was studied for EAC prediction. The fuzzy model was applied to solve the associated uncertainty in the tie series data.
[88]	A fuzzy neural network was used to determine the EAC. The modeling was piloted based on various factors (both qualitative and quantitative) that influence the EAC value. The results demonstrated good outcomes from the contractors' and managers' aspects.
[90]	The authors investigated a relatively new model based on the Bayesian theory integrated with the EVM framework aiming to compute the EAC. The proposed model evidenced its applicability and effectiveness in modeling the estimation at completion.
[46]	The scholars developed a new cost EAC methodology by integrating the Cost Estimate at Completion (CEAC) method and four growth models and concluded that the EAC formula based on the Gompertz model outperforms the other indexed formulas.
[96]	The support vector regression model was analyzed to perform the EVM. The authors concluded that their model outperformed the available best performing EVM methods through the training of the identical data set.
[91]	An automotive programming approach based on the ANN model was proposed for estimating the EAC element of a dam construction project. The results demonstrated a remarkable performance for the investigated case study.

Considering the limitations of the introduced EAC estimation methods, the use of AI techniques to develop a fast and effective system that will consider the problems related to cost control during the project execution for EAC prediction becomes necessary. In this regard, this study aims to address the identified project cost management-related issues by pooling the relevant historical data and studies on project cost management in order to identify the significant factors that affect project cost. Historical data were sourced from several construction projects located in the UAE region. The study information was used to set up the trend of a project cost flow while the estimation of the relationship between monthly cost and project EAC was based on historical experience & knowledge. The historical data was used to develop the extreme learning machine (ELM) model (a novel intelligent model) for the prediction and control of changes in EAC during the project cycle. The validation of the proposed ELM model was done against classical ANN models. In the second stage of this work, a hybridized predictive model was implemented by coupling the ELM and ANN models with global harmony search (GHS) and brute force (BF). Those input selection phases were applied as a prior stage for the predictive model to ensure the allocation of the correlated attributes and to develop a predictive model that is accurate.

3
METHODOLOGY

3.1 Introduction

The aim of this chapter is to address the applied stand-alone and the hybridized machine learning models for predicting estimation at completion for civil engineering construction projects. In general, the chapter provides an overview of the machine learning modeling relevantly to this thesis and in particular for supervised learning processes. This is followed by the proposed hybridized non-tuned machine learning approach “extreme learning machine” integrated with the global harmony search algorithm in addition to the classical artificial neural network model as a comparable machine learning data-driven approach.

3.1.1 Supervised Learning Approach

The problem that we deal with here is a regression problem in which the goal is to model the relationship between a set of explanatory variables(s) x_i and the corresponding target variable y_i, where the subscript i designates the sample. In more details, assume is given a set of data $(xi, yi)_{i=1}^{N}$and required to model the relationship between the input variable(s) x_i and the output variable y_i as a function of f, such that $f(x_i)$ matches $y_i$as closely as possible. This case is often denoted as a functional approximation. In case the target variable $y_i \in \Re$, this is known as a regression problem; whereas, if the target variable y_i corresponded to a category or class, this is known as a classification problem.

Supervised learning models normally strives to educate and learn the complex relationship between the inputs and output. For instance, the future pattern of the studied problem needed to be predicted based on the given related variables associated with the target variable variability. Models are normally used to learn and capture a particular relationship with a certain structure pre-determined by the model parameters and a related learning algorithm with its hyper-parameters. Sometimes, the set of possible models are referred to as the hypothesis space [97], and the learning algorithm is saddled with the task of determining the most appropriate model (based on certain criteria, such as accuracy) from the hypothesis space that can best represent the input-output data relationship and be accurately used to predict the output for potential inputs.

The optimization of a models' structure requires the evaluation of several models with different parameters using certain criteria. For instance, neural network models can differ in various aspects, such as the type or number of hidden layer neurons; the number and type of input variables, as well as the training algorithm & its parameters. Literature evidence suggests that model accuracy remains the commonly used criterion [98], but being that future samples normally differ from the currently available samples, there is a need to ensure model generalization to this new future data as accurate training data modeling may not just be enough.

3.1.2 Functional Approximation Theory

In this sub-section, a multivariate perdition problem which is an example of the functional approximation problem is highlighted. The task of predicting the future values at a specific regression problem is based on the anticipated prediction attributes (i.e., the correlated actually variables to the targeted variable). One possibility for using past data to predict the future event (i.e., the next value of time series at the time (t +1)) as a function of the previous values d time step. However, the problem of one-step-ahead time series forecasting can be expressed as follows:

$$y_i = f(x_i, \beta) \tag{3.1}$$

where x_i is a 1 x d vector $[x(t-d+1), \dots, x(t)]$ with d the number of past values that are used as input, and y_i the approximation of $x(t+1)$. Depending on what kind of relationship is expected to exist between the input variable(s) and output variable of a given problem, the regression is performed on either the input variables themselves or nonlinear transformations of them; for instance, artificial neural networks perform linear regression on nonlinear transformations of the input variables (i.e. the outputs of the hidden layer) and the target variables.

Machine learning models are a very interesting and challenging domain. As George Box (1970) defined them "All models are wrong, but some are useful" [99]. The main concern of the machine learning models is to extract useful information or insights from the given data set.

It is a very known context that EAC phenomena are characterized by high stochasticity in which having a random probability distribution or pattern that may be analyzed statistically but may not be predicted precisely [87,88]. Thus, it is very vital to establish an efficient computational approach (i.e., machine learning algorithm) that can yield a notable expert model in capturing the non-linearity and the complexity of the EAC pattern [100]. Most recently, one specific non-tuned machine learning algorithm has gained remarkable popularity which is an extreme learning machine (ELM) [93]. ELM is distinguished by processes. As a result, the effectiveness of this random initialization and fast training shows that the ELM model is very appealing for such a variance of EAC pattern.

Initially, the extreme learning machine approach is proposed by Huang et al. [93]. This name is represented the neural network that employs the randomization of the hidden layer weights and determines the output weights analytically. In the typical context, the foregoing features of the ELM model are superior over the iterative algorithms for example artificial neural network approach [101].

3.2 Extreme Learning Machine (ELM) Model

ELM comprises of a set of NN models that depend on a fast training algorithm and hidden layer weights randomization [94]. In the ELM, the hidden layer is randomly initialized rather than the hidden layer and output weights optimization using an iterative algorithm such as backpropagation [102]. ELM training involves solving the linear system that is defined by the outputs and targets of the hidden layer. The ELM has been proven capable of universal non-constant piecewise continuous function optimization despite the randomness of its hidden layer weights [93,103]. Owing to the speed and universal acceptance of the ELM, it has become a popular framework over the past decade. The name ELM has popularized the randomization concept of the hidden layer of NN; the name has also been associated with numerous types of models and extensions of NN with randomized weights, such as Single-Layer Feedforward Networks (SLFNs) [93].

Owing to the issues of the conventional machine learning models (e.g., ANN), the ELM was proposed as a new technique to address these problems [93,103]. In this context, the term "*extreme*" depicts a high capability of the algorithm to mimic the behavior of the human brain within a short modeling time [103]. The ELM has a simple and unique learning process because the hidden neurons do not require any tuning process during the learning phase [93]. Contrarily, human intervention is required in the conventional learning methods like the ANN or SVM especially in establishing the most appropriate model parameters. The ELM has an advantage over the conventional data-intelligent model's framework due to its role in formulating data-intelligent expert systems for application in real-life situations (*e.g.*, [104,105]). The ELM has over the last five years been used in solving several problems such as clustering, feature learning, classification, and regression with a significant level of performance and learning capacity [106–110].

Up to date, studies on the predictive ability of the ELM in modeling project management are yet to be reported. Hence, in this work, the novelty of the ELM lies in its rapid rate of learning based on the single-layer feedforward network (SLFN), which was proposed for EAC simulation. It can also generalize data features with greater efficiency compared to other soft computing techniques [111]. Figure 3.1 displayed the graphical representation of the ELM general architecture for the applied application. In the current study, the input parameters in this study are cost variance (CV), schedule variance (SV), cost performance index (CPI), schedule performance index (SPI), subcontractor billed index, owner billed index, change order index, construction price fluctuation (CCI), climate effect index. Whereas, the EAC is the response that will be evaluated. The input and output variables are connected by the hidden nodes in the phase space in a fashion that allows features determination by the randomly generated input and output weights.

The ELM was used to process the input data through an M-dimensional mapping feature space which randomly determines the internal weights. The following mathematic procedures governed the output network [93]:

$$F_{(x)} = \sum_{i=1}^{M} \beta_i h_i(x) \tag{3.2}$$

where β_i represents the weight of the output matrix that connected the targeted phase to the hidden layer space, h_i is the output of the hidden nodes for the input variables (x), while M is the dimension of the feature space of the ELM. Thus, the ELM model can be used to solve the regression problem that featured the EAC and the various construction project variables. The learning process of the ELM model can present the following form [93]:

$$H\beta = T \tag{3.3}$$

Where H is the feature space for the "hidden zone output matrix" M, while T defines the target matrix. The ELM learning operation mainly targets at obtaining the least error as per the term: $Minimize$: $\|H\beta - T\|$ and $\|\beta\|$ while the hidden output layer H can be expressed thus:

$$H = \begin{bmatrix} h_1 x_1 & \cdots & h_M x_1 \\ \vdots & \ddots & \vdots \\ h_1 x_N & \cdots & h_M x_N \end{bmatrix} \tag{3.4}$$

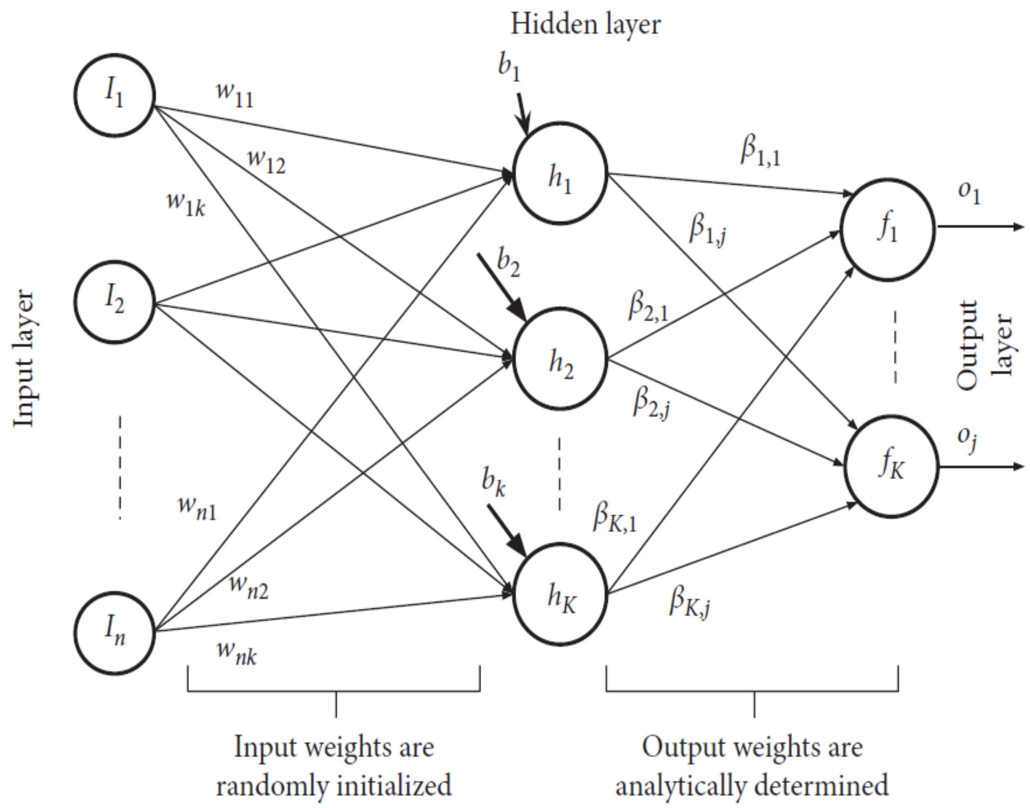


Figure 3.1 The basic structure of the ELM model network [112]

The ELM model was established based on reported Algorithm 1.

Algorithm 1 standard ELM

Given a training set$\{(x_1, y_1), \dots, (x_t, y_t)\}$, $x_t \in \Re^d$ and $y_t \in \Re$. The probability distribution to draw the random weights, an activation function $f: \Re \mapsto \Re$ and Λ the number of hidden nodes:

1: - Randomly assign input weights and biases.

2: - Calculate the hidden layer output matrix

3: - Calculate output weights matrix

3.3 Artificial Neural Network (ANN) Model

The ANN is developed as a statistical optimization method that mimics the behavior of the biological nervous system [113,114]. They can generate logical models composed of several neurons that are interconnected in a computing environment. ANNs are ideal in establishing solutions to complicated modeling problems like classifying, pattern recognition, or estimating [115]. These three modeling procedures are predominately used in the development of an ANN. The ANN is symbolized like a graph where patterns are represented in terms of the numerical values attached to the nodes of the graph, and transformations between patterns achieved via simple message passing algorithms (Figure 3.2).

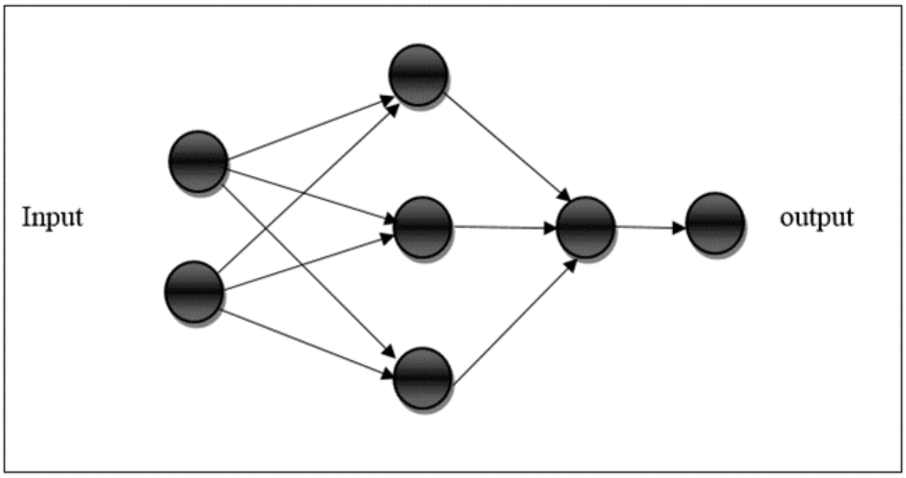


Figure 3.2 ANN architecture [116]

The input value and the corresponding set the desired target (output value used to train and test the ANN) is called a pattern. ANN may be trained to perform a particular function by adjusting the values of the connection (weights) between elements. Commonly ANN is adjusted or trained so that a particular input leads to the specific target output. Such a situation is shown in Figure 3.3. The network weights are adjusted based on a comparison of the output (output calculated by the network) and the target (desired output that corresponds to the output pattern) until the network output matches the target.

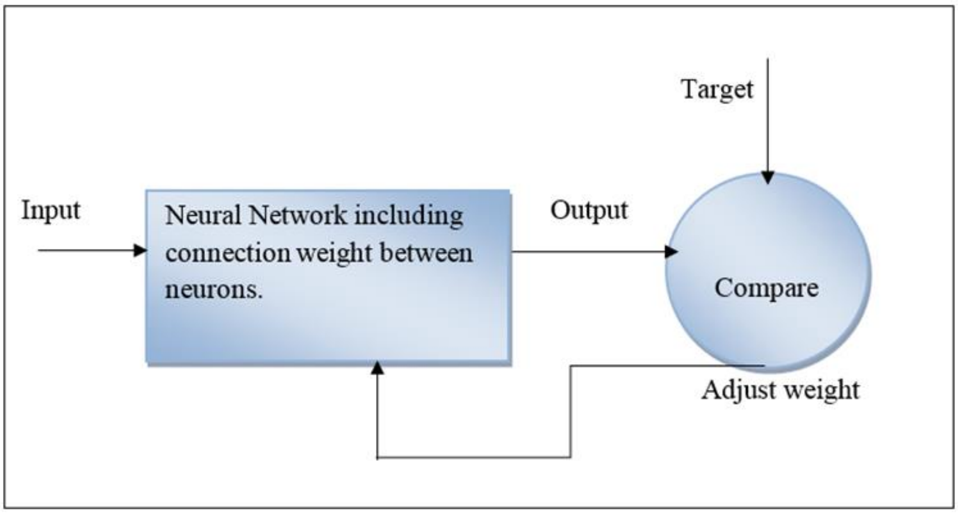


Figure 3.3 Adjust weight between neurons [117]

The McCulloch-Pitts (M-P) PE make simply a sum-of-products followed by threshold nonlinearity as shown in Figure 3.4 [118]. Its input-output equation is:

$$Y = f(net) = \sum_{i=1}^{D} W_i x_i + b) \tag{3.5}$$

where D is the number of inputs, x_i are the inputs, W_i are the input connection weights, b is the bias and Y is the output. The activation function f is a threshold function defined by:

$$f(net) = \begin{cases} 1, & net \geq 0 \\ -1, & net < 0 \end{cases} \tag{3.6}$$

The McCulloch-Pitts concept is created by the concatenation of a synapse and an axon. The synapse contains the weights W_i and performs the sum-of-products. The synapse shows that the element has 2 inputs and one output. The number of inputs x_i is set by the input axon.

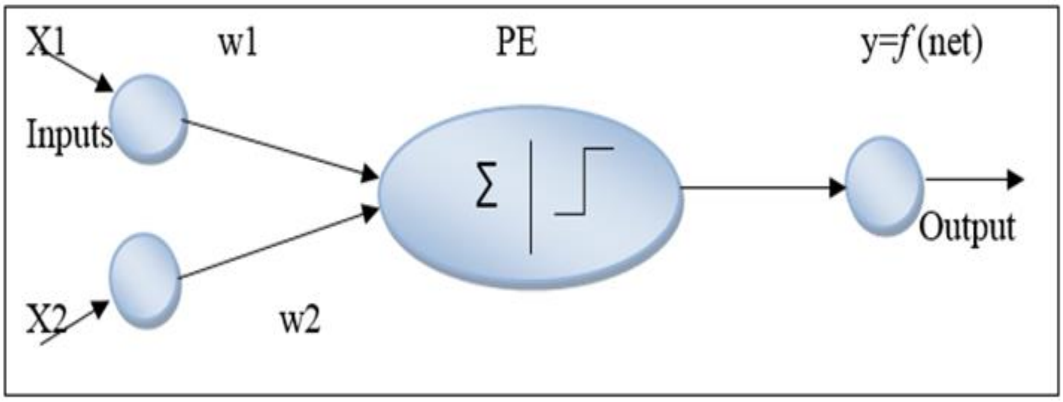


Figure 3.4 Two inputs, one output McCulloch-Pitts PE [119]

A trained ANN has to be able to generalize, in other terms, it should produce the correct output for given inputs. The inputs that belong to the same class but were not used for training. The input-output relationships are reconstructed by the activation function. The activation function controls the amplitude of the output of the neuron. The choice of the activation function can considerably change the behavior of the network. The most popular activation functions for perceptron are described below:

i. Hard Limit activation function: it limits the output of the neuron to either 0, if the net input argument n is less than 0; or 1 if n is greater or equal to 0. This function is used in Perceptron's, to create neurons that make classification decisions. In the Neural Networks Toolbox of Matlab 7.14, the hardlim function realizes the mathematical hard-limit activation function.
ii. Logarithmic Sigmoid activation function: this function takes the input, which can have any value between plus and minus infinity and squashes the output into the range 0 to 1. This activation function is commonly used in Backpropagation networks because it is differentiable and continues. In the Neural Networks Toolbox of Matlab 7.14, the logsig function realizes the mathematical logarithmic sigmoid activation function.
iii. Hyperbolic tangent sigmoid activation function: it takes the input, which can have any value between plus and minus infinity and squashes the output into the range -1 to +1. This activation function is commonly used in Backpropagation networks because it is differentiable and continues. In the Neural Networks Toolbox of Matlab 7.14, the tansig function realizes the mathematical tangent sigmoid activation function.

The graphical presentation of the three types of activation function is reported in Figure 3.5.

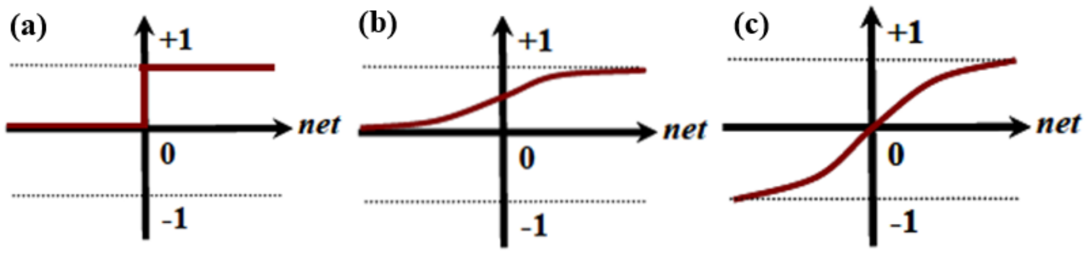


Figure 3.5 a) Hard Limit activation function, b) Logarithmic Sigmoid activation function and c) Hyperbolic tangent sigmoid activation function [120]

It is worth to mention, there are two main forms of ANN for classification or regression tasks. These are supervised and unsupervised ANNs. In the supervised ANNs, training is performed via regulation of the values of the inter-neuronal weights so that it will be possible to predict the values of the output after incorporating several input data from the previously executed experiments. For the unsupervised ANNs, no set target values exist while introducing the input into the system. The multi-layer perceptron (MLP) feedforward ANN as a common framework for training optimization algorithms, one or more hidden layers usually exists, and the input parameters are selected based on the analysts' experience and on the type of problem at hand [121]. For the feedforward backpropagation frameworks, the input traverses the network and later matched with the output at the end to estimate the level of error [122,123]. In the back-propagation framework, the learning rule ensures that an input-output relationship exists. This relation is usually based on the random allocation of initial weights to the input data prior to updating. Next, the outcome of the iteration process is compared to the desired output to update the weighted input data.

In most studies, neural computations are employed based on several transfer functions and the type of problem at hand. Recent engineering processes utilize the tangent sigmoid and the linear functions as transfer functions respectively for the hidden and output layers. The basis for the application of the tangent sigmoid transfer functions to the hidden neurons is to ensure a significant improvement in the systems' input-output behavior when varying the updated weights.

3.4 Input Variables Section

One of the central components influencing the performance of machine learning models is the selection of the input variable. Higher data dimensionality implies the need for more samples to reliably train a model (a situation sometimes described as the curse of dimensionality). Owing to the occasional limited availability of training samples, dimensionality reduction has become an important step. During data dimensionality reduction, no vital information must be lost in order to reliably train a model. The recent technological advancements of the past decades have simplified the process of gathering huge volumes of data, but the major problem remains the mining of relevant information from such data for knowledge sake. Contributing to this problem is the ability to scale the applied predictive model to a specific size of important input attributes. In addition to the challenge of model scaling to modern data (due to the huge number of samples), there is also the issue of high data dimensionality which poses problems to reliable and accurate models training due to the curse of dimensionality [124]. The predictive performance is affected by the correlated number of input variables that are required to be constructed for the training process. Thus, dimensionality must be drastically reduced to ensure accurate and reliable models training.

3.4.1 Global Harmony Search (GHS) Optimization Algorithm

The global harmony search algorithm is a population-based metaheuristic optimization algorithm, which was initially proposed by [125] for optimizing problems with continuous and discrete variables. Since then, it has obtained great success in various engineering applications, resulting in numerous publications as indicated in the latest review research [126]. The global harmony search framework was developed based on the pattern of a musical process when searching for the optimized solution. In the GHS algorithm, the best harmony is considered as a new harmony memory. One of the applications of the GHS is in searching for the influence of highly dimensional input parameters [127].

The harmony search algorithm basically works as follows. Let's assume there is an objective function that depends on several input variable(s) and the number of those variables denotes the decision or the design variables. For an appropriate minimization objective function, it can be expressed mathematically as follows:

$$Minimise f(x) = x_i \tag{3.7}$$

Here $x_i \in [x_i^L, x_i^U]$, for a continuous variable. The main targeted variable in the current study is the EAC; whereas, the dependent variables all the related project construction variables. The basic flowchart for the GHS algorithm is presented in Figure 3.6. In this research and for the best knowledge of the authors, the GHS algorithm is applied as input variables selection approach for the ELM and ANN predictive models.

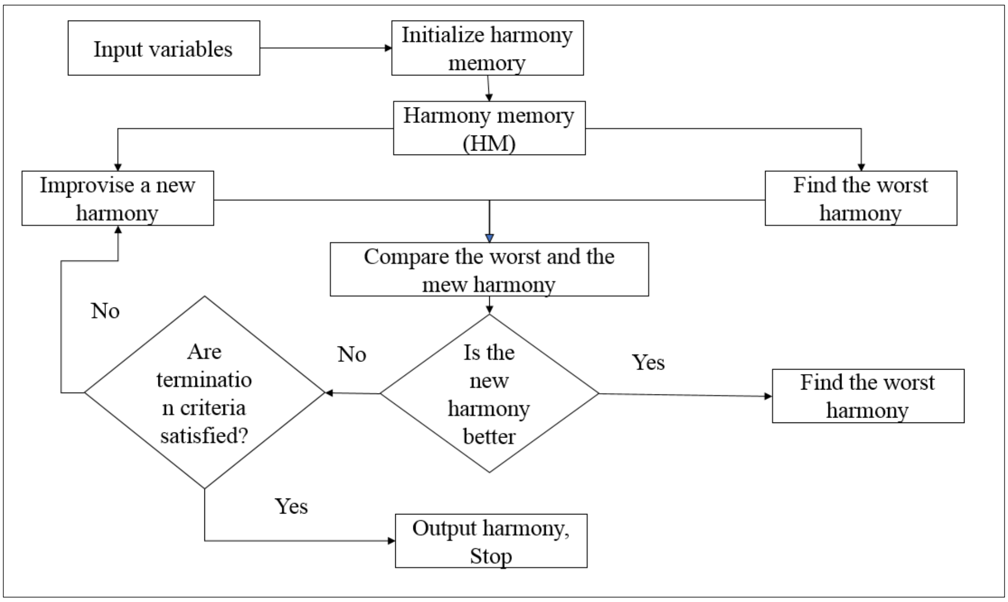


Figure 3.6 The flow chart of the global harmony search algorithm

3.4.2 Brute-Force Input Optimization Method

Brute-force (BF) is a problem-solving approach that requires the systematic enumeration of the whole possible features [128] in order to establish a specific solution to a specific problem, as well as to ascertain the appropriateness of each option towards addressing the stated problem [129]. The BF concept normally involves finding the divisors of a number *n* that would list the whole integers [1 to *n*] and check that *n* will be perfectly divided by each integer without any remainder. Despite the ease of BF implementation and the assurance of a solution to the considered problem, it is relatively expensive in terms of cost considering the number of available options. In many practical applications, the cost of BF implementation normally increases with the problem size. Hence, BF is only suitable in cases with limited problem size or where no specific heuristic method that can be used effectively to reduce the number of solutions to a considerable size exist. One important application of BF is in benchmarking other algorithms in terms of their performance since it is among the easiest searching methods. The capability of BF in solving feature selection problems formed the basis for its selection and integration with the proposed predictive model in this study.

3.5 Modelling Procedure Phase

3.5.1 Programming Information and Used Codes

In this research, MATLAB software running on an Intel(R) Core i7-4770 CPU 3.4 GHz, Windows 10 platform served in modeling the EAC prediction. For the ELM model, free available online code is utilized in this research in which available at (https://www.ntu.edu.sg/home/egbhuang/elm_codes.html). Figures 3.7-3.13 show that the screenshots for the MATLAB Codes of ELM, ANN, BF-ELM, GHS-ELM, BF-ANN, and GHS-ANN Algorithm, where ELM code consists of 425lines, while ANN code consists of 416 lines. The hydride Algorithms have higher codes lines numbers, where GH-ELM consists of 824 lines as shown in Figure 3.10, BF-ELM consists of 1690 lines as shown in Figure 3.9, GHS-ELM consists of 1682 lines as shown in Figure 3.12.

The reason behind using MATLAB in this study return to MATLAB is an interpreted language. This implies that the source code is not compiled but interpreted on the fly. This is both an advantage and a disadvantage. MATLAB allows for easy numerical calculation and visualization of the results without the need for advanced and time-consuming programming. The disadvantage is that it can be slow, especially when bad programming practices are applied.

Applying the selected algorithms on the MATLAB software program needs a group of steps. Firstly, make the required code for each algorithm as shown in Figures (3.7-3.12) for (ELM, ANN, GHS-ELM, BF-ELM, GHS-ANN, and BF-ELM) respectively.

After preparing the code, the creation of GUIs in MATLAB comes in the second step, Create apps with graphical user interfaces (GUI) in MATLAB. Graphical user interfaces (GUIs), also known as apps, provide point-and-click control of your software applications, eliminating the need for others to learn a language or type commands in order to run the application. You can share apps both for use within MATLAB and also as standalone desktop or web apps.

3.5.2 The Work Methodology

3.5.2.1 For Single ELM and ANN

Working of single models ELM and ANN are shown in Figure 3.13 ELM and ANN methodologies, first, it takes input and targets data than it trains the ELM and ANN systems using 75% of data and tests using the remaining 25% of data. After that numerical indicators are calculated. The graphical user interface is designed for the proposed system, the screenshot of which is shown below.

Figure 3.7 ELM and ANN Methodologies

Figure 3.14 shows the design of the proposed ELM and ANN models. When click on load data/targets pop up window comes and asks to select the data/targets which we want to use as shown in Figure 3.14, through this proposed system can be easily usable for the different datasets. Once data and targets are selected train button should be pressed and it will train the system. After that when calculating the numerical indicators button is pressed these indicators are calculated along with the predicted output and shows in the edit box and their scatter plot is also plotted in axes as shown in Figure 3.15 for both ELM and ANN the same procedure will be used. One can save the results in an excel file by clicking on save file and it will ask for the location where the user wants to save the file.

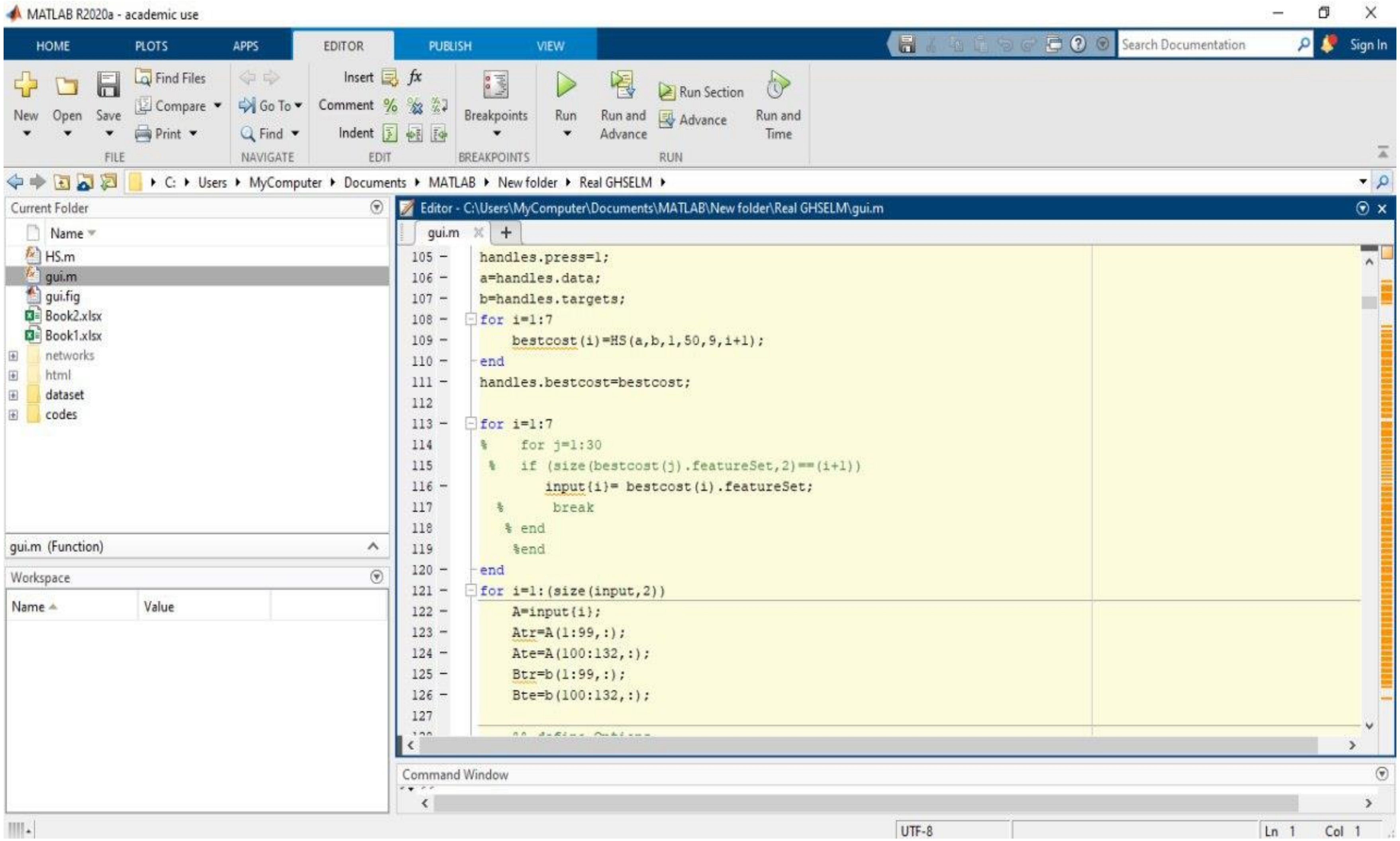


Figure 3.8 Screenshot for the MATLAB Codes of ELM Algorithm

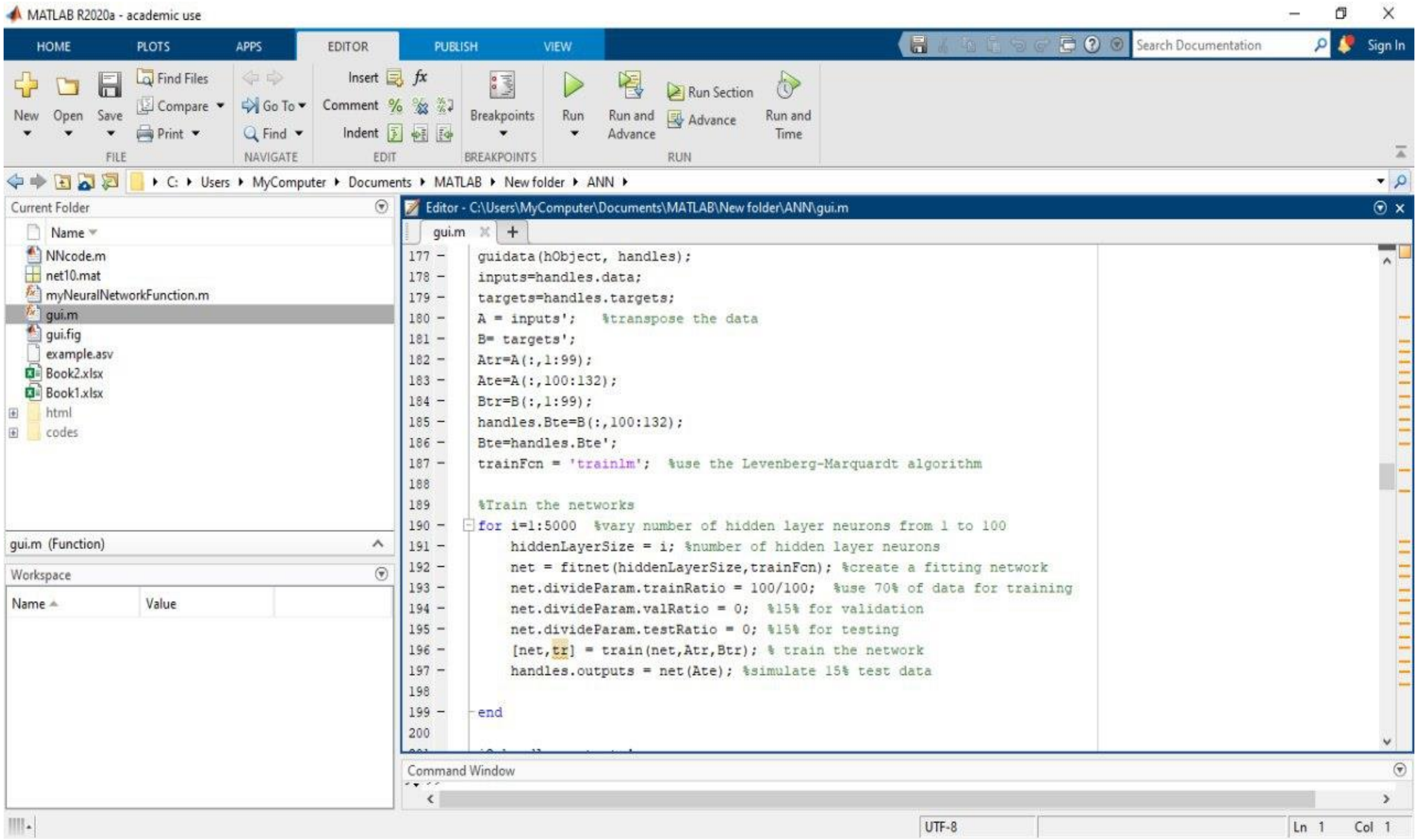


Figure 3.9 Screenshot for the MATLAB Codes of ANN Algorithm

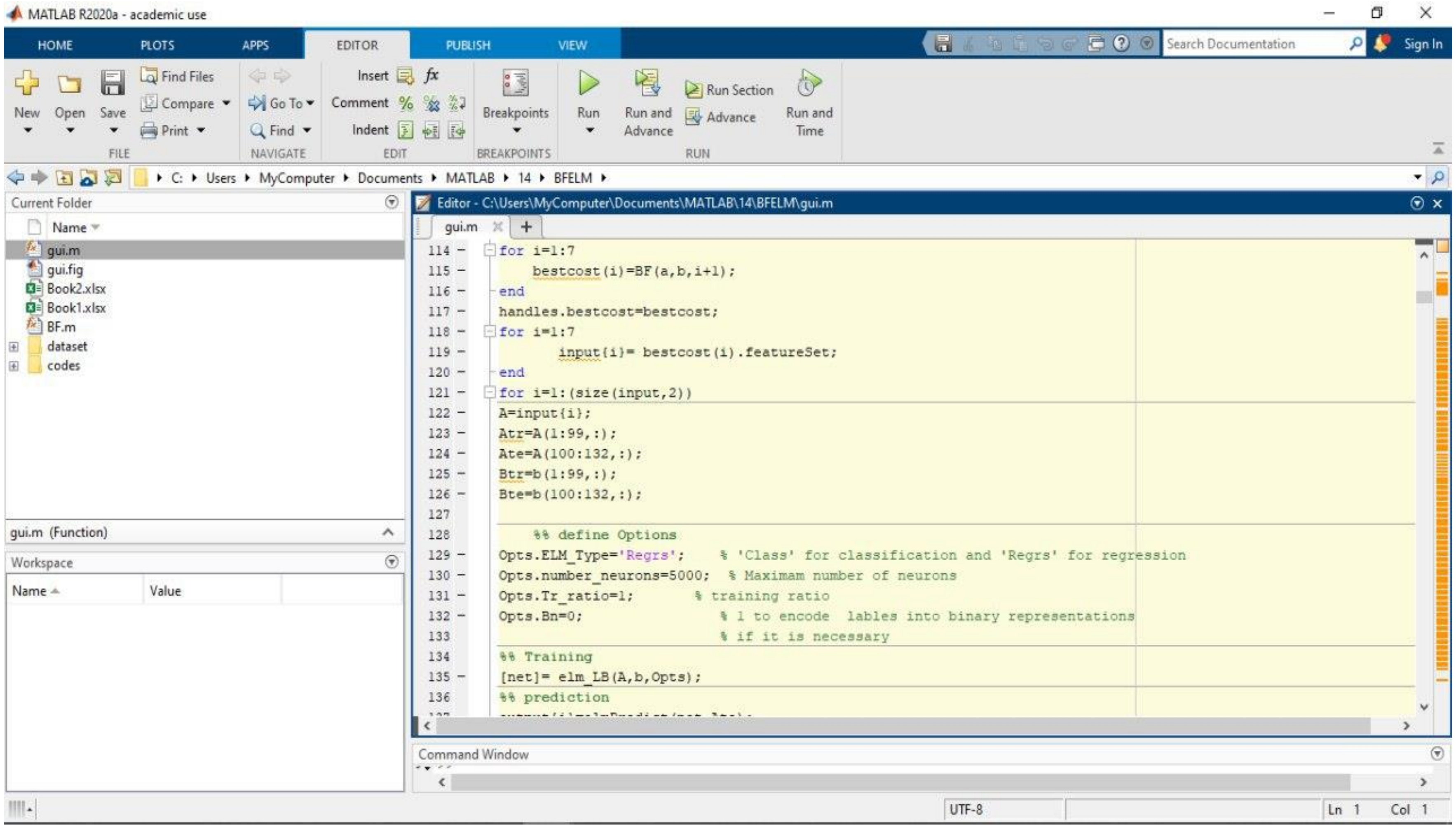


Figure 3.10 Screenshot for the MATLAB Codes of BF-ELM Algorithm

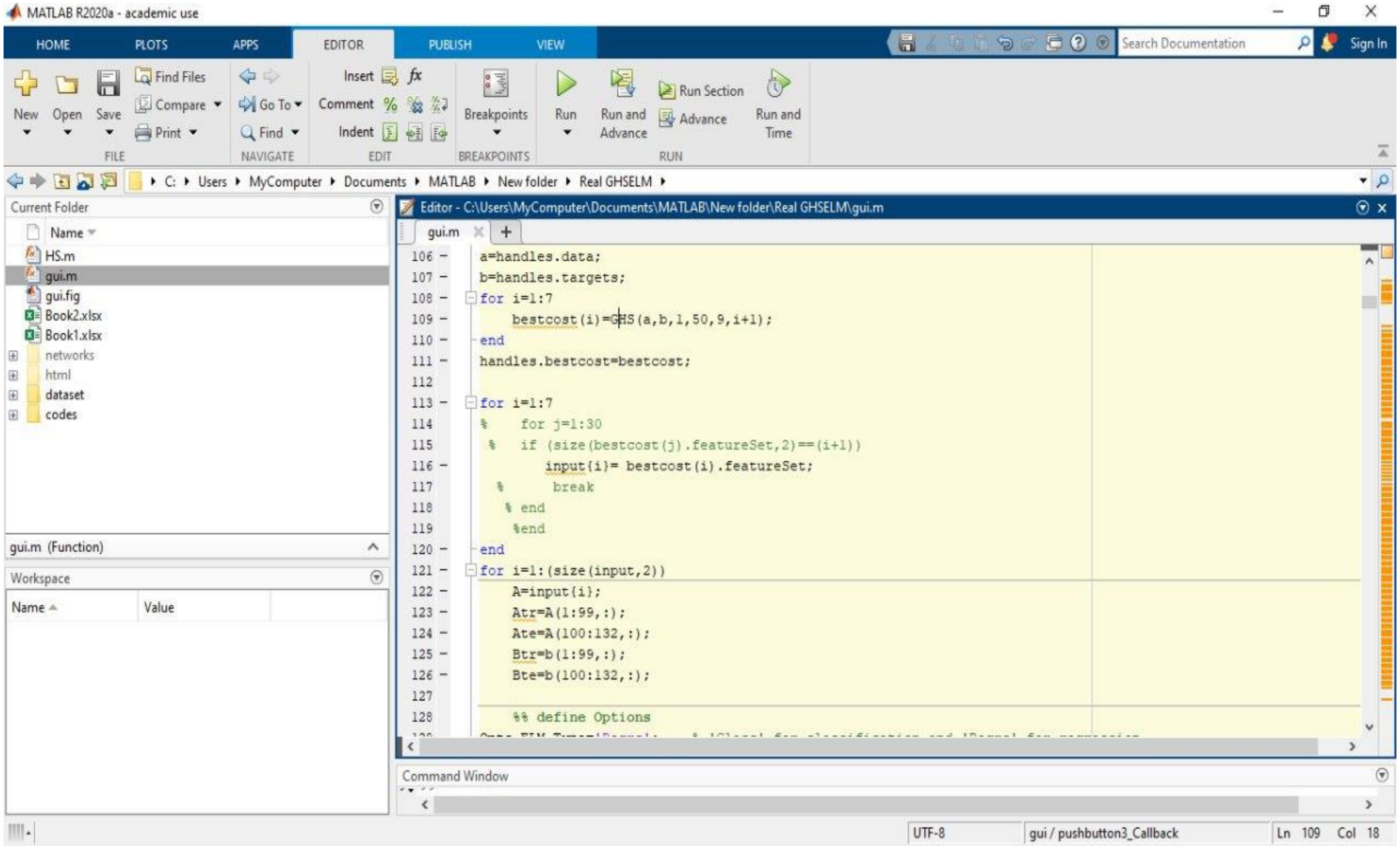


Figure 3.11 Screenshot for the MATLAB Codes of GHS-ELM Algorithm

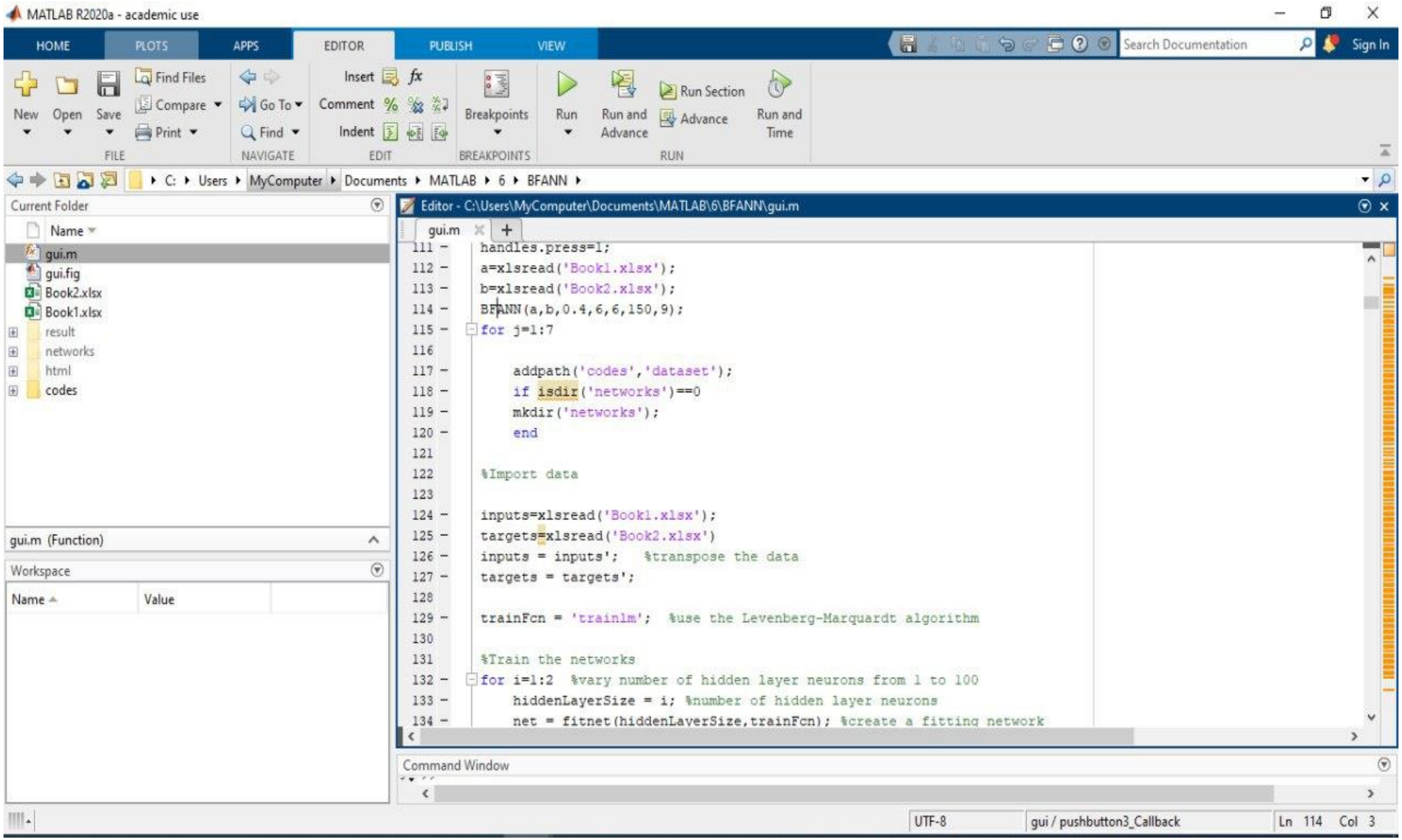


Figure 3.12 Screenshot for the MATLAB Codes of BF-ANN Algorithm

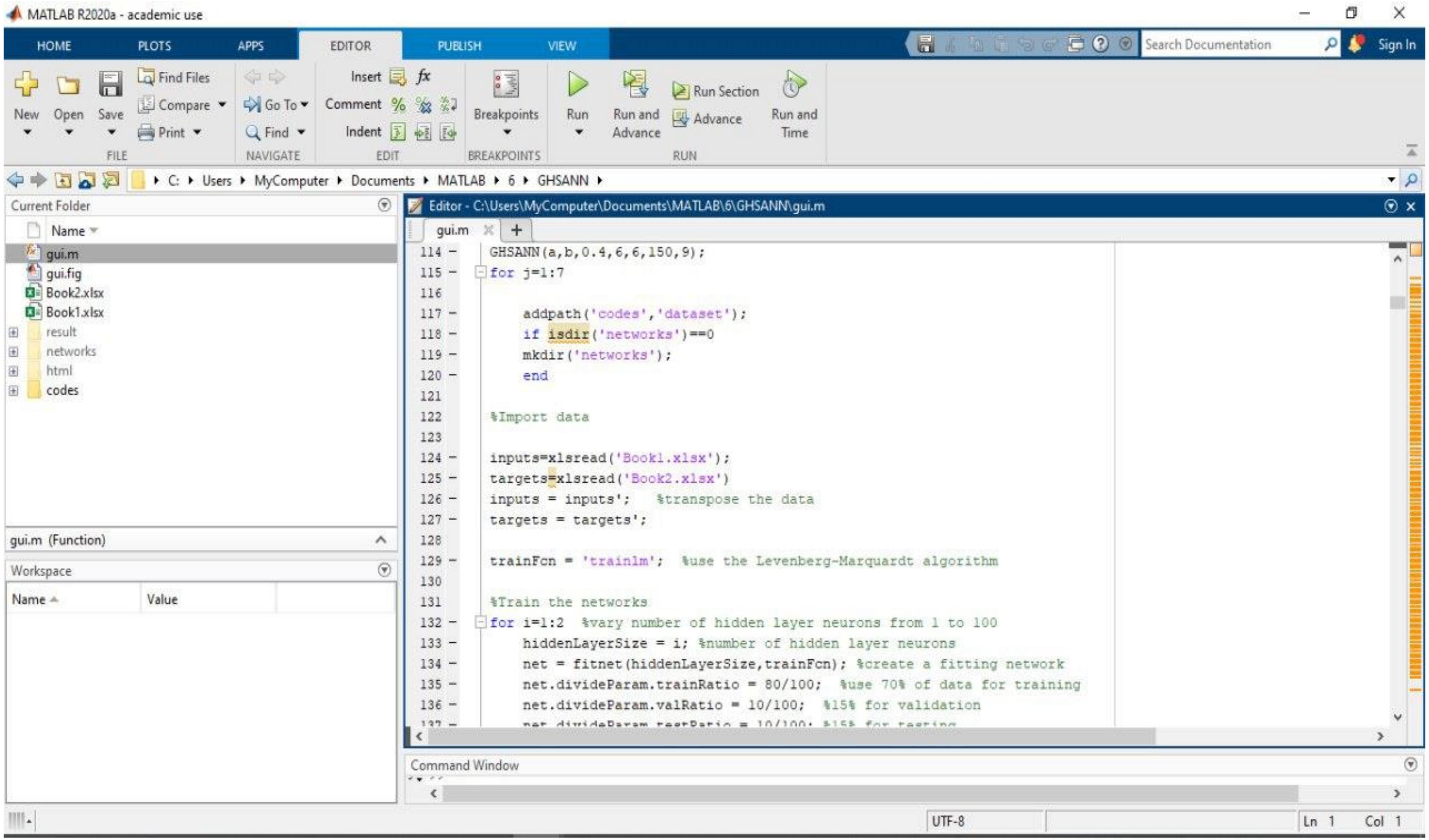


Figure 3.13 Screenshot for the MATLAB Codes of GHS-ANN Algorithm

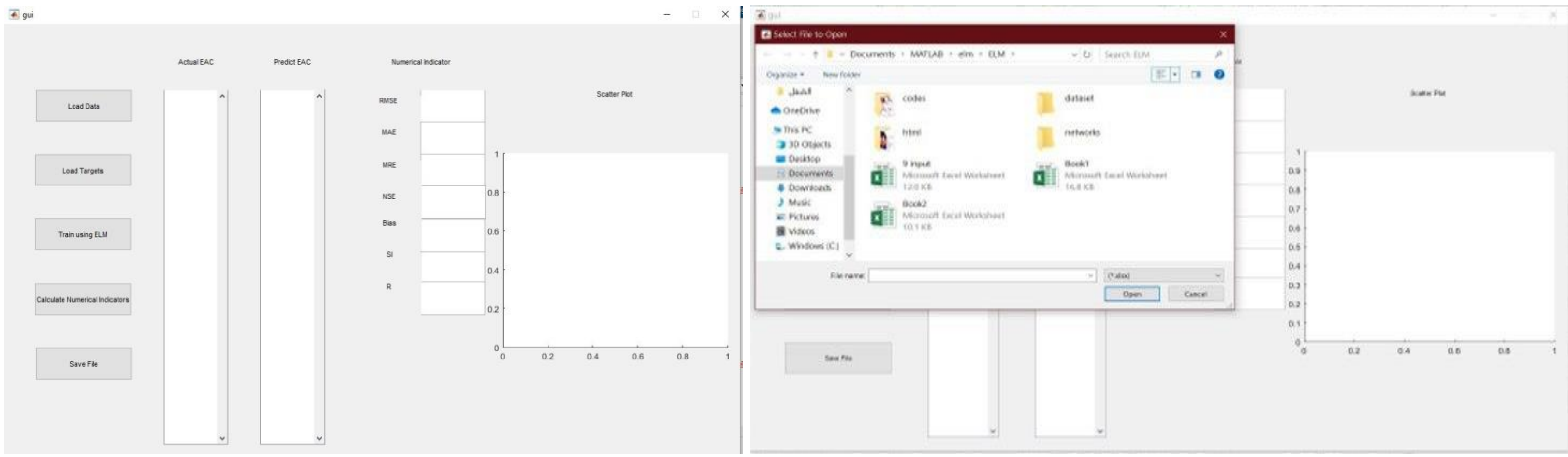


Figure 3.14 GUI and Data selection for ELM and ANN models

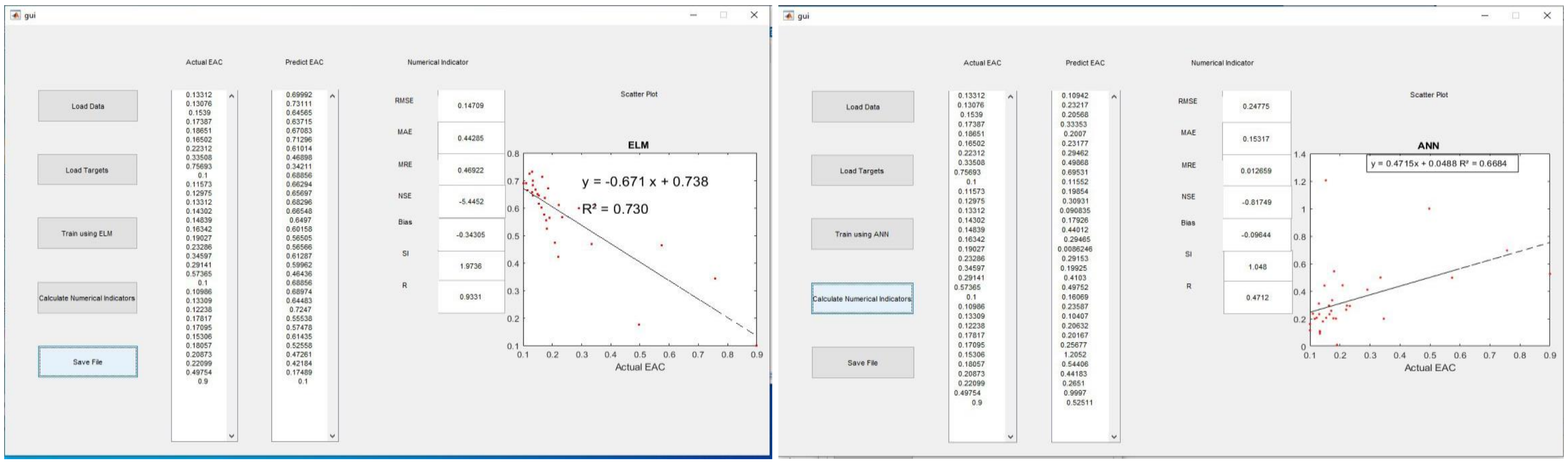


Figure 3.15 Data Results of ELM and ANN models based-GUI

3.5.2.2 GHS-ELM Algorithm

The proposed system working is defined in Figure 3.16. First, it takes training data and targets data as an input, once user input data it will be given to Global Harmony Search Algorithm. GHS will check the system one by one like first It will look for the best input combination for Model 1 (2 inputs) based on selecting a various combination of 2 inputs and optimizing it as per the criteria of minimizing RMSE and maximizing R and then for model 2 and so on up to model 7 same process will be followed. When input combination is finalized this data will be given to the ELM model for training and testing of the system, after that numerical indicators RMSE, MSE, R, etc. are calculated to compare which model is performing well. These steps are implemented and step-by-step results are shown in the below pictures.

A Graphical user interface in MATLAB designed for all 6 proposed models, so we can easily train and test them to know which one is better. Figure 2 shows the GUI of GHS-ELM model.

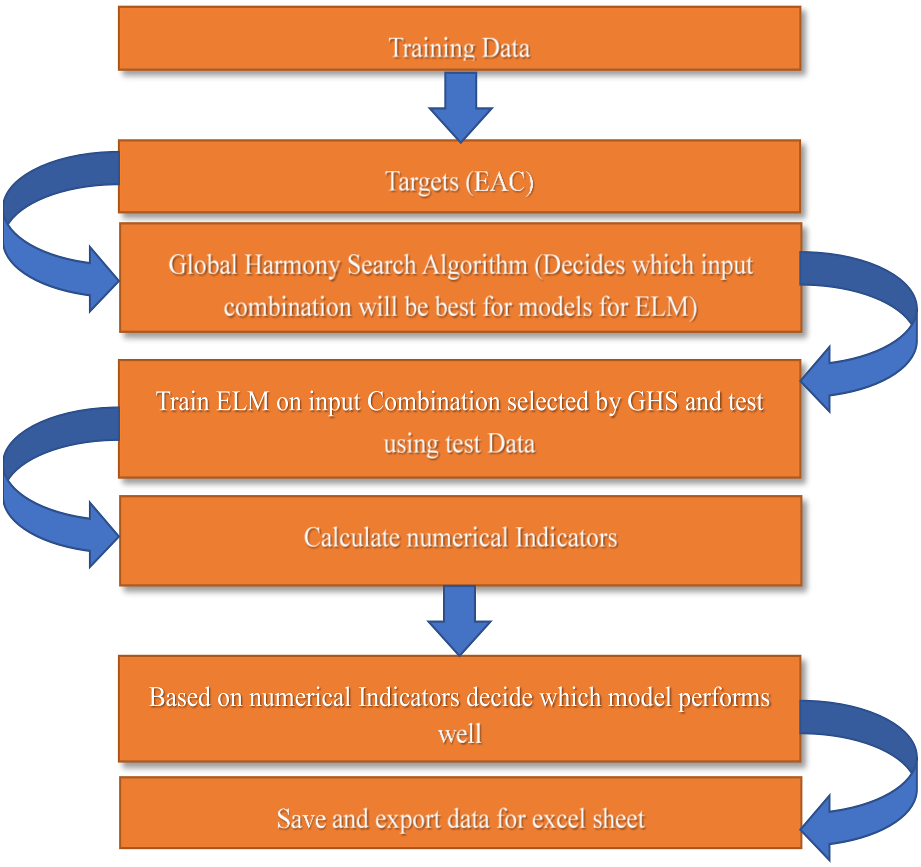


Figure 3.16 Methodology for GHS-ELM

Working of GUI is like first we click on load data and give input data file to it and, then we click on targets to give the actual EAC as per the basis of inputs. After that click on the train using GHS-ELM, this will do the input selection part and check on which combination of input the performance is best by minimizing RMSE and maximizing R for model 1-model 7 as shown in Figure 3.17. Then we have buttons to calculate numerical indicators which can be helpful to decide which model is best as per requirements and the output is shown in Figure 3.18. After that, it could be clicked on to show models input contributions and can see what input combination was selected as best for models from one to seven and we can also find which model is best for predicting the EAC as shown in Figure 3.19.

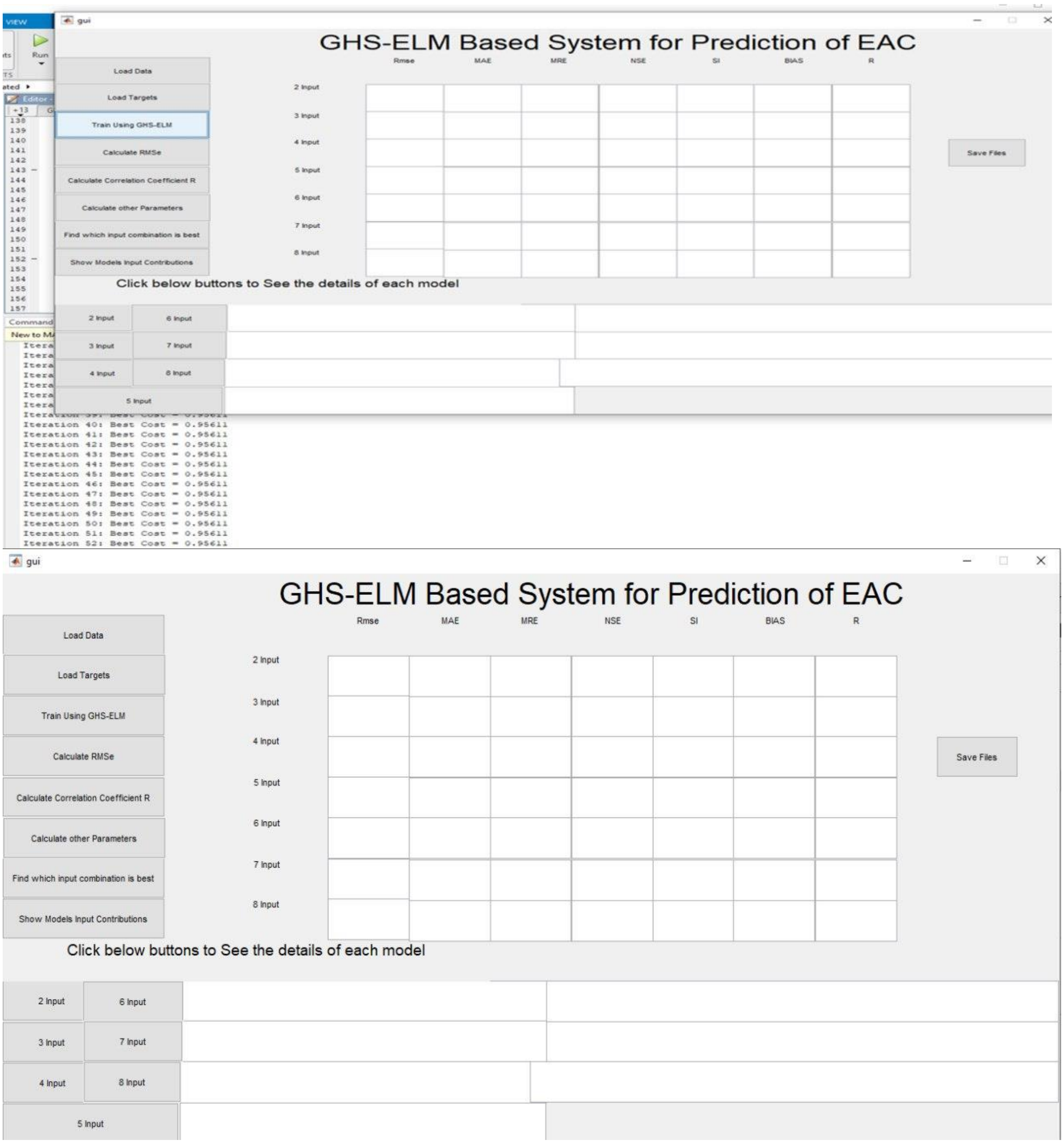


Figure 3.17 GUI and Training using GHS-ELM model

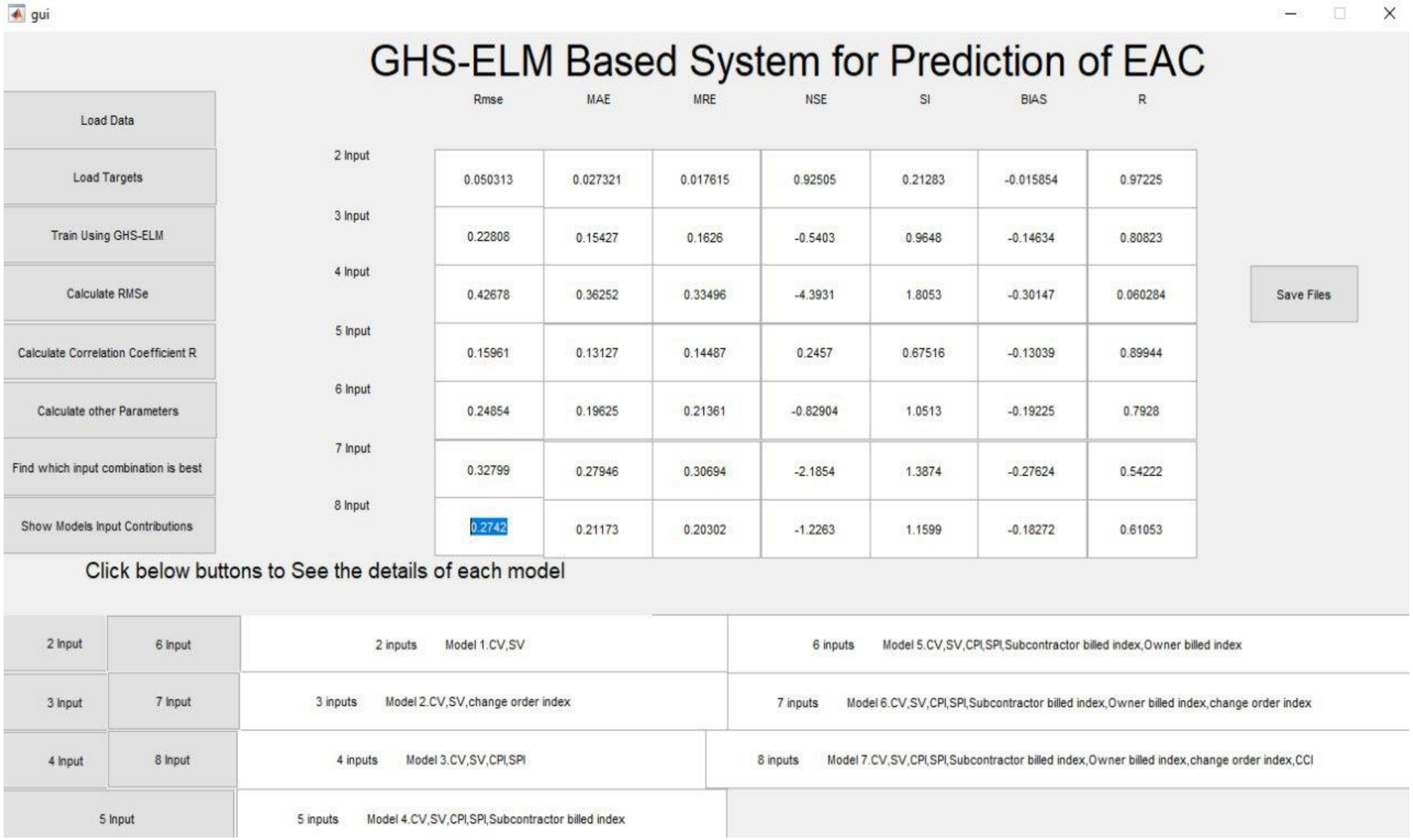
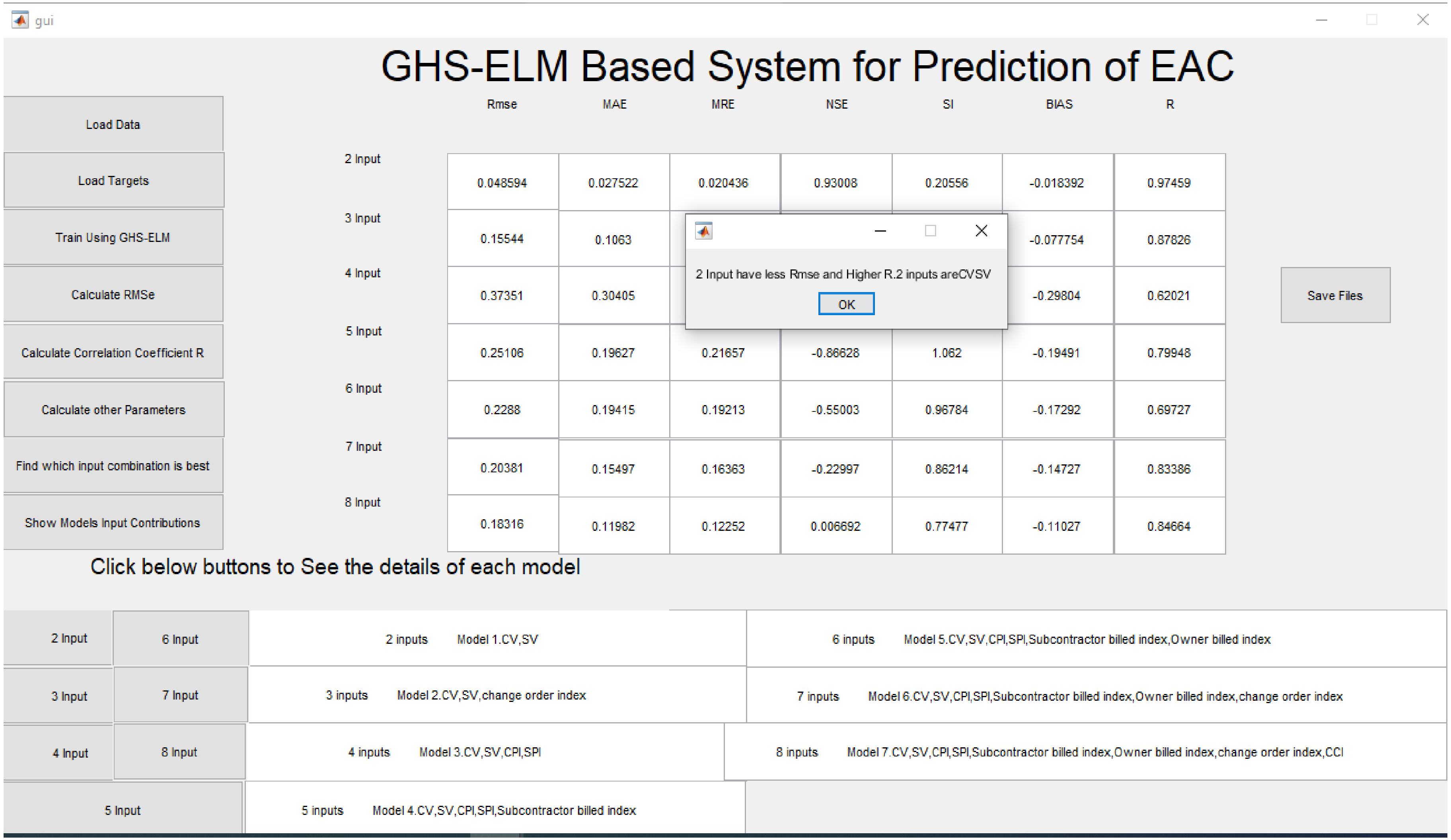


Figure 3.18 Numerical indicators



1Figure 3.19 Models inpuzt Combinations

Designed GUI saved files option to export the data to excel files like actual EAC, predicted EAC, and numerical indicators. As it could be seen the detailed data for all models by clicking the buttons as input 2, input3 up to input 8. Detailed data includes actual EAC, predicted EAC, numerical indicators and their scatter plot as shown in Figure 3.19.

3.5.2.3 For GHS-ANN and BF-ANN Algorithms

Figure 3.20. shows the working methodology of GHS-ANN and BF-ANN systems for predicting the EAC as defined in the previous model. This model use ANN instead of ELM for the training of the system. Figure 3.21 shows the GUI of the GHS-ANN system it's the same as the previous GUI but working is different as ANN is used instead of ELM in this system. Figure 3.21 shows how ANN is being trained using GHS for input selection.

3.5.2.4 For BF-ELM Algorithm

The proposed system working is defined in Figure 3.23. First, it takes training data and targets data as an input, once user input data it will be given to Brute Force Algorithm. BF will check the system one by one like first It will look for the best input combination for Model1 (2 inputs) based on selecting the various combination of 2 inputs and optimizing it as per the criteria of minimizing RMSE and maximizing R and then for model 2 and so on up to model 7 same process will be followed. When

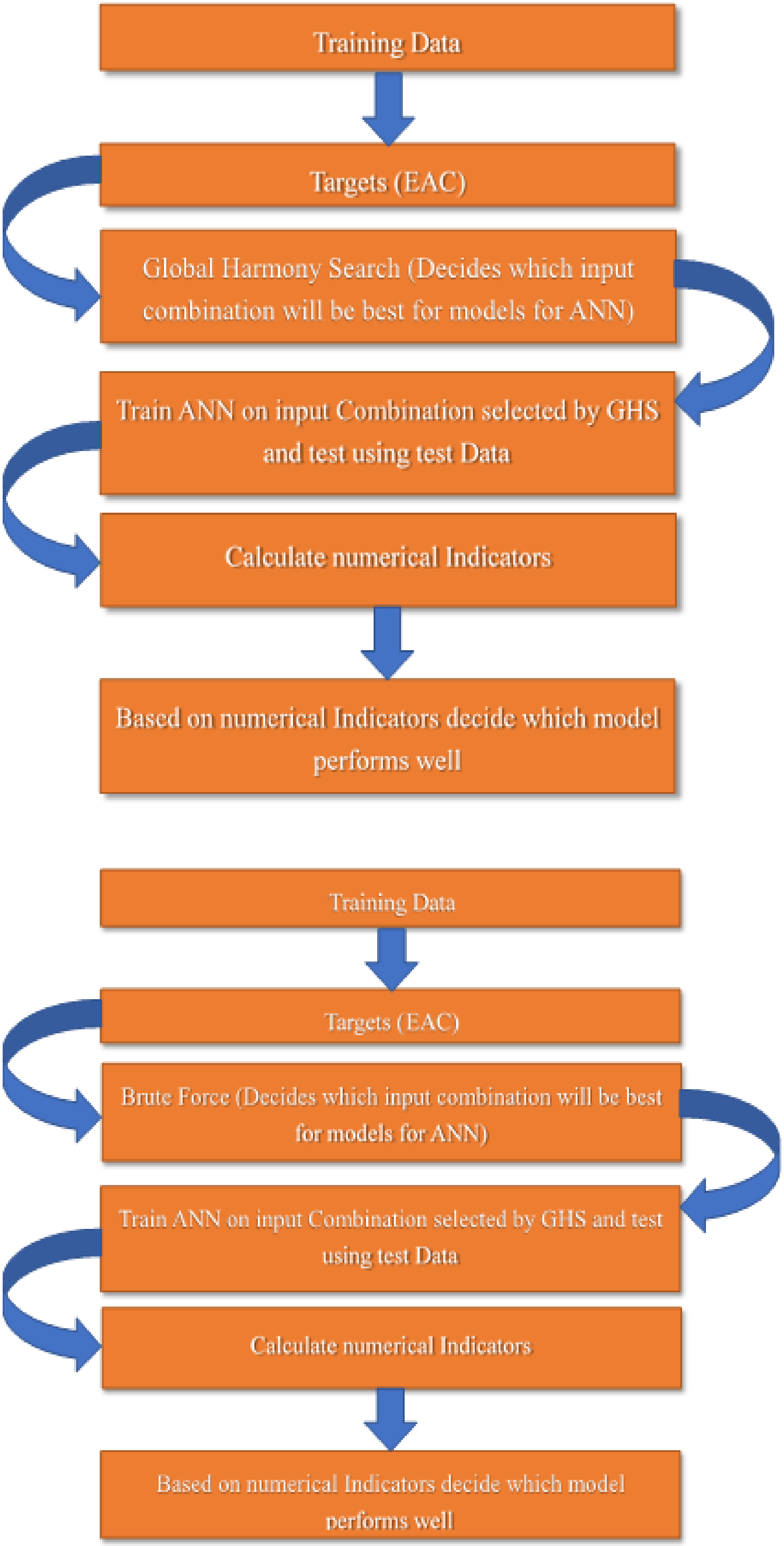


Figure 3.20 The methodology of GHS-ANN and BF-ANN systems

input combination is finalized this data will be given to the ELM model for trainingand testing of the system, after that numerical indicators RMSE, MSE, R, etc. are calculated to compare which model is performing well. These steps are implemented and step by step results are shown in the below pictures.

Figure 3.24 shows GUI of the BF-ELM system. Working of GUI is like first we click on load data and give input data file to it and, then we click on targets to give the actual EAC as per the basis of inputs. After that click on the train using BF-ELM, this will do the input selection part and check on which combination of input the performance is best by minimizing RMSE and maximizing R for model 1-model 7 as shown in Figure 3.24. Then we have buttons to calculate numerical indicators which can be helpful to decide which model is best as per requirements and the output is shown in Figure 3.25.

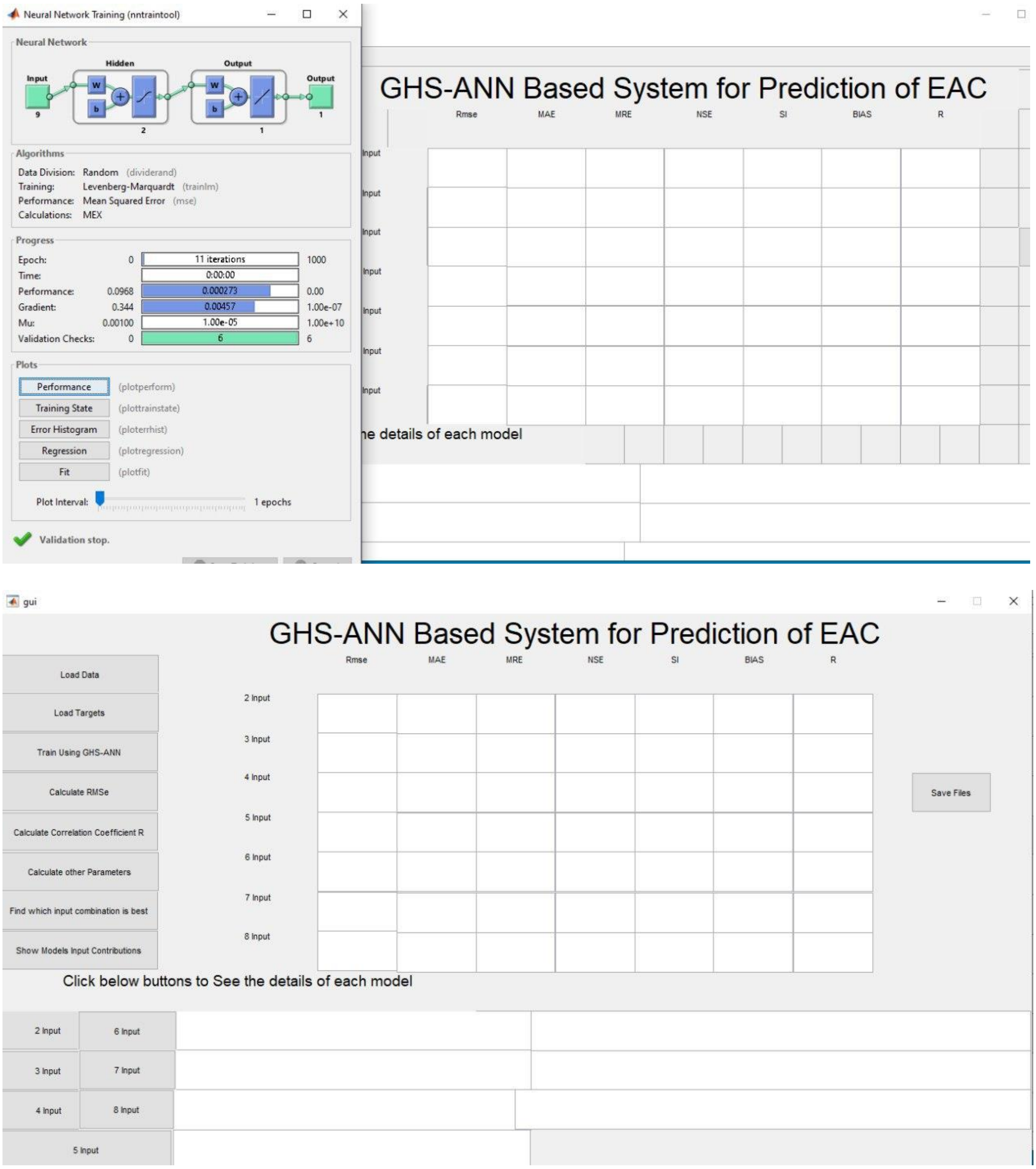


Figure 3.21 GUI and Training of GHS-ANN with Levenberg-Marquardt

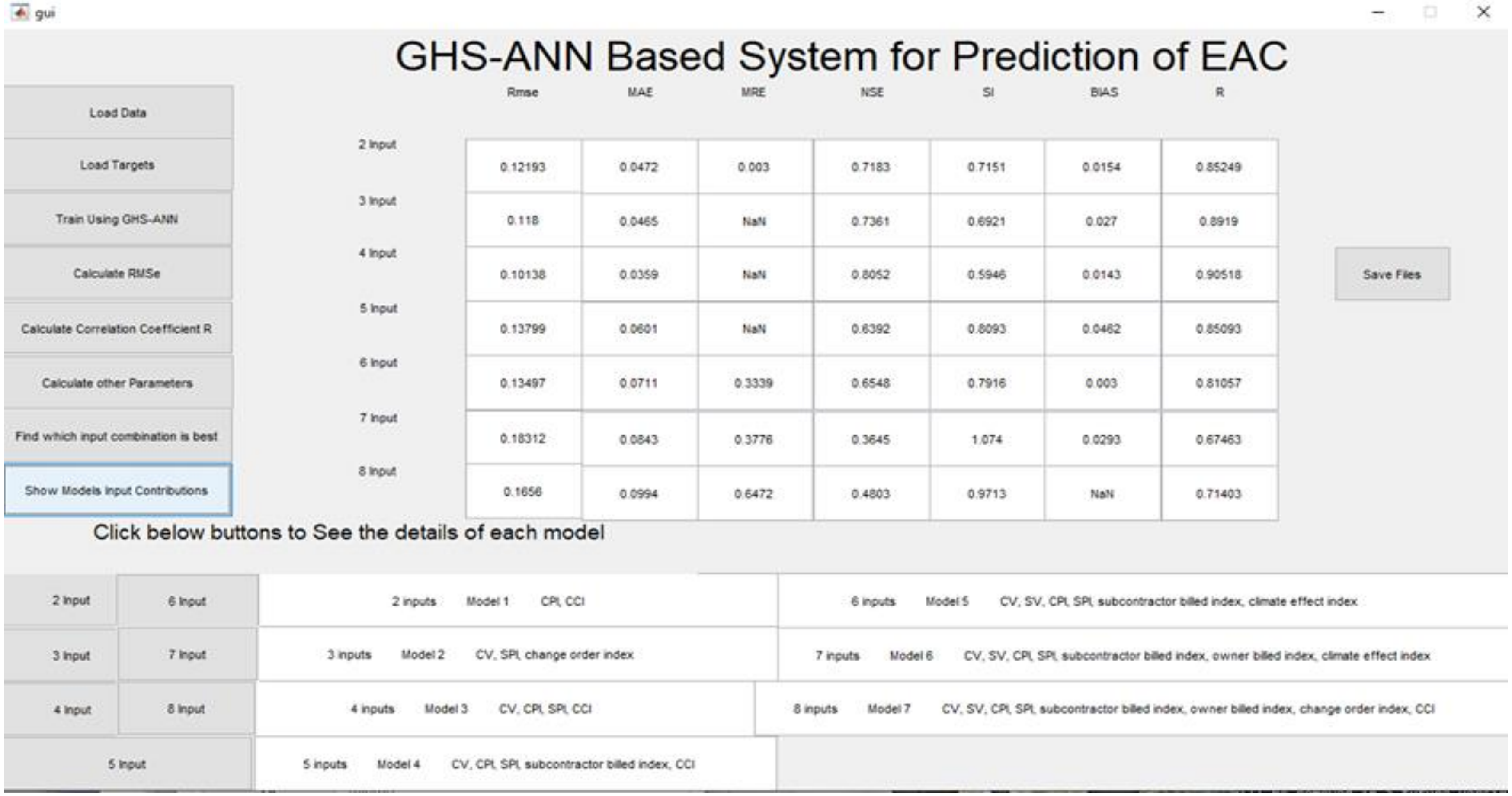


Figure 3.22 Numerical Indicators and Models input combination

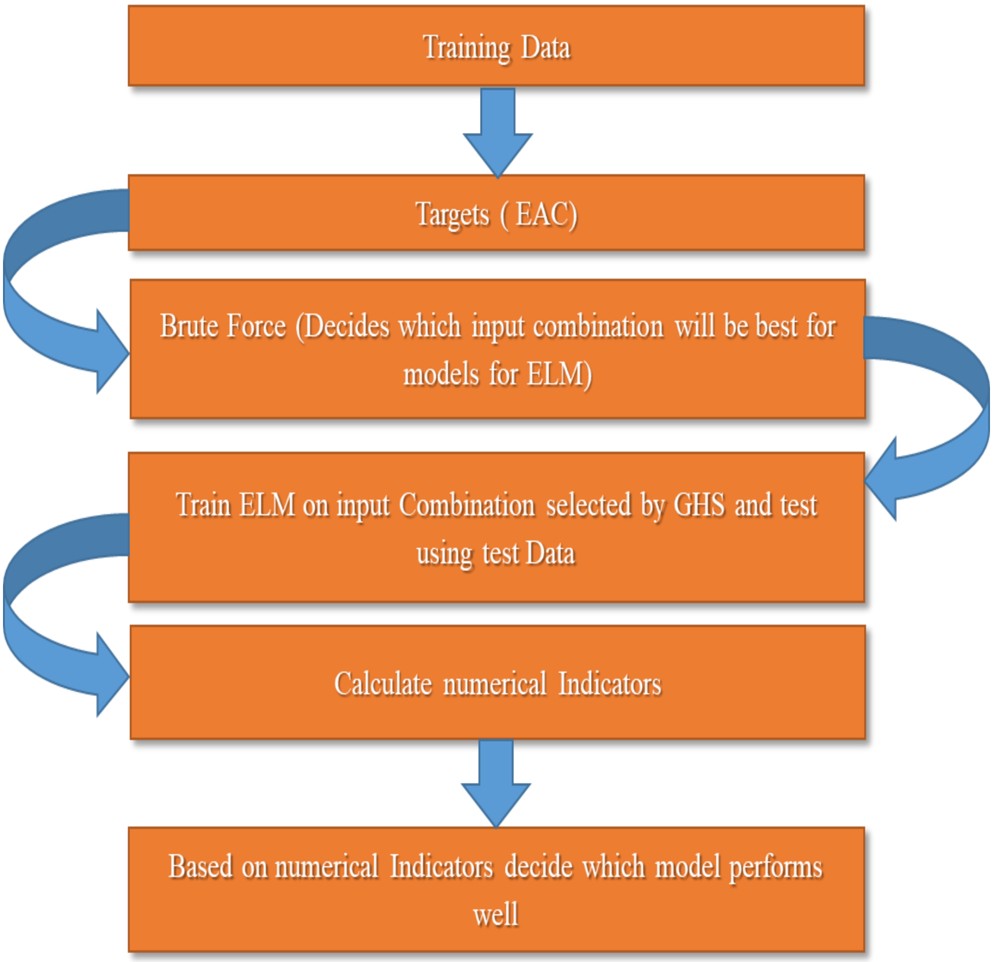


Figure 3.23 Methodology of BF-ELM system.

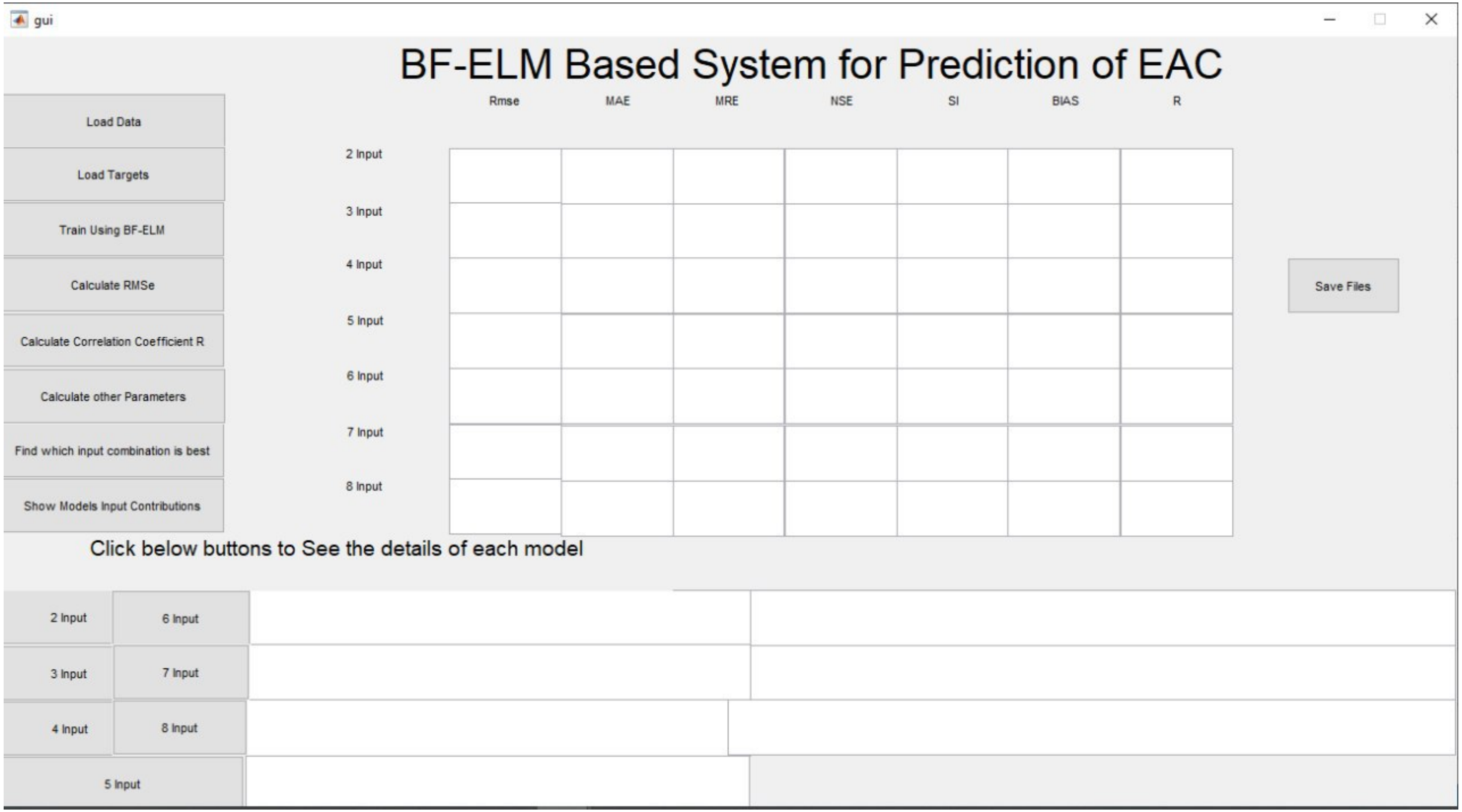
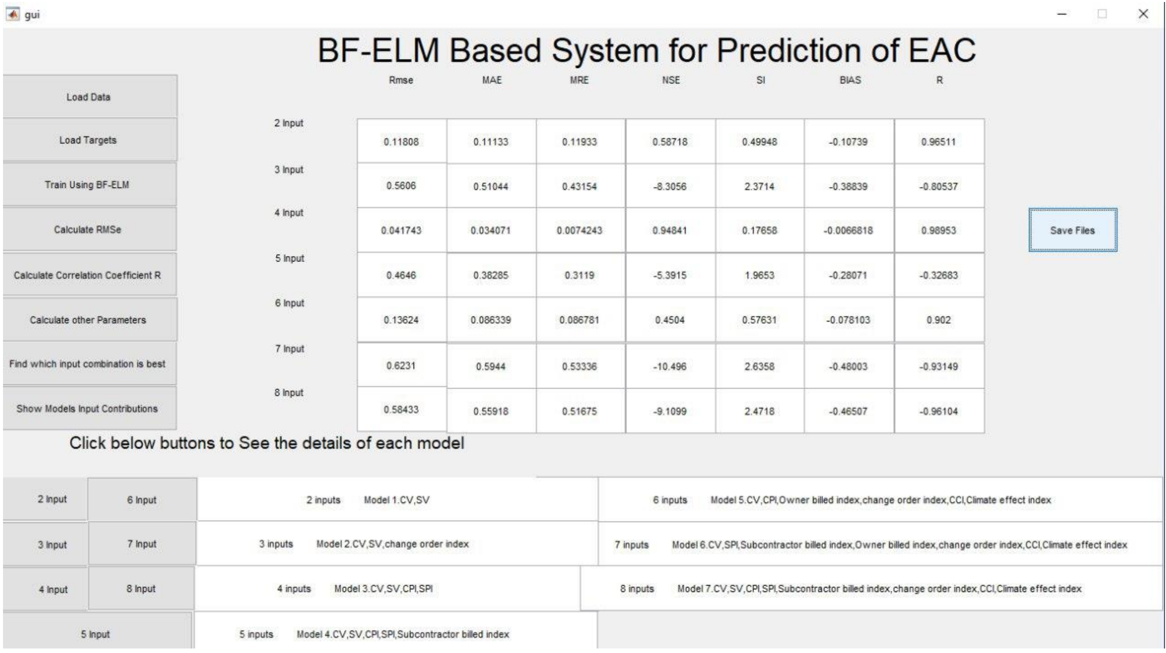


Figure 3.24 GUI and Training using BF-ELM model



	Rmse	MAE	MRE	NSE	SI	BIAS	R
2 Input	0.11808	0.11133	0.11933	0.58718	0.49948	-0.10739	0.96511
3 Input	0.5606	0.51044	0.43154	-8.3056	2.3714	-0.38839	-0.80537
4 Input	0.041743	0.034071	0.0074243	0.94841	0.17658	-0.0066818	0.98953
5 Input	0.4646	0.38285	0.3119	-5.3915	1.9653	-0.28071	-0.32683
6 Input	0.13624	0.086339	0.086781	0.4504	0.57631	-0.078103	0.902
7 Input	0.6231	0.5944	0.53336	-10.496	2.6358	-0.48003	-0.93149
8 Input	0.58433	0.55918	0.51675	-9.1099	2.4718	-0.46507	-0.96104

Figure 3.25 Numerical indicators

After that, we can click on show models input contributions and can see what input combination was selected as best for models from one to seven and we can also find which model is best for predicting the EAC as shown in Figure 3.26.

Designed GUI has to save files option to export the data to excel files like actual EAC, predicted EAC, and numerical indicators. It could be seen the detailed data for all by clicking the buttons as input 2, input3 up to input 8. Detailed data includes actual EAC, predicted EAC.

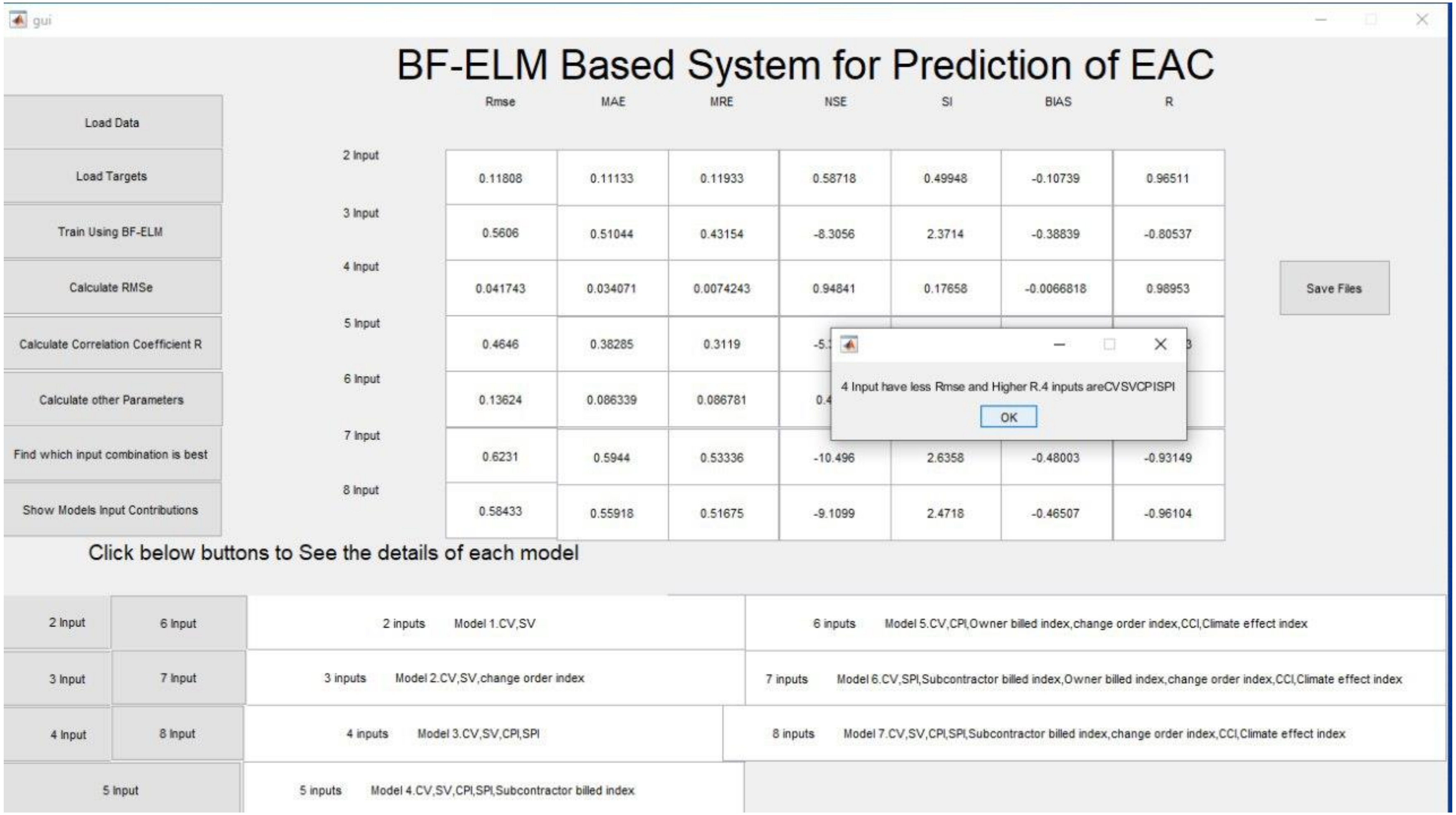


Figure 3.26 Models input combinations

3.5.3 The Applied Parameters

The application applied using historical information related to civil engineering construction projects located in the United Arabian Emirates. Possible explanations are that UAE projects do truly perform better than those in an international context or alternatively, project managers do not want to report poor performance as it reflects badly on them [130]. It is possible that the delays have been picked up within a revised program and project managers are reporting on the amended objectives [131]. This aspect would make an interesting case for further study of all stakeholders to find the true picture. The type of construction is a residential project and the project period between eleven to twelve months. And the reason behind studying residential complexes and not commercial or industrial projects is due to the fact that most commercial and industrial projects obtain a full investment for the project before its inception, and this investment can be for five, ten, fifteen, twenty, and even for twenty-five years. This makes the possibility of these projects suffering from financial problems considered low. But residential projects are rarely sold before completion of 70% or more of the project, so it is possible that you will suffer from financial problems and in many cases stop for reasons related to financial is higher. The data used in this study was collected from ten projects from three private companies in the United Arab Emirates. The total number of training cases from different periods of these ten projects is 132, and all data is represented in the Appendix. This data size can be considered as appropriate since, in the literature, the studies about the prediction of EAC have been performed using a similar number of data. For instance, Cheng et al. [40] used 11 projects for 269 training case results, similarly, Huang [87] used 289 training data from 15 projects, and Narbaev and Demarco [46] exploited training cases from nine projects. The associated project information is presented in the following forms: schedule variance (SV), cost variance (CV), schedule performance index (SPI), cost performance index (CPI), subcontractor billed index, construction price fluctuation, owner billed index, change order index, climate effect index. Depending on National Defence Industrial Association Integrated Program Management Division [132], Schedule Metrics which included schedule performance index (SPI) and schedule variance (SV), Cost Metrics such as Cost Performance Index (CPI) and cost variance (CV) are the main parameters that effect on the project completion date. As well as according to Anbari [37], the earning value of project management is mainly depending on cost and schedule variances and performance indices, and forecasts of project cost and schedule at completion, therefore, those parameters will have a great effect on the project completion date.

Schedule Variance (SV) [133] and Cost Variance (CV) are two essential parameters in Earned Value Management. They help you analyze the project's progress, i.e., how you are performing in terms of schedule and cost. These basic elements that help to find Schedule Variance and Cost Variance. Schedule Variance helps to understand if you are behind or ahead of schedule. Cost Variance helps determine if you are under or over budget. Variance analysis is the key to the success of any project, which is finished on time and within the approved budget [134]. Schedule Variance and Cost Variance are great tools for analyzing project health. As a project manager, you should monitor these variances for any deviations. If both variances are positive, this means that your project is progressing well. However, something is wrong if either variance is negative and you have to take corrective action to bring the project back on track [135].

Management is always looking at these parameters for any deviations from the baseline. Deviations from the baseline cost a great deal in project management. The Schedule Performance Index (SPI) [136] shows how you are progressing compared to the planned project schedule. According to the PMBOK Guide [137], "The Schedule Performance Index (SPI) is a measure of schedule efficiency, expressed as the ratio of earned value to planned value." The Schedule Performance Index gives you information on the time efficiency of your project. The Performance Indexes helps to compare the health of a project among many projects. Therefore, the Performance Index is the ratio between the parameters, and a glimpse of these ratios will help you determine the health of the project. This makes it easier for you to compare the relative health of projects. You can find efficiency through indexes. Schedule Performance Index and Cost Performance Index help you analyze the progress of a project. These measures can help you determine if you are performing up to standard. You are doing well if the ratio is higher than one. If the ratio is less than one, there is a problem with the project and you should take corrective action. In ideal conditions, the ratio should be one.

The price index of items determines the values of such items; some items have their value increase over the period of time. Time items that belong to such categories include landed properties such as buildings, pieces of land, and other related items. For this reason, it has a massive impact on the control of the construction project [138].

The Subcontractor may be ordered in writing by the Contractor, without invalidating this Subcontract, to make changes in the Work within the general scope of this Subcontract consisting of additions, deletions, or other revisions, including those required by Modifications to the Prime Contract issued subsequent to the execution of this Agreement, the Subcontract Sum and the Subcontract Time being adjusted accordingly. The Subcontractor, prior to the commencement of such changed or revised Work, shall submit promptly to the Contractor written copies of a claim for adjustment to the Subcontract Sum and Subcontract Time for such revised Work in a manner consistent with requirements of the Subcontract Documents, therefore the whole project completion will effect [139].

Contract payment Owner Billed Index which refers to Owner billed amount/Earned Value. Within the context of EVM methodology, there is an important value widely known as Estimate at Completion (EAC) [140]. The essentiality of EAC is emphasized due to the fact that EAC enables the project manager to appraise the total cost with the assumption that past occurrence will affect the future project's consequence. In practice, the EAC is often computed by formulas using cost management data provided by the contractor to the owner in progress report, usually monthly report. Additionally, for the contractors, in order to form the periodic report to the owner, their site engineers must collect sufficient data summarized in the daily man-hours summary, daily material summary, and daily equipment summary. At any period during construction, contractors may not be able to execute any work if cash is not available, despite the obligation to abide by the schedule. A critical factor for construction organizations in running a profitable business is their ability to carry out construction operations with minimal financing costs. In lump sum projects, contractors are typically paid based on their demonstrated percentage complete, together with the approved revenue (as stipulated in the contract) for the completed work [141].

Subcontractor management, Subcontractor Billed Index, Subcontractor billed amount/Actual Cost. Note that the term contractor can refer to either a prime contractor or a subcontractor. On average, 40% of production cost is due to material procurement; therefore, subcontractor management is extremely important. It follows that a substantial portion of quality problems is related to the subcontractor. The establishment of a partnership is essential in order for both parties to succeed in their business. The subcontractor should make a positive contribution to design, production, and cost reduction. Emphasis should be placed on the total material cost, which includes that of price and quality [142].

Subcontractor management activities include:

1. Subcontractor qualification & Approved Vendor List control
2. Control of bill of material (BOM) and process.
3. Package IQC
4. Monthly key process Cpk1(>1.67)report
5. Reliability monitoring (plus de-lamination, die crack, and cratering check)
6. Foundry/ Assembly/ Testing house rating
7. Monthly/ Quarterly meeting with key subcontractors1Cpk is an index of process capability. It measures the process stability with respect to the standards over a certain period. To calculate Cpk, it is necessary to calculate another index, Cp, which measures the data bias toward the standard center.

$$C_p = \frac{(Upper\ Limit - Lower\ Limit}{6\sigma} \tag{3.8}$$

$$C_{pk} = \frac{|Standar\ limit\ closest\ to\ the\ average\ value - average|}{3\sigma} \tag{3.9}$$

Where σ is the standard deviation,

1. In-process monitor.
2. Process control (Man, Machine, Material, Method).
3. Product output (inspect good and reject parts in each stage).

4. ISSI finding and reporting.
5. Subcontractor’s action and continuous improvement.
6. Review FMEA (corrections effectiveness validation).
7. Regular and non-regular on side audit.

Change orders can occur and are often unavoidable during the construction process. A change order is a work that is added or deleted from the original scope of work and as a result, the original contract amount and/or a completion date of your project is modified [139]. Despite the project team’s best effort to avoid change orders during construction, they are common. There are many reasons changes can occur. Most of the time they result from unknown field conditions, design changes, or owner requests. If change orders occur, here is what you can expect and how to best handle them [143].

Change orders can increase the cost of your project. One way to avoid going over budget is to plan for a 5-10% contingency to handle these items. This way if changes occur, they will not exceed your budget. When a change is required it is best to notify the team immediately. This way the issue can be discussed and a solution developed. Many times the changes will require the architect or engineer to revise the project drawings or make permitting changes and then additional work must be priced for owner acceptance. Depending on the magnitude of the change, the project schedule may be extended or completion of certain work could be delayed [144].

The cost of your project will increase and the project schedule will extend if custom, pre-ordered or installed items, (i.e. structural steel) need to be revised or re-ordered. The timing of changes can also have varying effects on construction. Changes can result in several week delays as the trickle-down effect of one change impacts other progress. If changes are significant throughout the duration of the project, contingency budgets could be exceeded resulting in additional bank financing. Depending on the financing package, it could take a few weeks or several months to secure the necessary funds. Changes throughout a project may be unavoidable, but planning ahead with your design and project team can minimize changes along the way [145]. Changes must be factored into the overall plan as they can extend project completion. The key to the entire construction process is good communication with the project team. This will help ensure that the final product meets the owner's building, budget, and schedule requirements [146].

Yaseen, et al., [147] used a machine learning model namely extreme learning machine (ELM) is proposed to predict the compressive strength of foamed concrete. The potential of the ELM model is validated in comparison with multivariate adaptive regression spline (MARS), M5 Tree models, and support vector regression (SVR). The Lightweight foamed concrete is produced via creating a cellular structure in a cementitious matrix during the mixing process and is widely used in heat insulation, sound attenuation, roofing, tunneling, and geotechnical applications. Achieving product consistency and accurate predictability of its performance is key to the success of this technology. In the present study, an experimental database encompassing pertinent data retrieved from several previous studies has been created and utilized to train and validate the ELM, MARS, M5 Tree, and SVR machine learning models. The input parameters for the predictive models include the cement content, oven-dry density, water-to-binder ratio, and foamed volume. The predictive accuracy of the four models has been assessed via several statistical score indicators. The results showed that the proposed ELM model achieved an adequate level of prediction accuracy, improving MARS, M5 Tree, and SVR models where the whole data size for each factor was 92. Hence, the ELM model could be employed as a reliable and accurate data intelligent approach for predicting the compressive strength of foamed concrete, saving laborious trial batches required to attain the desired product quality.

Yaseen, et al., [95] used An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area. This paper aims to investigate the viability of the enhanced version of the extreme learning machine (EELM) model in river flow forecasting applied in a tropical environment. Herein, we apply the complete orthogonal decomposition (COD) learning tool to tune the output-hidden layer of the ELM model's internal neuronal system, instead of the conventional multi-resolution tool (e.g., singular value decomposition). To demonstrate the application of the EELM model, the Kelantan River, located in the Malaysian peninsular, was selected as a case study. For a comparison of the EELM model, and further model evaluation, two distinct data-intelligent models are developed (i.e., the classical ELM and the support vector regression, SVR model) and the data size that selected was 92. An exhaustive list of diagnostic indicators is used to evaluate the EELM model with respect to the benchmark algorithms, namely, SVR and ELM. The model performance indicators exhibit superior results for the EELM model relative to ELM and SVR models. In addition, the EELM model is presented as a more accurate, alternative predictive tool for modeling the tropical river flow patterns and its underlying characteristic perturbations in the physical space.

Huang, et al., [148] This paper proposes a multivariate chaotic Extreme Learning Machine (ELM) model for the prediction of the displacement of reservoir landslides. The displacement time series of the Baishuihe and Bazimen landslides in the Three Gorges Reservoir Area in China are used as examples. The results show that there is evidence of chaos in the displacement time series. The univariate chaotic ELM model and the multivariate chaotic model based on Particle Swarm Optimization and Support Vector Machine (PSO-SVM) model are also applied for the purpose of comparison. The comparisons show that the multivariate chaotic ELM model achieves higher prediction accuracy than the univariate chaotic ELM model and the multivariate chaotic PSO-SVM model.

Sun, et al., [149] Sales forecasting is a challenging problem owing to the volatility of demand which depends on many factors. This is especially prominent in fashion retailing where a versatile sales forecasting system is crucial. This study applies a novel neural network technique called extreme learning machine (ELM) to investigate the relationship between sales amount and some significant factors which affect demand (such as design factors). Performances of our models are evaluated by using real data from a fashion retailer in Hong Kong. The experimental results demonstrate that our proposed methods outperform several sales forecasting methods that are based on backpropagation neural networks and the data size was (12, 52, and 182).

Miche, et al., [150] the optimally pruned extreme learning machine (OP-ELM) methodology is presented. It is based on the original extreme learning machine (ELM) algorithm with additional steps to make it more robust and generic. The whole methodology is presented in detail and then applied to several regression and classification problems. Results for both computational time and accuracy (mean square error) are compared to the original ELM and to three other widely used methodologies: multilayer perceptron (MLP), support vector machine (SVM), and Gaussian process (GP). As the experiments for both regression and classification illustrate, the proposed OP-ELM methodology performs several orders of magnitude faster than the other algorithms used and the selected data size was ranging from (100 to 6344), except the original ELM. Despite the simplicity and fast performance, the OP-ELM is still able to maintain an accuracy that is comparable to the performance of the SVM.

Ding, et al., [151] compared with the conventional neural network learning the algorithm it overcomes the slow training speed and over-fitting problems. ELM is based on empirical risk minimization theory and its learning process needs only a single iteration. The algorithm avoids multiple iterations and local minimization. It has been used in various fields and applications because of better generalization ability, robustness, and controllability, and fast learning rate. In this paper, we make a review of ELM's latest research progress about the algorithms, theory, and applications. It first analyzes the theory and the algorithm ideas of ELM, then tracking describes the latest progress of ELM in recent years, including the model and specific applications of ELM and the selected data size that been used between (20-500), finally points out the research and development prospects of ELM in the future.

Wan, et al., [152] used an accurate and reliable forecast of wind power to power system operation and control. However, due to the non-stationarity of wind power series, traditional point forecasting can hardly be accurate, leading to increased uncertainties and risks for system operation. This paper proposes an extreme learning machine (ELM)-based probabilistic forecasting method for wind power generation with data size ranging between (20 and 1000). To account for the uncertainties in the forecasting results, several bootstrap methods have been compared for modeling the regression uncertainty, based on which the pairs bootstrap method is identified with the best performance. Consequently, a new method for prediction intervals formulation based on the ELM and the pairs bootstrap is developed. Wind power forecasting has been conducted in different seasons using the proposed approach with the historical wind power time series as the inputs alone. The results demonstrate that the proposed method is effective for probabilistic forecasting of wind power generation with a high potential for practical applications in power systems.

Pusil et al [153] make a comparative study of three variants of harmony search (the original Harmony Search, Global-best Harmony Search, and New Global Harmony Search), a memetic algorithm from the state of the art denominated MELM and a random walk algorithm named RW-ELM on 20 classical classification datasets available in the UCI repository. The results show that the best algorithm for training ELMs is Harmony Search and that the other two variants of this algorithm are better than M-ELM and RW-ELM when cross-validation is used. The experiments were performed at first using separate archives for training and testing, then using cross-validation with 5 folders. The data size that used was ranged between 70 and 1152 trains, the test was ranged between 30 and 576 and using single hidden layer with 50 nodes.

Raoof [154] In this research, a relatively new intelligent model called deep neural network (DNN) is proposed to calculate the EAC. The proposed DNN model is authenticated against one of the predominated intelligent models conducted on the EAC prediction, namely support vector regression model (SVR). In order to demonstrate the capability of the model in the engineering applications, historical project information obtained from fifteen projects in the Iraq region is inspected in this research. The second phase of this research is about the integration of two input optimization algorithms hybridized with the proposed and the comparable predictive intelligent models. These input optimization algorithms are a genetic algorithm (GA) and brute force algorithm (BF). The aim of integrating these input optimization algorithms to approximate the input attributes and investigate the highly influenced factors on the calculation of EAC. Overall, the enthusiasm of this study is to provide a robust intelligent model that estimates the project cost accurately over the traditional methods. Also, the second aim is to introduce a reliable methodology that can provide efficient and effective project cost control. The proposed GA-DNN is demonstrated as a reliable and robust intelligence model for EAC calculation.

On the other hand, the estimation at completion is organized to predict and variable in the learning process. The modeling was constructed using ten construction projects with 132 periods was appropriate based on the previous studies that mention that the data size was ranging from (20- 6344), 75 percent of the total data was for the learning processes of the predictive model. Whereas, 25% (33 periods) was used to initiate the testing phase for the modeling evaluation. Full detail of the studied projects is displayed in Table 3.1, which has been collected from Al Naboodah Construction Group that available online (http://www.alnaboodahconstruction.com/), Arabian Construction Company Dubai that available online (https://www.accsal.com/), and Al Jaber LEGT Engineering and Contracting (ALEC) that available online (http://alec.ae/) depending on my personal relations. The developed EAC predictive model is presented in Figure 3.27.

Table 3.1 The details of the modelled construction project used in the current research

Project name	Total area (m2)	Underground floors	Ground floors	Buildings	Start date	Finish date	Duration (days)	Contract amount-$	Prediction periods
1	11,254	1	1	3	3/2/2008	4/24/2009	418	7445825	13
2	9,326	1	1	1	8/15/2008	7/28/2009	347	6329548	14
3	12,548	1	1	2	4/23/2003	2/28/2004	311	9518465	12
4	9,482	0	1	1	10/10/2009	11/3/2010	389	7458124	11
5	10,554	2	1	2	6/5/2005	7/2/2006	392	8452847	12
6	8,751	1	1	2	7/5/2011	4/30/2012	300	6895348	14
7	9,458	0	1	1	8/13/2005	7/25/2006	346	7518452	13
8	13,758	1	1	3	9/20/2004	10/15/2005	390	9548249	16
9	11,249	1	1	3	4/20/2007	4/18/2008	364	8628945	13
10	7,851	0	1	1	12/24/2011	1/19/2013	392	5936461	14
Total									132
Training									99
Testing									33

The predictive models are examined using several numerical indicators that present the absolute error evaluation (the closest to zero) the best-goodness (the closest to one). In that way, more justification can be done on the optimal model for the best input combination. The numerical indicators are root mean square error (*RMSE*)

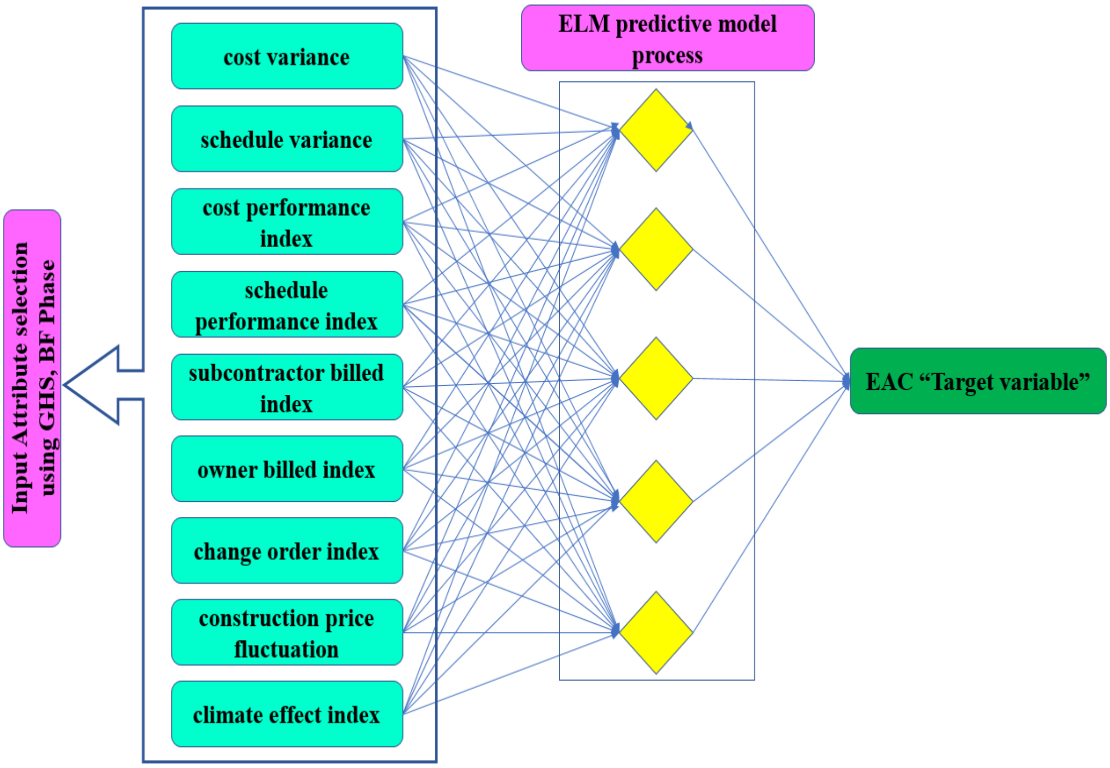


Figure 3.27 The developed EAC predictive model

[155], mean absolute error (*MAE*), mean relative error (MRE), Nash-Sutcliffe coefficient (*NSE*) [156], scatter index (*SI*), and correlation coefficient (*R*). The mathematical can be described as followed:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(EAC_a - EAC_p)^2}{n}} \tag{3.10}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|EAC_a - EAC_p\right|}{n} \tag{3.11}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{EAC_a - EAC_p}{EAC_a}\right) \tag{3.12}$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(EAC_a - EAC_p)^2}{\sum_{i=1}^{n}(EAC_a - \overline{EAC_a})^2}\right] \tag{3.13}$$

$$SI = \frac{\sqrt{\frac{\sum_{i=1}^{n}(EAC_a - EAC_p)^2}{n}}}{\overline{EAC_a}} \tag{3.14}$$

$$R = 1 - \left[\frac{\sum_{i=1}^{n}(EAC_a - \overline{EAC_a})(EAC_p - \overline{EAC_p})}{\sqrt{\sum_{i=1}^{n}(EAC_a - \overline{EAC_a})^2} \sqrt{\sum_{i=1}^{n}(EAC_p - \overline{EAC_p})^2}} \right] \tag{3.15}$$

where EAC_a is the actual observation, EAC_p is the predicted value, $\overline{EAC_a}$ and $\overline{EAC_p}$ are the mean values of the actual and predicted value. All equations were applied by the Matlab software program after investigating the predicted value by the same program as previously mentioned.

4

RESULTS AND DISCUSSION

4.1 Introduction

This section presents the applicability of the hybrid predictive models (i.e., ELM, ANN, GHS-ELM, GHS-ANN, BF-ELM, and BF-ANN) for simulating the estimation at the completion of construction projects. As a concluding stage of the prediction process, the data cost of the selected projects was determined by computing the differences between the planned and actual costs for each month. The applied intelligence models were used to compute the mathematical relationship between nine attributes (the abstracted input combinations) and the targeted variable (EAC). The applied hybrid models were used in this computation process to overcome the challenges of the classical indexed formulations. Worth to mention, hybrid intelligence models have been proven to stimulate human intelligence in finding solutions to complex real-life problems. Several statistical indicators we used to present the absolute error measures and the best fit goodness as tabulated in Tables 4.1-4.9.

4.2 Classical Predictive Models

The primary objective of the current research is the proposition of the ELM predictive model as a new data intelligence model for the investigated cost at completion problem. The indicators of the prediction performances of the classical ELM and ANN-based model using all the input variables are presented in Table 4.1.

Table 4.1 The numerical evaluation indicators for the ELM and ANN predictive models "Based-models' versions" over the testing modeling phase

Predictive Models	RMSE	MAE	MRE	NSE	SI	BIAS	R
ELM	0.14709	0.4428	0.4692	-5.4452	1.9736	-0.34305	0.9331
ANN	0.2478	0.5321	0.0126	-0.8175	1.0480	-0.0964	0.4712

In accordance to the tabulated result in table 4.1 the table, the ELM was observed to achieve a better prediction performance compared to the ANN model. Quantitatively, the ELM achieved RMSE-MAE and NSE-R values of 0.147–0.4428 and

-5.4452–0.9331, while the ANN model achieved RMSE-MAE and NSE-R values of 0.2478–0.5321 and -0.8175–0.4712. The ELM model presented a notable improvement in the performance compared to the classical data-intelligence ANN model. This has satisfied the first aim of this research where the new model was introduced to the construction engineering field as a reliable solution for calculating EAC.

4.3 The Performance of the Proposed Coupled Soft Computing Models

The input selection approach was mainly incorporated into the predictive model to explore the predominant combination of inputs that correlate to the EAC magnitude. This is mainly important in the recognition of the main influencing factors which can bring about differences in the EAC results as the project progresses. The ELM and ANN model were hybridized with a modern input variable selection approach called global harmony search to search for the suitable input combination. In this article, the BF algorithm input selection was used as a benchmark for the performance of the GHS algorithm.

Tables 4.2 and 4.3 respectively presented the input combinations and the outcome of the prediction task using the hybrid GHS-ELM model.

Table 4.2 The input combination attributes used to determine the value of the EAC using the GHS-ELM model

The Number of Inputs	Models	The Type of Input Variables	Output
2 inputs	**Model 1**	CV, SV	EAC
3 inputs	**Model 2**	CV, SV, change order index	EAC
4 inputs	**Model 3**	CV, SV, CPI, SPI	EAC
5 inputs	**Model 4**	.CV, SV, CPI, SPI, Subcontractor billed index	EAC
6 inputs	**Model 5**	CV, SV, CPI, SPI, Subcontractor billed index ,Owner billed index	EAC
7 inputs	**Model 6**	CV,SV,CPI,SPI,Subcontractor billed index,Owner billed index,change order index	EAC
8 inputs	**Model 7**	CV,SV,CPI,SPI,Subcontractor billed index,Owner billed index,change order index,CCI	EAC

Table 4.3 The numerical evaluation indicators for the GHS-ELM predictive model over the testing modeling phase (Bold is the best input combination)

Method	RMSE	MAE	MRE	NSE	SI	BIAS	R
Model 1	0.050313	0.027321	0.017615	0.92505	0.21283	-0.015854	0.97225
Model 2	0.22808	0.15427	0.1626	-0.5403	0.9648	-0.14634	0.80823
Model 3	0.42678	0.36252	0.33496	-4.3931	1.8053	-0.30147	0.060284
Model 4	0.15961	0.13127	0.14487	0.2457	0.67516	-0.13039	0.89944
Model 5	0.24854	0.19625	0.21361	-0.82904	1.0513	-0.19225	0.7928
Model 6	0.32799	0.27946	0.30694	-2.1854	1.3874	-0.27624	0.54222
Model 7	0.2742	0.21173	0.20302	-1.2263	1.1599	-0.18272	0.61053

The review of the results presented in Table 4.3 showed that Model 1 achieved an excellent EAC prediction using a combination of CV, and SV variables as the inputs for the prediction process. The model achieved the least RMSE-MAE values of 0.050313–0.027321and the best-fit-goodness NSE-R values of 0.92505–0.97225.

The hybridized BF-ELM model showed different prediction performance (Tables 4.4 and 4.5) in terms of the 4 input variables (CV, SV, CPI, SPI). At its optimal performance, it presented a minimum RMSE value of approximately 0.0429 and R *of* approximately 0.98559.

Table 4.4 The input combination attributes used to determine the value of the EAC using the BF-ELM model

The Number of Inputs	Models	The Type of Input Variables	Output
2 inputs	**Model 1**	CV, SV	EAC
3 inputs	**Model 2**	CV, SV, change order index	EAC
4 inputs	**Model 3**	.CV, SV, CPI, SPI	EAC
5 inputs	**Model 4**	CV, SV, CPI, SPI, Subcontractor billed index	EAC
6 inputs	**Model 5**	CV,SV,CPI,SPI, Subcontractor billed index, Owner billed index	EAC
7 inputs	**Model 6**	CV, SPI, Subcontractor billed index, Owner billed index, change order index, CCI, Climate effect index	EAC
8 inputs	**Model 7**	CV, SV, CPI, SPI, Subcontractor billed index, change order index, CCI, Climate effect index	EAC

Table 4.5 The numerical evaluation indicators for the BF-ELM predictive model over the testing modeling phase (Bold is the best input combination)

Models	RMSE	MAE	MRE	NSE	SI	BIAS	R
Model 1	0.11808	0.11133	0.11933	0.58718	0.49948	-0.10739	0.96511
Model 2	0.5606	0.51044	0.43154	-8.3056	2.3714	-0.38839	-0.80537
Model 3	**0.041743**	**0.034071**	**0.0074243**	**0.94841**	**0.17658**	**-0.0066818**	**0.98953**
Model 4	0.4646	0.38285	0.3119	-5.3915	1.9653	-0.28071	-0.32683
Model 5	0.13624	0.086339	0.086781	0.4504	0.57631	-0.078103	0.902
Model 6	0.6231	0.5944	0.53336	-10.496	2.6358	-0.48003	-0.93149
Model 7	0.58433	0.55918	0.51675	-9.1099	2.4718	-0.46507	-0.96104

Based on the reported prediction accuracy in Table 4.5, the performance of the BF-ELM model was demonstrated a superior capacity to the GHS-ELM model. However, it should be noticed that the BF-ELM model required more execution time to abstract the internal relationship between the predictors and the predicted. Yet, it is true that the GHS-ELM model attained the best prediction results using CV, schedule variance (SV), it is still acceptable from the prospect where minimal parameters were used to construct the predictive model. The results of the input combinations variables and the prediction performances of the GHS-ANN are displayed in Tables 4.6 and 4.7, respectively.

Table 4.6 The input combination attributes used to determine the value of the EAC using the GHS-ANN model

The Number of Inputs	Models	The Type of Input Variables	Output
2 inputs	**Model 1**	CPI, CCI	EAC
3 inputs	**Model 2**	CV, SPI, change order index	EAC
4 inputs	**Model 3**	CV, CPI, SPI, CCI	EAC
5 inputs	**Model 4**	CV, CPI, SPI, subcontractor billed index, CCI	EAC
6 inputs	**Model 5**	CV, SV, CPI, SPI, subcontractor billed index, climate effect index	EAC
7 inputs	**Model 6**	CV, SV, CPI, SPI, subcontractor billed index, owner billed index, climate effect index	EAC
8 inputs	**Model 7**	CV, SV, CPI, SPI, subcontractor billed index, owner billed index, change order index, CCI	EAC

Table 4.7 The numerical evaluation indicators for the GHS-ANN predictive model over the testing modelling phase (Bold is the best input combination)

Method	*RMSE*	MAE	MRE	NSE	SI	BIAS	R
Model 1	0.1219	0.0472	0.0030	0.7183	0.7151	0.0154	0.8524
Model 2	0.1180	0.0465	-0.0948	0.7361	0.6921	0.0270	0.8919
Model 3	**0.1013**	**0.0359**	**-0.0153**	**0.8052**	**0.5946**	**0.0143**	**0.9051**
Model 4	0.1379	0.0601	-0.3018	0.6392	0.8093	0.0462	0.8509
Model 5	0.1349	0.0711	0.3339	0.6548	0.7916	0.0030	0.8105
Model 6	0.1832	0.0843	0.3776	0.3645	1.0740	0.0292	0.6746
Model 7	0.1656	0.0994	0.6472	0.4803	0.9713	-0.0237	0.7140

The optimum input combination of the GHS-ANN model was performed using the 4^{rd} combination by including the CV, CPI, SPI, and CCI variables. On the other hand, BF-ANN allocates its best predictability using the 3^{nd} input combination by incorporating the CV, SV, and CPI variables (Tables 4.8 and 4.9). For more convenience, a comparative analysis was performed between the GHS-ELM and GHS-ANN models and the BF-ELM and BF-ANN models. The comparison of the GHS-ELM and GHS-ANN models showed that the GHS-ELM model was superior in terms of significant improvements based on the quantitative measurements.

Another way of evaluation usually used to visualize the predictive models' capability is a scatter plot. The scatter plot or the variation from the best fit line is a graphical way of representing the relationship between actual and predicted values. Figures 4.1-4.2 showed the deviation from the ideal 45° line for the ELM and ANN, for the GHS-ELM and GHS-ANN, and for the BF-ELM and BF-ANN models, respectively.

Figures 4.1 and 4.2 demonstrate the correlation between predicted EAC and actual EAC by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The first graph refers to using the ELM-based model to represent the Variables and the R^2 value was 0.7299, while Figure 4.2 refers to using the ANN-based model to represent the Variables and the R^2 value was 0.222. The determination coefficient (R^2) has a value ranging from 0 to 1. And when this value becomes near to 1, it will show that most of the variation of the response data is explained by the various input values, while R^2 values near to zero indicate that little of the variation is explained by the various input values. And that clearly shows that the user of an ELM-based model gives a better determination coefficient (R^2)

Table 4.8 The input combination attributes were used to determine the value of the EAC using the BF-ANN model

The Number of Inputs	Models	The Type of Input Variables	Output
2 inputs	**Model 1**	SV, CV	EAC
3 inputs	**Model 2**	CV, SV, CPI	EAC
4 inputs	**Model 3**	CV, SV, CPI, SPI	EAC
5 inputs	**Model 4**	CV, SV, CPI, SPI, subcontractor billed index	EAC
6 inputs	**Model 5**	CV, SV, CPI, SPI, subcontractor billed index, owner billed index	EAC
7 inputs	**Model 6**	CV, SV, CPI, SPI, subcontractor billed index, owner billed index, change order index	EAC
8 inputs	**Model 7**	CV, SV, CPI, SPI, subcontractor billed index, owner billed index, change order index, CCI	EAC

Table 4.9 The numerical evaluation indicators for the BF-ANN predictive model over the testing modelling phase (Bold is the best input combination)

Method	RMSE	MAE	MRE	NSE	SI	BIAS	R
Model 1	0.1114	0.0353	-0.0967	0.7646	0.6537	0.0291	0.9023
Model 2	**0.0982**	**0.0318**	**-0.0125**	**0.8171**	**0.5763**	**0.0206**	**0.9277**
Model 3	0.1044	0.0468	0.0462	0.7931	0.6129	-0.0042	0.8919
Model 4	0.1198	0.0610	0.0418	0.7279	0.7028	-0.0029	0.8585
Model 5	0.1342	0.0711	0.3784	0.6583	0.7876	-0.0201	0.8214
Model 6	0.1525	0.0888	0.7292	0.5589	0.8948	-0.0265	0.7634
Model 7	0.1656	0.0994	0.6472	0.4803	0.9713	-0.0237	0.7140

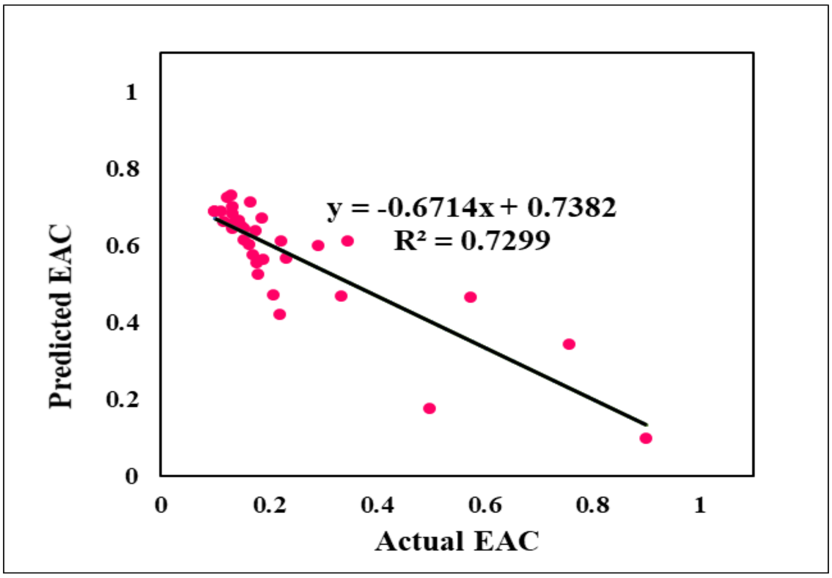


Figure 4.1 The correlation variance between the classical ELM predictive models over the testing phase

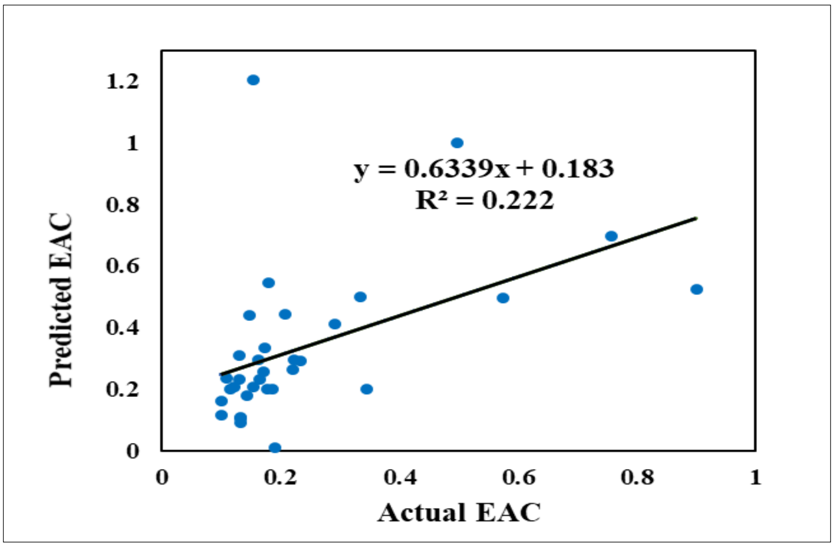


Figure 4.2 The correlation variance between the classical ANN predictive models over the testing phase

Figure 4.3 demonstrates the correlation between predicted EAC and actual EAC for GHS-ELM and GHS-ANN predictive models for model 1 with (CV and SV) and (CPI and CCI) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of GHS-ELM gives an R^2 value = 0.9453 while using GHS-ANN to represent the Variables gives a lower R^2 value = 0.7267. And that clearly shows that the use of GHS-ELM gives a better determination coefficient (R^2) comparison with GHS-ANN for the same number of variables.

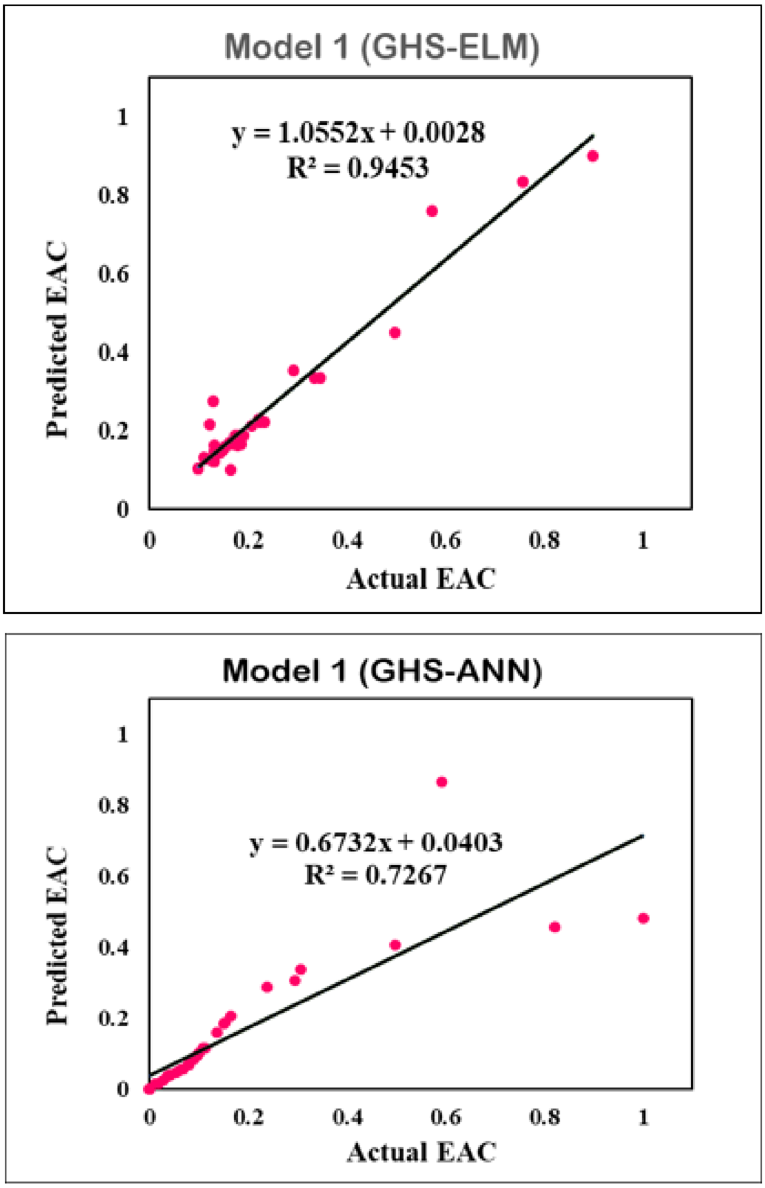


Figure 4.3 The correlation variance between the hybrid GHS-ELM and GHS-ANN predictive models 1

Figure 4.4 demonstrates the correlation between predicted EAC and actual EAC for GHS-ELM and GHS-ANN predictive models for model 2 with (CV, SV, and change order index) and (CV, SPI and change order index) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of GHS-ELM gives an R^2 value = 0.6532 while using GHS-ANN to represent the Variables gives a higher R^2 value = 0.7955. And that clearly shows that the using of GHS-ANN give a better determination coefficient (R^2) comparison with GHS- ELM for the same number of variables.

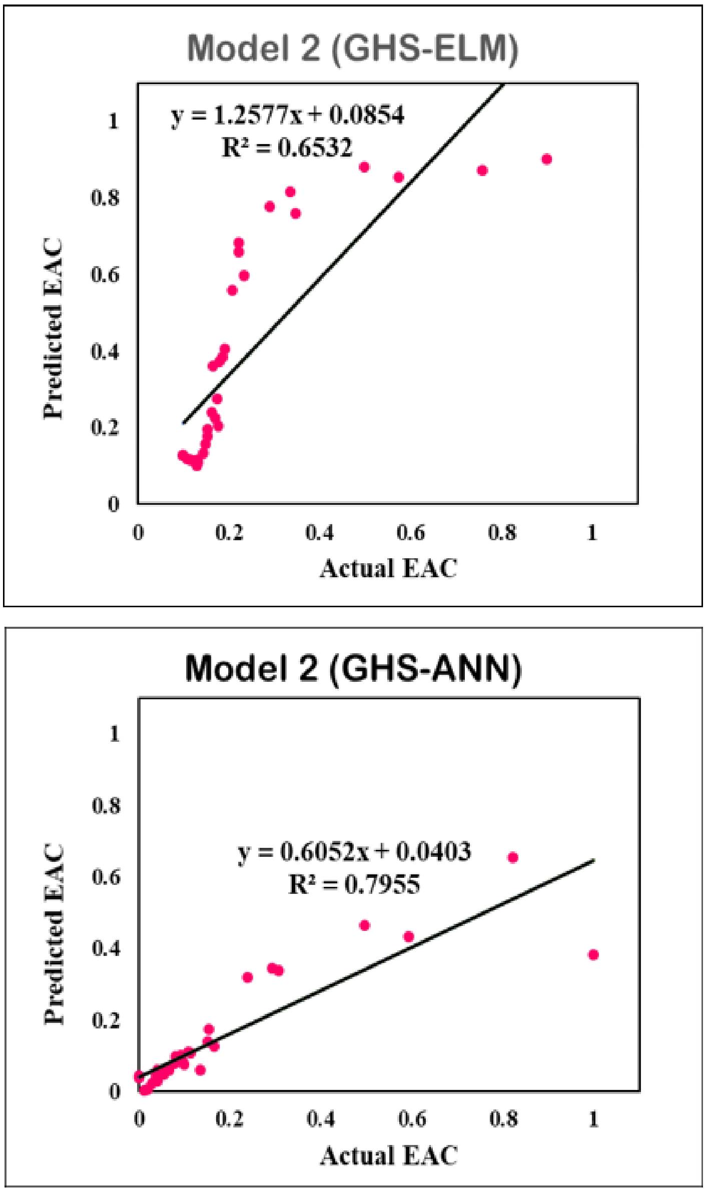
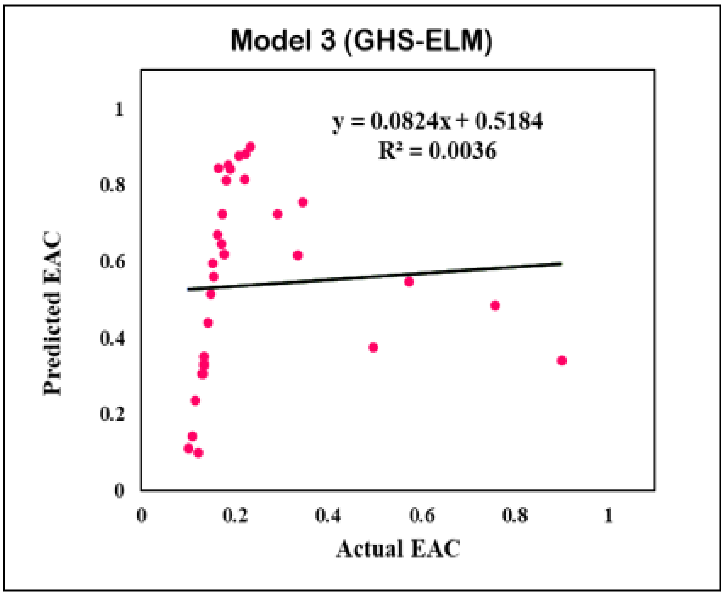


Figure 4.4 The correlation variance between the hybrid GHS-ELM and GHS-ANN predictive models 2

Figure 4.5 demonstrates the correlation between predicted EAC and actual EAC for GHS-ELM and GHS-ANN predictive models for model 3 with (CV, SV, CPI, and SPI) and (CV, CPI, SPI, and CCI) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R2) value and the line formula. The use of GHS-ELM gives an R2 value = 0.0036 while using GHS-ANN to represent the Variables give a lower R2 value = 0.8194. And that clearly shows that the use of GHS-ELM gives a better determination coefficient (R2) comparison with GHS-ANN for the same number of variables.



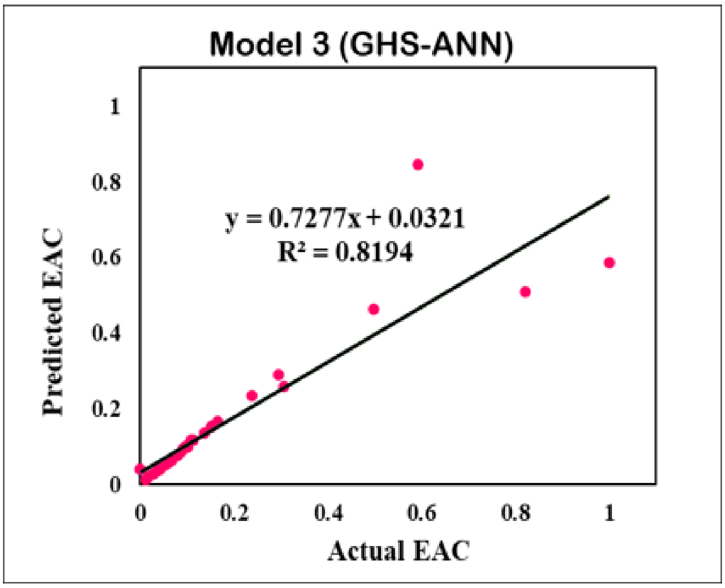
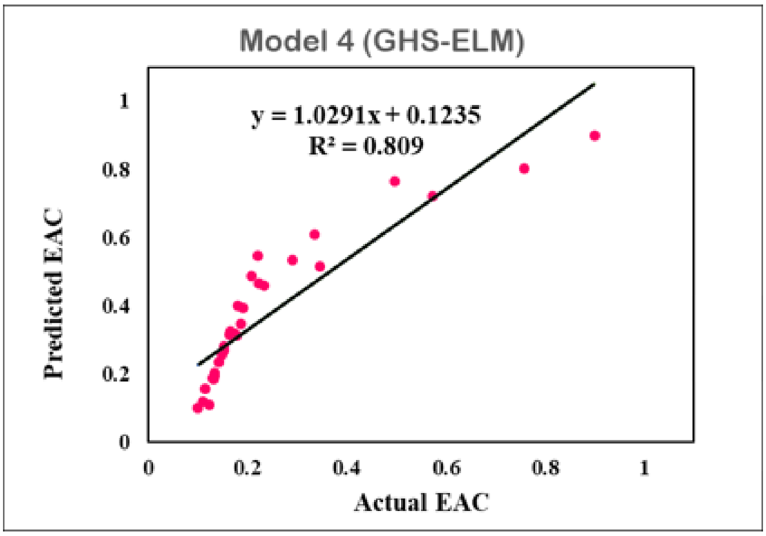


Figure 4.5 The correlation variance between the hybrid GHS-ELM and GHS-ANN predictive models 3

Figure 4.6 demonstrates the correlation between predicted EAC and actual EAC for GHS-ELM and GHS-ANN predictive models for model 4 with (CV, SV, CPI, SPI, and subcontractor billed index) and (CV, CPI, SPI, subcontractor billed index and CCI) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of GHS-ELM gives an R^2 value = 0.809 while using GHS-ANN to represent the Variables gives a higher R^2 value = 0.7241. And that clearly shows that the use of GHS-ANN gives a better determination coefficient (R^2) comparison with GHS-ELM for the same number of variables.



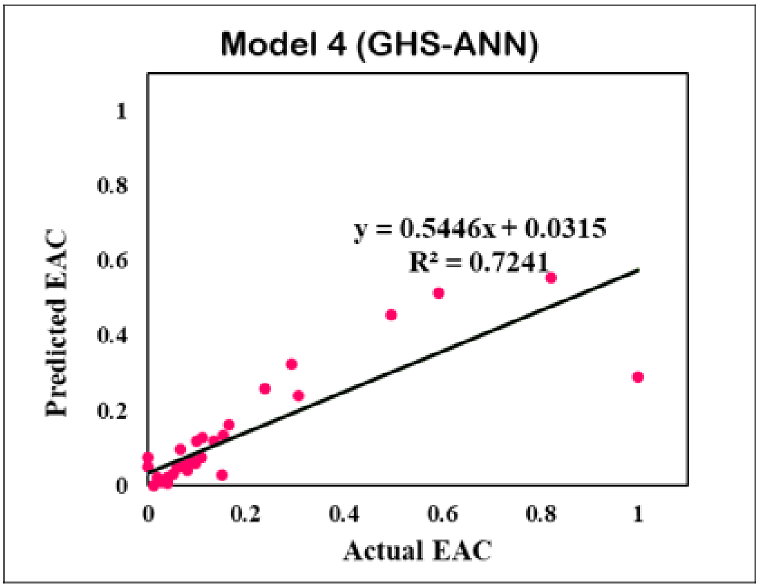


Figure 4.6 The correlation variance between the hybrid GHS-ELM and GHS-ANN predictive models 4

Figure 4.7 demonstrates the correlation between predicted EAC and actual EAC for GHS-ELM and GHS-ANN predictive models for model 5 with (CV, SV, CPI, SPI, subcontractor billed index, and owner billed index) and (CV, SV, CPI, SPI, subcontractor billed index, and climate effect index) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The using of GHS-ELM gives R^2 value = 0.6285, while the using GHS-ANN to represent the Variables give higher R^2 value = 0.657. And that clearly show that the using of GHS-ANN give a better determination coefficient (R^2) comparison with GHS-ELM for the same number of variables.

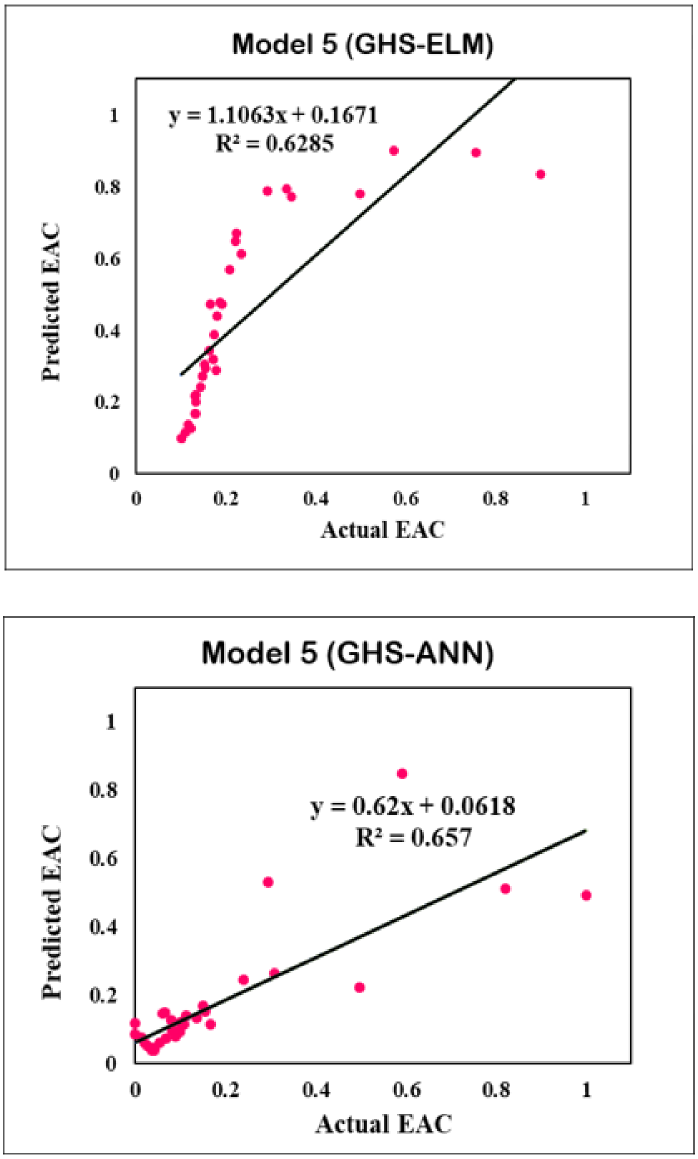
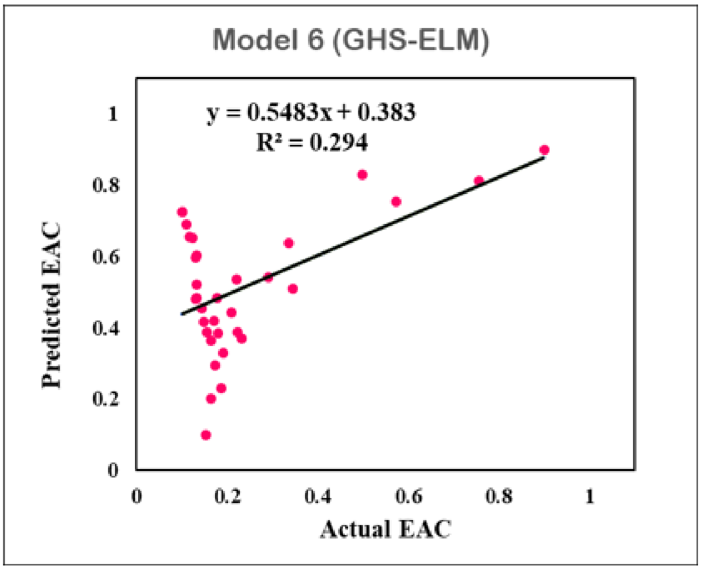


Figure 4.7 The correlation variance between the hybrid GHS-ELM and GHS-ANN predictive models 5

Figure 4.8 demonstrates the correlation between predicted EAC and actual EAC for GHS-ELM and GHS-ANN predictive models for model 6 with (CV, SV, CPI, SPI, subcontractor billed index, owner billed index, and change order index) and (CV, SV, CPI, SPI, subcontractor billed index, owner billed index, and climate effect index) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of GHS-ELM gives R^2 value = 0.264 while using GHS-ANN to represent the Variables gives a lower R^2 value = 0.4551. And that clearly shows that the use of GHS-ELM gives a better determination coefficient (R^2) comparison with GHS-ANN for the same number of variables.



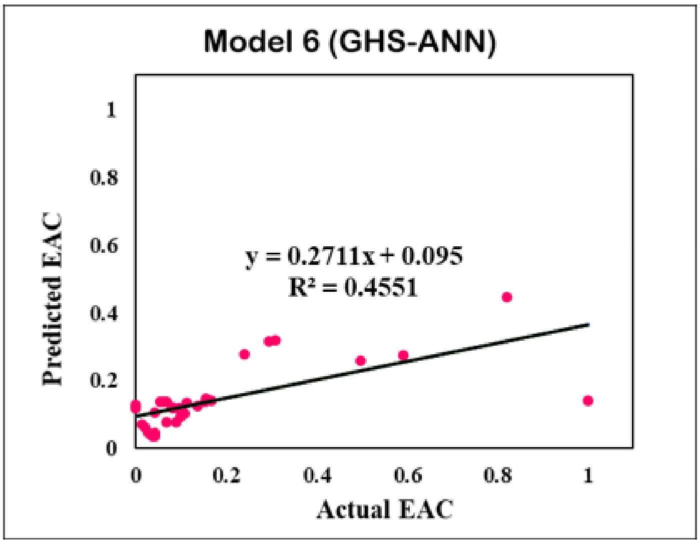
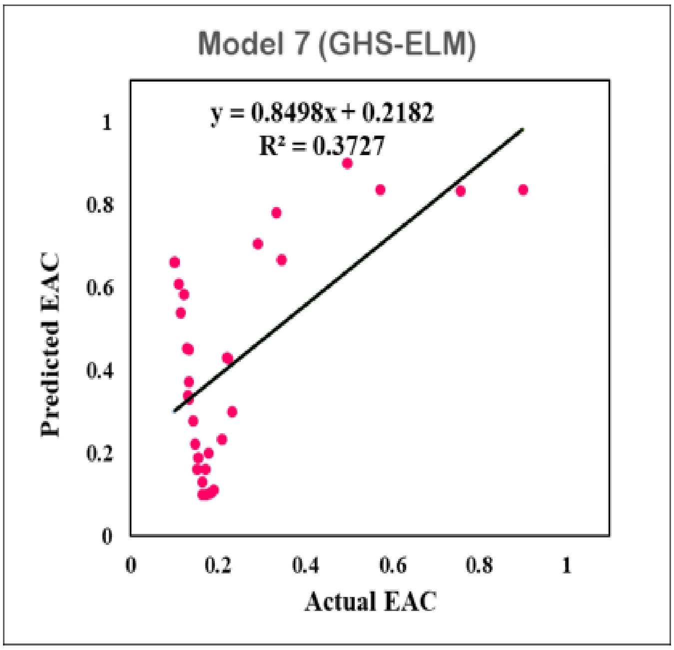


Figure 4.8 The correlation variance between the hybrid GHS-ELM and GHS-ANN predictive models 6

Figure 4.9 demonstrates the correlation between predicted EAC and actual EAC for GHS-ELM and GHS-ANN predictive models for model 7 with (CV, SV, CPI, SPI, subcontractor billed index, owner billed index, change order index, and CCI) and (CV, SV, CPI, SPI, subcontractor billed index, owner billed index, change order index, and CCI) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of GHS-ELM gives an R^2 value = 0.3727, while using GHS-ANN to represent the Variables gives a lower R^2 value = 0.5098. And that clearly shows that the using of GHS-ELM give a better determination coefficient (R^2) comparison with GHS-ANN for the same number of variables.



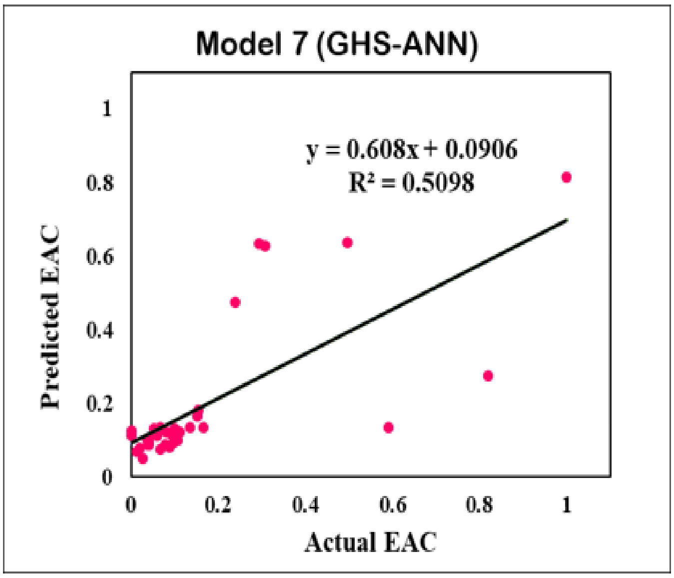
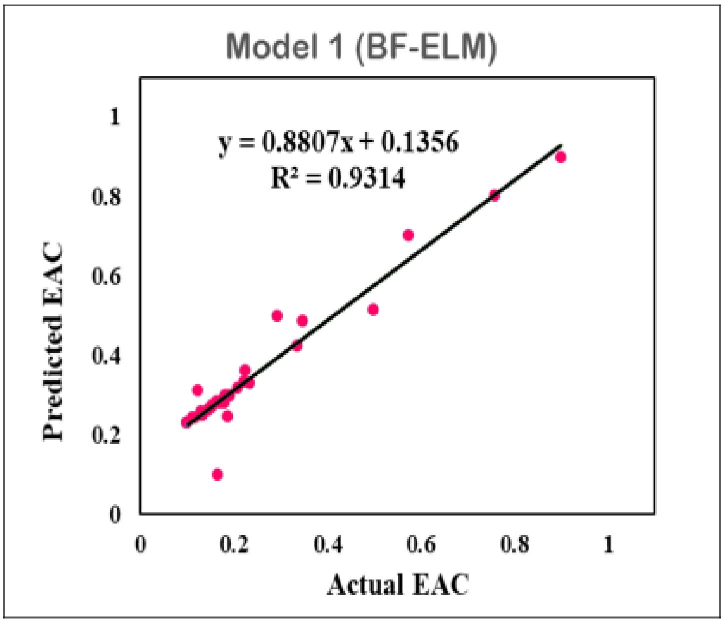


Figure 4.9 The correlation variance between the hybrid GHS-ELM and GHS-ANN predictive models 7

Figure 4.10 demonstrates the correlation between predicted EAC and actual EAC for BF-ELM and BF-ANN predictive models for model 1 with (CV, and SV) and (SV and CV) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of BF-ELM gives an R^2 value = 0.9314 while using BF-ANN to represent the Variables give a lower R^2 value = 0.8143. And that clearly shows that the using of BF-ELM give a better determination coefficient (R^2) comparison with BF-ANN for the same number of variables.



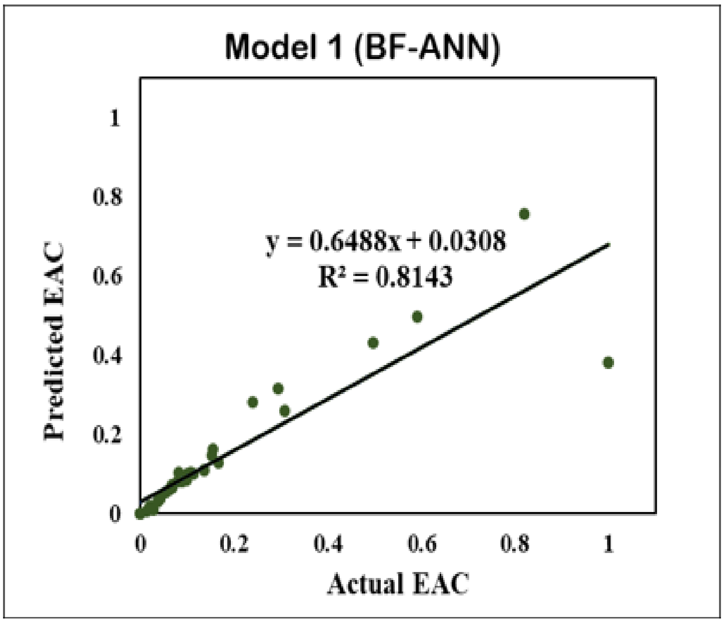
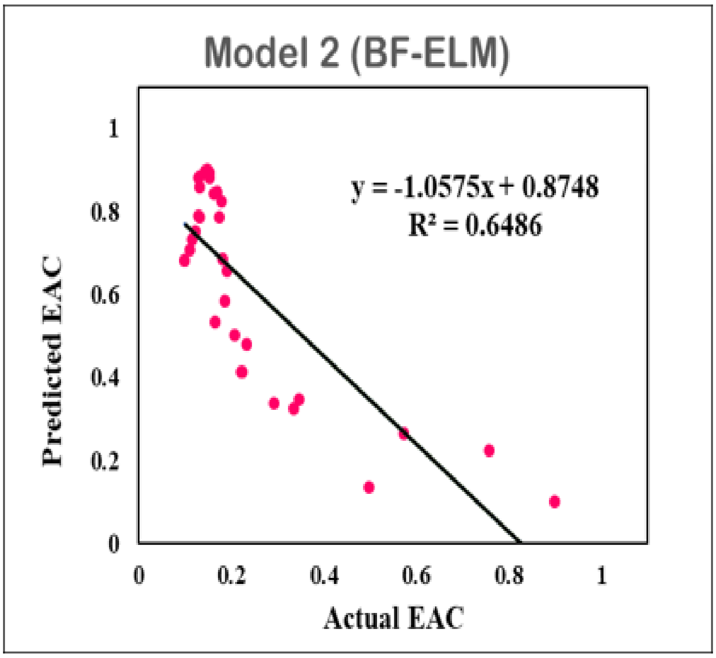


Figure 4.10 The correlation variance between the hybrid BF-ELM and BF-ANN predictive models 1

Figure 4.11 demonstrates the correlation between predicted EAC and actual EAC for BF-ELM and BF-ANN predictive models for model 2 with (CV, SV, and change order index) and (CV, SV, and CPI) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of BF-ELM gives an R^2 value = 0.6486, while using BF-ANN to represent the Variables gives a higher R^2 value = 0.8607. And that clearly shows that the using of BF-ANN give a better determination coefficient (R^2) comparison with BF-ELM for the same number of variables.



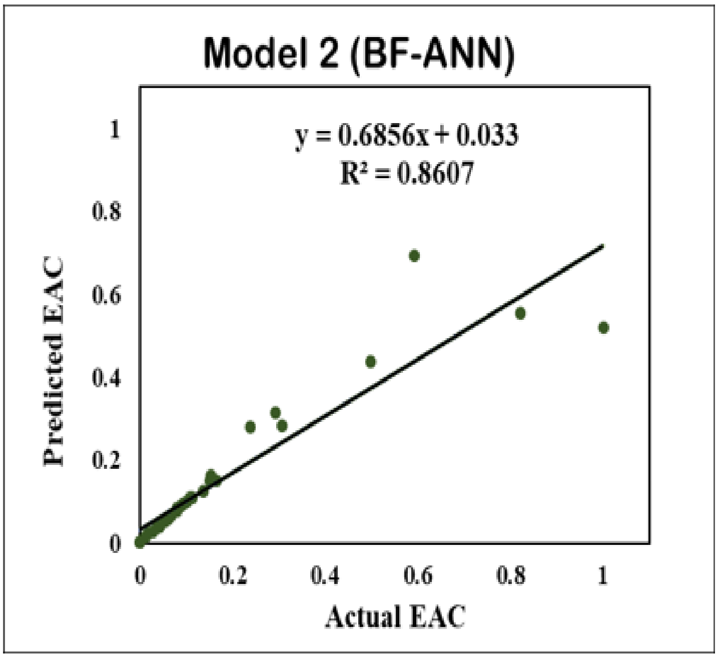


Figure 4.11 The correlation variance between the hybrid BF-ELM and BF-ANN predictive models 2

Figure 4.12 demonstrates the correlation between predicted EAC and actual EAC for BF-ELM and BF-ANN predictive models for model 3 with (CV, SV, CPI, and SPI) and (CV, SV, CPI, SPI) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of BF-ELM gives R^2 value = 0.9597, while the using BF-ANN to represent the Variables give R^2 value = 0.7938.

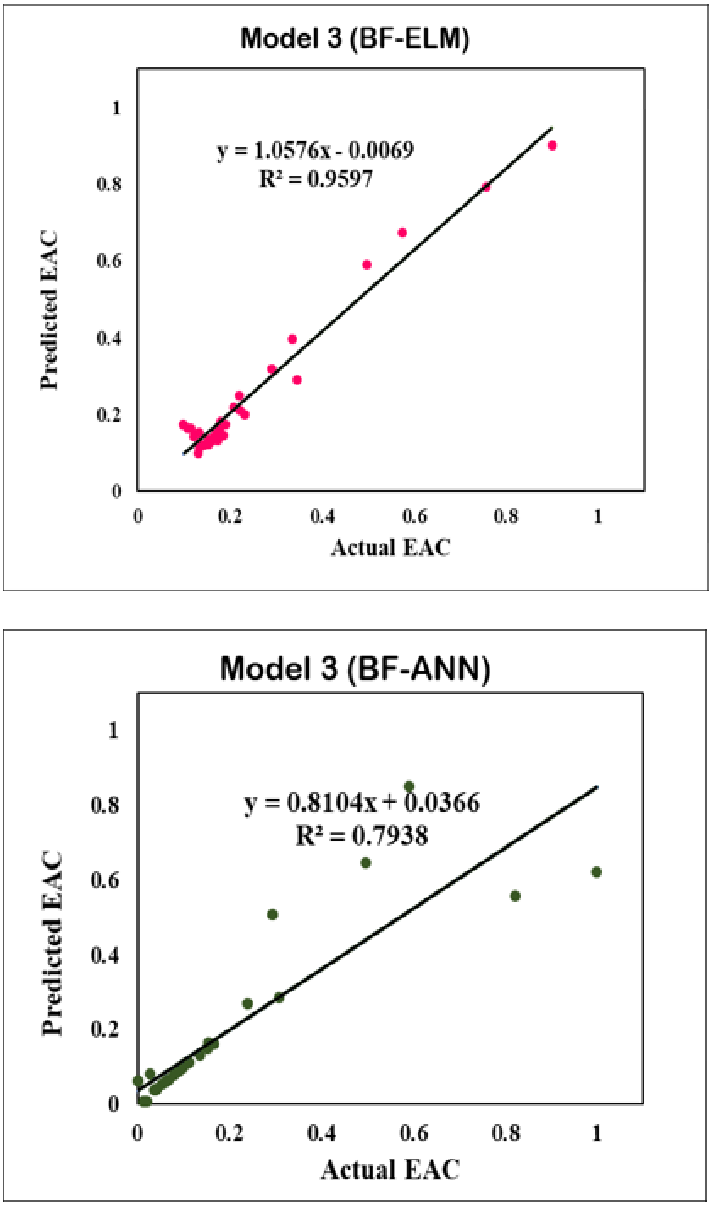


Figure 4.12 The correlation variance between the hybrid BF-ELM and BF-ANN predictive models 3

Figure 4.13 demonstrates the correlation between predicted EAC and actual EAC for BF-ELM and BF-ANN predictive models for model 4 with (CV, SV, CPI, SPI, and subcontractor billed index) and (CV, SV, CPI, SPI, and subcontractor billed index) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of BF-ELM gives an R^2 value = 0.1068 while using BF-ANN to represent the Variables give a higher R^2 value = 0.737. And that clearly shows that the using of BF-ANN give a better determination coefficient (R^2) comparison with BF-ELM for the same number of variables.

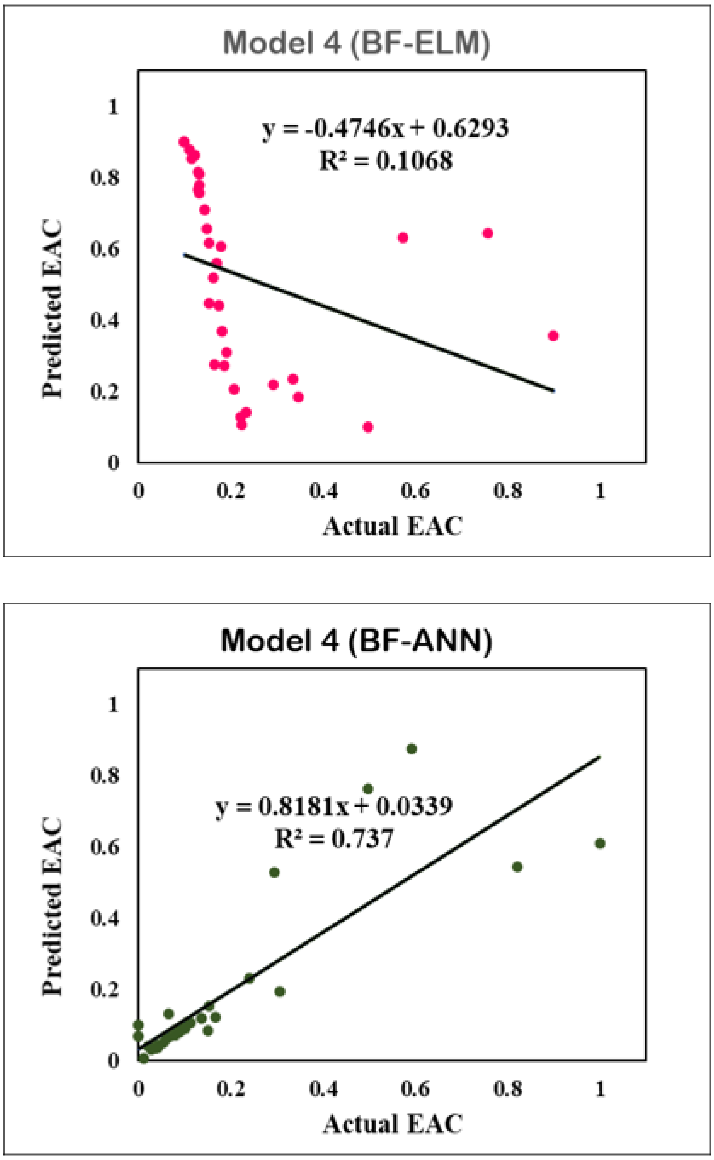
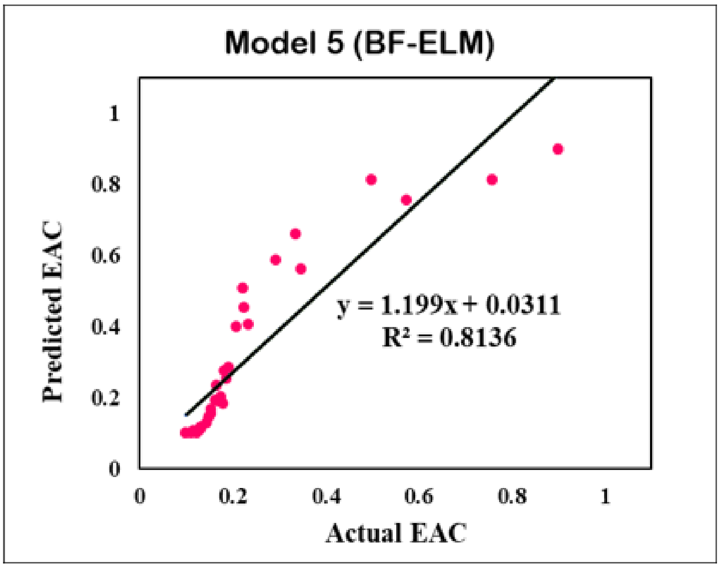


Figure 4.13 The correlation variance between the hybrid BF-ELM and BF-ANN predictive models 4

Figure 4.14 demonstrates the correlation between predicted EAC and actual EAC for BF-ELM and BF-ANN predictive models for model 5 with (CV, CPI, owner billed index, change order index, CCI, climate effect index) and (CV, SV, CPI, SPI, subcontractor billed index, and owner billed index) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of BF-ELM gives an R^2 value = 0.8136 while using BF-ANN to represent the Variables give a lower R^2 value = 0.6748. And that clearly shows that the using of BF-ELM give a better determination coefficient (R^2) comparison with BF-ANN for the same number of variables.



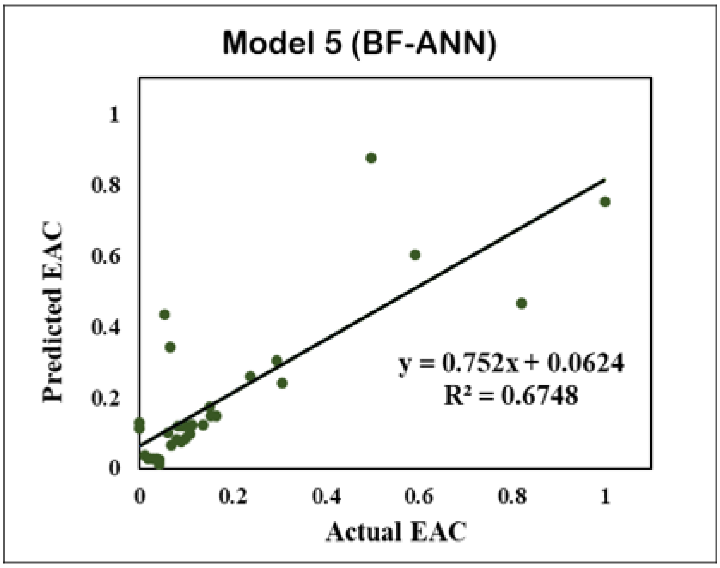
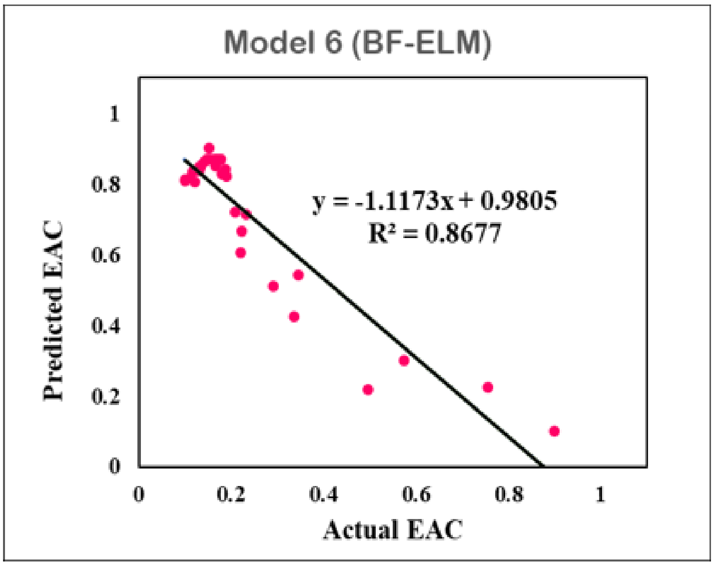


Figure 4.14 The correlation variance between the hybrid BF-ELM and BF-ANN predictive models 5

Figure 4.15 demonstrates the correlation between predicted EAC and actual EAC for BF-ELM and BF-ANN predictive models for model 6 with (CV, SPI, subcontractor billed index, owner billed index, Change order index, CCI, and climate effect index) and (CV, SV, CPI, SPI, subcontractor billed index, owner billed index, and change order index) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R2) value and the line formula. The use of BF-ELM gives an R2 value = 0.8677, while using BF-ANN to represent the Variables gives a lower R2 value = 0.5828. And that clearly shows that the using of BF-ELM give a better determination coefficient (R^2) comparison with BF-ANN for the same number of variables.



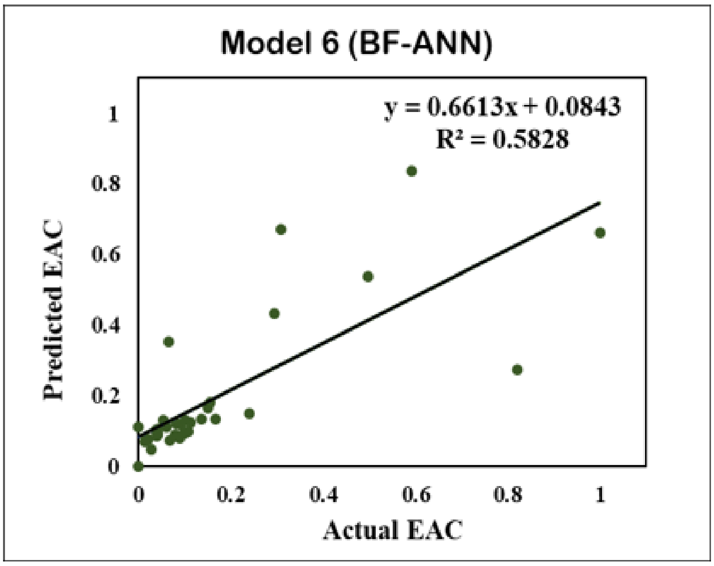
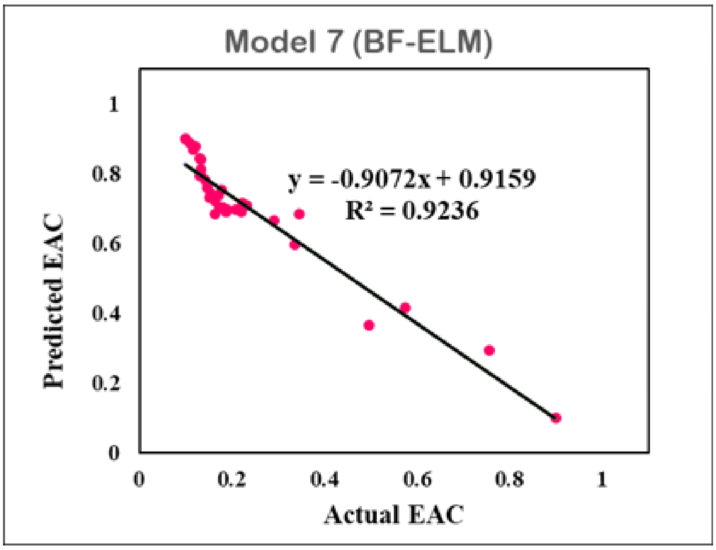


Figure 4.15 The correlation variance between the hybrid BF-ELM and BF-ANN predictive models 6

Figure 4.16 demonstrates the correlation between predicted EAC and actual EAC for BF-ELM and BF-ANN predictive models for model 7 with (CV, SV, CPI, SPI, subcontractor billed index, change order index, CCI, climate effect index) and (CV, SV, CPI, SPI, subcontractor billed index, owner billed index, change order index, and CCI) Variables respectively. And by several attempts utilizing mathematical equations to achieve the best model expression for the determination coefficient (R^2) value and the line formula. The use of BF-ELM gives an R^2 value = 0.9236 while using BF-ANN to represent the Variables gives a lower R2 value = 0.5098. And that clearly shows that the using of BF-ELM give a better determination coefficient (R^2) comparison with BF-ANN for the same number of variables.



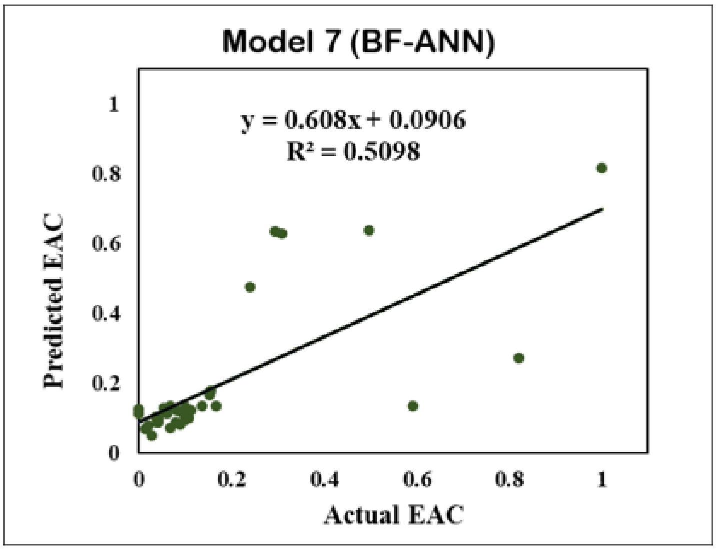


Figure 4.16 The correlation variance between the hybrid BF-ELM and BF-ANN predictive models 7

This is evidence of a perfect agreement between the performance of the hybrid intelligent model over the classical one. A graphical representation of the three metrics (standard deviation, correlation, and root mean square error), which is observed in Figure 4.17 present a screenshot for using Taylor Diagram. The diagrams of Taylor give a brief summary of statistical analysis which shows the matching between patterns with each other depending on the variances ratio, difference in root-mean-square, and correlation of those patterns. As well as any other information like percentage bias could be added to the normal Taylor diagram. The diagram of Taylor gives a graphical framework that allows a suite of variables from a variety of one or more models or reanalyses to be compared to reference data. The reference data could be observationally-based (for example, reanalysis) or to another model or a control run. All variables should be on the same grid so regrinding might be required [157].

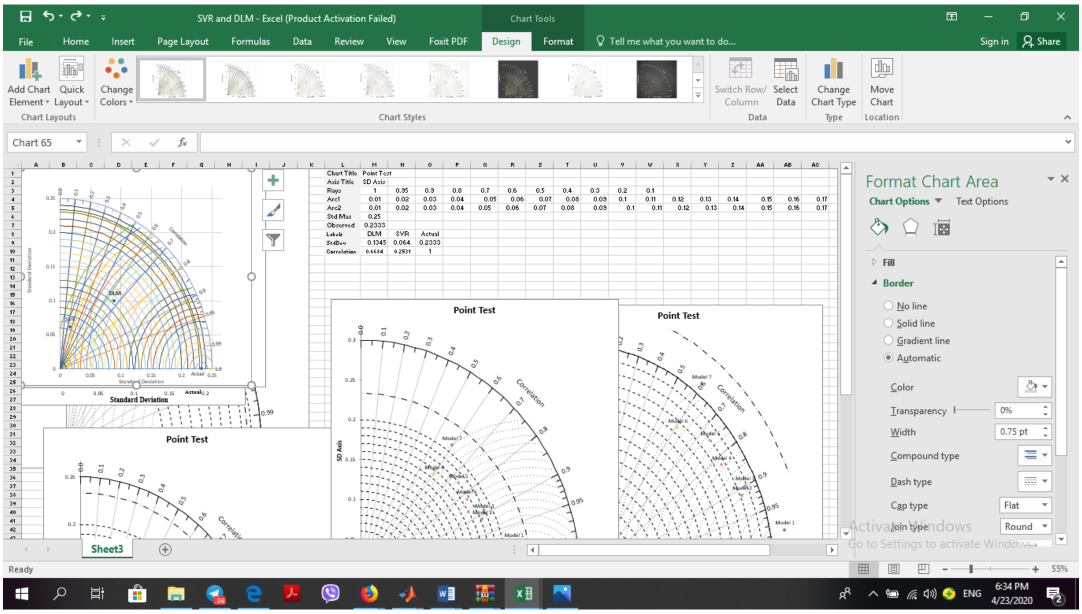


Figure 4.17 A screenshot for preparing the Taylor diagram by excel sheet

Figure 4.18 presents the Taylor Diagram for the relationship between correlation and Stander deviation of Actual data and predictive data using ELM and ANN. Figure 4.18 clearly demonstrated that the use of ELM gives a better correlation and near to the actual result compared with the use of ANN in all models.

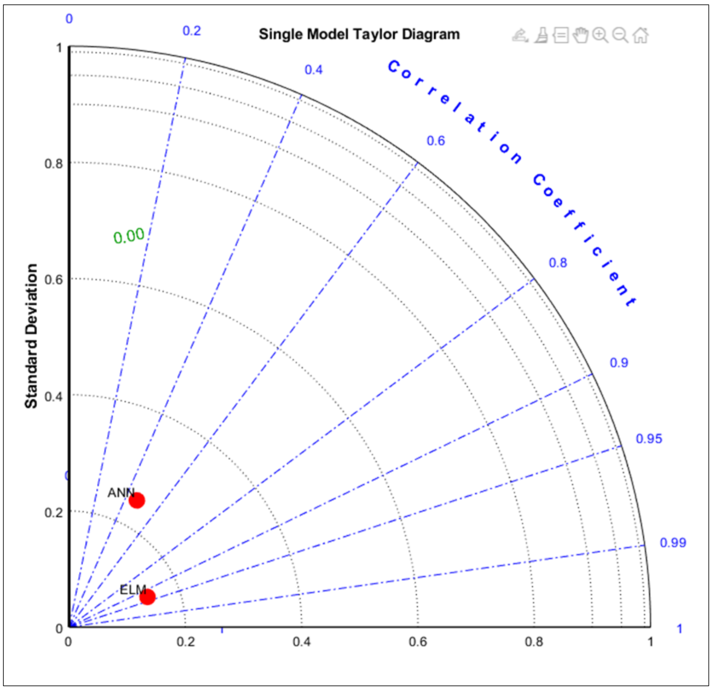


Figure 4.18 The Taylor diagram presentations of the proposed hybrid predictive models (ELM and ANN)

Figure 4.19 presents the Taylor Diagram for the relationship between correlation and Stander deviation of Actual data and predictive data using GHS-ELM. Figure 4.19 clearly demonstrated that the use of GHS-ELM gives better correlation and near to the actual result in model 1 with just two variables which are (CV, and schedule variance (SV)).

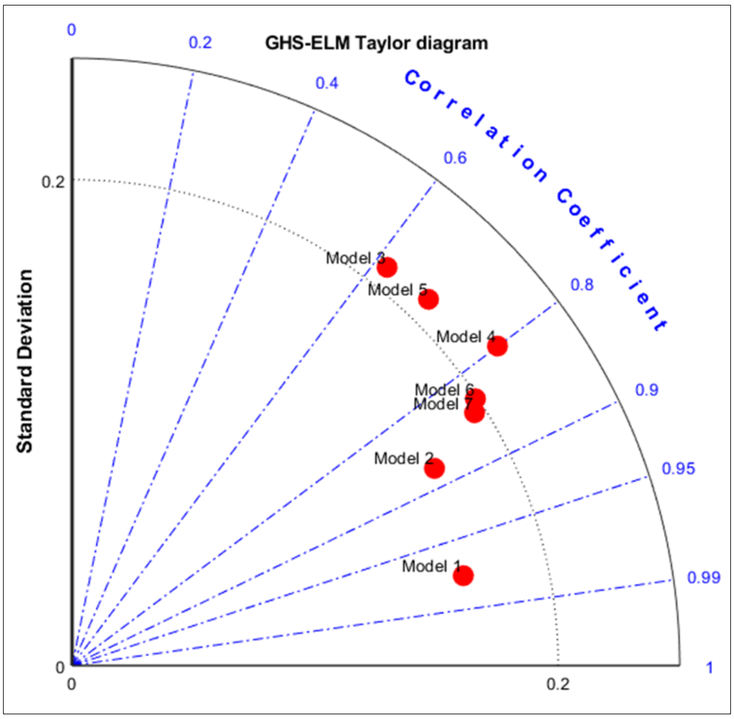


Figure 4.19 The Taylor diagram presentations of the proposed hybrid predictive models (GHS-ELM)

Figure 4.20 presents the Taylor Diagram for the relationship between correlation and Stander deviation of Actual data and predictive data using GHS-ANN. Figure 4.22 clearly demonstrated that the use of GHS-ANN gives better correlation and near to the actual result in model 3 with just four variables which are (CV, CPI, SPI, and CCI).

Figure 4.21 presents the Taylor Diagram for the relationship between correlation and Stander deviation of Actual data and predictive data using BF-ELM. Figure 4.21 clearly demonstrated that the use of BF-ELM gives better correlation and near to the actual result in model 3 with just two variables which are (CV, SV, CPI, and SPI).

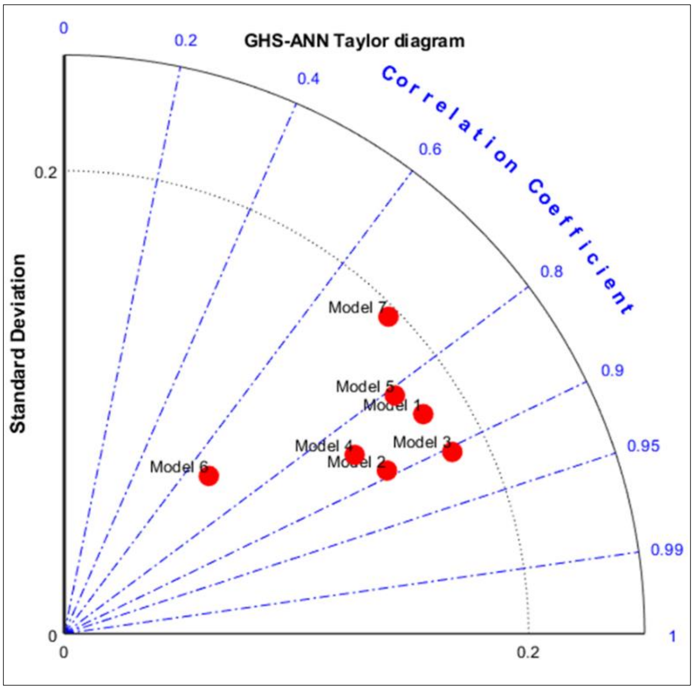


Figure 4.20 The Taylor diagram presentations of the proposed hybrid predictive models (GHS-ANN)

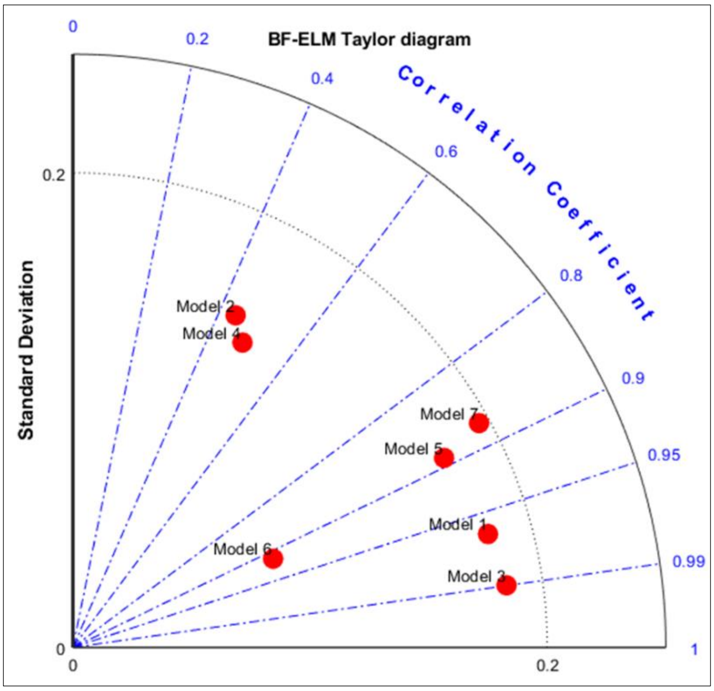


Figure 4.21 The Taylor diagram presentations of the proposed hybrid predictive models (BF-ELM)

Figure 4.22 presents the Taylor Diagram for the relationship between correlation and Stander deviation of Actual data and predictive data using BF-ANN. Figure 4.22 clearly demonstrated that the use of BF-ANN gives better correlation and near to the actual result in model 2 with just three variables which are (CV, SV, and CPI).

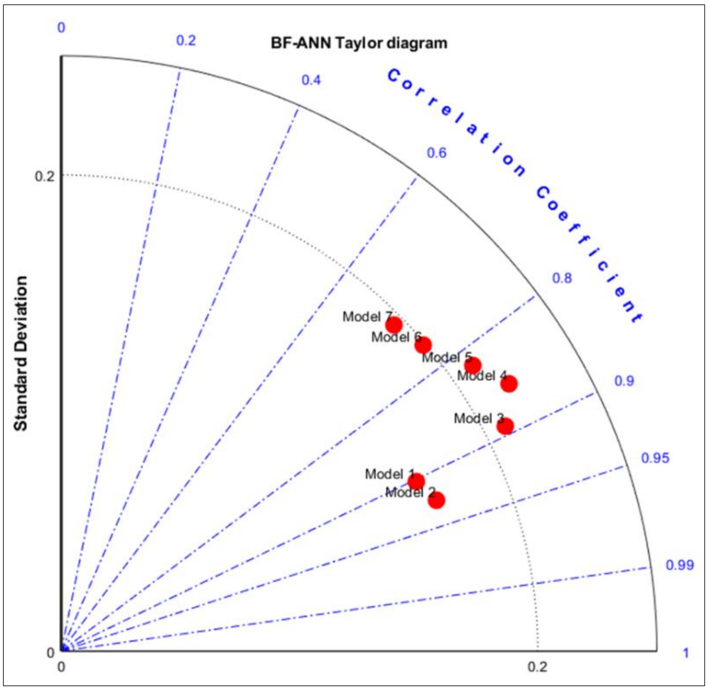


Figure 4.22 The Taylor diagram presentations of the proposed hybrid predictive models (BF-ANN)

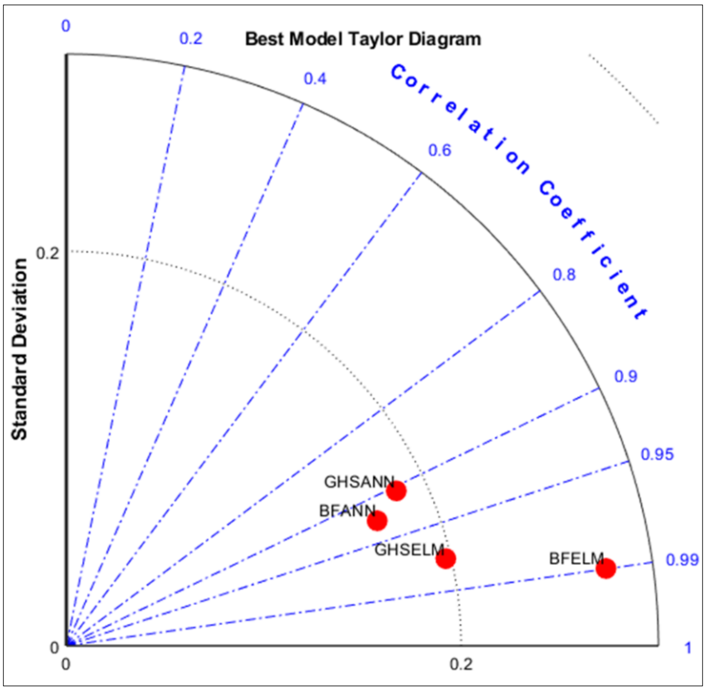


Figure 4.23 The Taylor diagram presentations of the best hybrid predictive models

With this diagram, it is easier to determine the optimal combination of model inputs based on the distance from the observed EAC benchmarking data. As shown in Figures 4.18, ELM was more accurate compared to ANN in terms of the level of correlation and the standard deviation whereas Figure 4.23 shows that the best hybrid models were BF-ELM. Figures 4.18-4.20 showed that the hybrid GHS-ELM model of Model 1 achieved a closer prediction value to the actual EAC. On the other hand, the GHS-ANN model achieved the best input variables with Model 3. The modeling in general does not show consistency in the input variability due to the nature of the studied problem. Based on the attained predictability performance, the utilized construction data span is adequately sufficient to build the proposed hybrid predictive model. It is worth mentioning, this is an offline modeling inspection. Indeed, for any targeted online expert system, there must be an approval for the offline applicability. Hence, the current study is established based on this concept. In conclusion, the main contribution of1 this study is that it highlighted the effectiveness of the hybrid GHS-ELM model which is comprised of the input selection optimizer and ELM as the predictive model. The proposed BF-ELM is a robust framework that can contribute to the monitoring of engineering project costs by assisting the project managers in monitoring the completion cost of an ongoing project.

4.4 Conclusion

The limitations of this research are divided into two sections: the first one related to the collecting of the data, which was the most difficult part because almost all the construction companies try to keep their information and construction mistakes and error away from the government or other local authorities. Therefore, this information is not available online. As, Ph.D. student, I use all my personal, my family, and my friends' relationships to get that information. The second part related to the result that obtained by applying each method, as a researcher should take into the consideration the differences between the best result and the best available result because the first one give the nearest result to the actual one, while the second one gives the best result by using fewer data and that what happened in this research.

This research explored a new hybrid data-intelligence predictive model called global harmony search integrated with extreme learning machine which can assist construction managers to reliably control project cost and make accurate EAC predictions. There are two phases performed in this intelligence system; first is the attribute-based variable selection phase where the GHS algorithm was used to determine the related variables that can influence the prediction task, and second is the implementation of the predictive ELM model for the EAC. For reliability purposes, the proposed ELM model was validated against the classical ANN model by performing the same hybridization process for the input selection. Another input selection approach was used to analyze the GHS algorithm in the form of a variable assortment called brute force. In this research, civil construction projects' information was used to construct the predictive models. Based on the ELM and ANN-based model results, the ELM model achieved better results compared to the classical ANN. However, the incorporation of the input selection algorithm remarkably enhanced the predictability of the ELM model. Furthermore, the predictability of the hybridized intelligent model exhibited more reliable and accurate results. Worth to report, this research can be extended with the possibility of investigating the uncertainty of error that exists in construction project costs. The current research is considered as a particular site investigation where the residential construction data gathered from a specific region and thus the exploration for other regions or other firms like industrial is the motivation of the future investigation.

The optimization issue in project management engineering, and specifically in construction project management, has been a challenging area of study for decades. Additionally, optimization methods play a vital role in the training of AI models. As an illustration, standard types of AI use mathematical techniques, such as traditional gradient-based optimization methods, are used to resolve the problems of interest. Some researchers reported the successful practice of certain types of gradient-based optimization methods like the Levenberg-Marquardt algorithm in modeling project management. Nonetheless, due to their several shortcomings in dealing with complexities in non-linear, chaotic, and stochastic phenomenal of project management, researchers have been developing effective and reliable nature-inspired optimization techniques called meta-heuristic algorithms. Due to their robustness and efficiency in coping with the complexities of the projects, they are superior to traditional mathematical algorithms for both exploration and exploitation of the problems search space. Based on the reported merit, future researches can be conducted in this area.

Another possible future direction is the assessment of prediction uncertainty, which has become a necessity for most modeling studies within the project management community. By attempting to address uncertainty analysis on a novel hybrid double feedforward neural network model for generating accurate prediction.

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The Applied Historical Data Set of the Construction Project

Projects	CV	SV	CPI	SPI	Subcontractor billed index	Owner billed index	change order index	CCI	Climate effect index	EAC
1-1	1250	750	3.5	1.75	1	0.98	1.05	1.11	0.99	8600
1-2	2500	1550	2.612903	1.62	1.21	0.99	1.06	1.11	0.98	11519.75
1-3	983.3333	-666.667	1.293532	0.866667	1.22	1	1.11	1.12	1	23269.62
1-4	983.3333	-1616.67	1.182099	0.797917	1.43	1	0.98	1	1	25463.19
1-5	200	-2900	1.027027	0.72381	1.34	1.23	0.96	1	1	29307.89
1-6	-4180	-8580	0.513953	0.34	1	1.11	1	1	1	58565.61
1-7	-2750	-7850	0.747706	0.509375	1	1.22	1	1	0.65	40256.44
1-8	-5616.67	-12016.7	0.580846	0.393098	1	0.68	1	1	0.82	51820.99
1-9	-7966.67	-15316.7	0.509744	0.350989	1	0.63	1	1	1	59049.3
1-10	-11600	-20200	0.372973	0.254613	1	1	1	1	0.94	80702.9
1-11	-16516.7	-25866.7	0.163713	0.111111	1.11	1	1	1	0.92	183858.2
1-12	-17250	-26600	0.168675	0.116279	0.99	1	0.98	1	0.82	178450
1-13	1500	1100	3.5	2.1	1.14	1	0.99	1.12	1	8600
2-1	1650	500	2.222222	1.2	1	0.97	1.03	1.15	0.63	13545
2-2	733.3333	-1416.67	1.25731	0.716667	1	0.96	1.01	1.16	0.82	23940

2-3	400	-3250	1.091954	0.59375	1	1.02	1	1	0.87	27565.26
2-4	1400	-2750	1.220472	0.738095	0.95	1.11	1	11	1	24662.58
2-5	-50	-4400	0.99422	0.661538	1	1	1	1	1	30275
2-6	-1510	-6210	0.866372	0.611875	1.34	1	1	1.12	0.92	34742.59
2-7	-4525	-9775	0.689003	0.506313	1.25	1	1	1.18	1	43686.28
2-8	-7900	-13650	0.557423	0.42161	1	1.33	1	1	1	53998.49
2-9	-13800	-21050	0.304786	0.223247	0.98	1	1.11	1	0.92	98757.85
2-10	-17076.7	-24626.7	0.207579	0.153723	1.24	1	1	1	0.82	145004.8
2-11	-19550	-27300	0.12528	0.093023	1.33	0.71	1	1	0.63	240262.5
2-12	1750	1450	3.5	2.45	1.48	0.82	1	1.18	1	8600
2-13	3050	2450	2.605263	1.98	0.95	1.34	1	1.16	1	11553.54
2-14	1283.333	483.3333	1.305556	1.096667	1.22	1.22	1	1	0.98	23055.32
3-1	1133.333	-366.667	1.174359	0.954167	1	0.98	1	1	1	25631
3-2	900	-500	1.098901	0.952381	1	1.31	0.94	1	0.92	27391
3-3	-4800	-7200	0.54717	0.446154	1	1.11	0.95	1	1	55010.34
3-4	-3560	-6160	0.734328	0.615	1	0.97	1	1.19	0.63	40989.84
3-5	-7533.33	-11083.3	0.53641	0.440236	1	0.92	1	1.15	1	56113.77
3-6	-10316.7	-14566.7	0.466839	0.382768	0.84	0.63	1	1.16	0.82	64476.2
3-7	-13300	-18050	0.404922	0.333948	0.96	0.62	1.03	1.02	1	74335.36
3-8	-19833.3	-24933.3	0.173611	0.143184	1.34	0.98	1.11	1.05	0.99	173376
3-9	-22000	-27300	0.112903	0.093023	1.22	1.22	0.96	1.06	0.84	266600
3-10	1250	750	3.5	1.75	1.15	1.13	0.99	1	0.92	8600
3-11	1750	500	2.4	1.2	1	1	1.01	1	0.99	12541.67

3-12	500	-2000	1.2	0.6	1	1	1.01	1	1	25083.33
4-1	1750	-1500	1.368421	0.8125	1	0.63	1.05	1	1	21996.15
4-2	500	-3450	1.076336	0.671429	1	0.72	1.01	1	0.75	27965.25
4-3	-2095	-6895	0.744512	0.469615	0.84	0.98	1.01	1	1	40429.16
4-4	-3380	-9130	0.670244	0.429375	1	1.36	1.05	1.17	0.82	44909.02
4-5	-3925	-10475	0.703774	0.47096	0.82	1.33	1	1.15	1	42769.44
4-6	-7383.33	-14733.3	0.545641	0.375706	0.86	1.62	1	1.16	0.92	55164.47
4-7	-10900	-18950	0.427822	0.300738	0.78	1.02	1	1.12	1	70356.44
4-8	-16683.3	-25433.3	0.18018	0.126002	1	1.32	1.01	1.05	0.82	167055
4-9	-18350	-27300	0.132388	0.093023	1	1.22	1.01	1.06	0.84	227362.5
4-10	3000	3200	3.5	4.2	1	0.98	1	1	0.75	8600
4-11	4200	4700	2.4	2.88	0.83	1.06	1	1	0.63	12541.67
5-1	250	550	1.04717	1.11	0.91	1	1.01	1	1	28744.14
5-2	-366.667	-866.667	0.951111	0.891667	1.32	1	1.01	1	1	31647.2
5-3	-1325	-2125	0.863402	0.797619	1.41	0.72	1.01	1	1	34862.09
5-4	-3830	-4980	0.676793	0.616923	1	1	1.01	1	1	44474.44
5-5	-7060	-9210	0.490253	0.424375	1	1.32	1	1	0.85	61396.91
5-6	-8091.67	-11341.7	0.511078	0.427189	1	1.48	1	1.15	0.85	58895.17
5-7	-9783.33	-13383.3	0.510833	0.43291	1	0.98	1.01	1.13	0.92	58923.33
5-8	-14530	-18780	0.364114	0.307011	1	0.95	0.98	1.11	1	82666.47
5-9	-19423.3	-23673.3	0.218377	0.186483	1	1	1.03	1.08	0.95	137835.1
5-10	-23350	-28000	0.082515	0.069767	1.38	1	0.96	1.07	0.93	364783.3
5-11	3000	3200	3.5	4.2	1.26	1.34	1.03	1.11	1	8600

5-12	2700	2600	2.125	2.04	1.11	1.26	0.95	1.15	0.82	14164.71
6-1	716.6667	316.6667	1.155797	1.063333	1.43	1.08	0.94	1.16	1	26042.63
6-2	675	-625	1.100746	0.921875	1.32	1	1	1.11	1	27345.08
6-3	-300	-1900	0.966292	0.819048	1.11	1	1	1.13	1	31150
6-4	-4335	-6785	0.5891	0.478077	0.99	1	1	1.18	0.92	51094.93
6-5	-5770	-9420	0.532794	0.41125	1	1	1	1.16	0.85	56494.68
6-6	-6900	-11800	0.536913	0.40404	1	0.82	0.92	1.13	1	56061.25
6-7	-9425	-15475	0.462963	0.34428	1	0.86	0.96	1.18	0.92	65016
6-8	-12670	-19720	0.36808	0.272325	1	0.97	1.05	1.16	1	81775.75
6-9	-17806.7	-25506.7	0.167913	0.123482	1	0.84	1.04	1.11	1	179259.7
6-10	-19900	-28000	0.095455	0.069767	1	0.92	1.02	1	1	315333.3
6-11	1000	400	3.5	1.4	1	0.73	1.11	1	1	8600
6-12	2600	1400	3	1.56	1	0.52	1.11	1	1	10033.33
6-13	1450	-250	1.439394	0.95	0.96	0.82	1	1	1	20911.58
6-14	783.3333	-2116.67	1.153595	0.735417	0.91	0.94	1	1	1	26092.35
7-1	-850	-4850	0.869231	0.538095	1.38	1	1	1	0.82	34628.32
7-2	-920	-5320	0.893023	0.590769	1.33	1	1	1	0.86	33705.73
7-3	-3650	-9400	0.643902	0.4125	1.25	1	1	1	0.92	46746.21
7-4	-4816.67	-11766.7	0.625162	0.405724	1.14	1	1	1.08	0.98	48147.51
7-5	-7833.33	-15983.3	0.492988	0.32274	1.42	0.93	1	1.06	1	61056.24
7-6	-10550	-19450	0.42033	0.282288	1.41	0.82	1	1.08	0.96	71610.46
7-7	-15566.7	-24966.7	0.209814	0.142039	1	0.42	1.02	1.15	1	143460.5
7-8	-18200	-28000	0.103448	0.069767	1	0.62	1.05	1.13	0.72	290966.7

7-9	750	50	3.5	1.05	1	0.86	0.98	1.11	0.75	8600
7-10	1450	-200	2.705882	0.92	1	0.99	0.99	1.18	0.62	11123.91
7-11	3083.333	1733.333	1.844749	1.346667	0.89	1	0.92	1.06	0.78	16316.58
7-12	4350	3450	1.612676	1.43125	1.24	1	1.22	1	0.82	18664.63
7-13	-600	-1700	0.93617	0.838095	1	1	1.05	1	1	32152.27
8-1	-2490	-3590	0.790756	0.723846	1	1.02	1.06	1	0.92	38064.82
8-2	-5120	-6620	0.646897	0.58625	1	1.03	1	1.05	1	46529.85
8-3	-10950	-14550	0.324074	0.265152	1	1.22	1	1	1	92880
8-4	-11466.7	-16366.7	0.386809	0.306497	1.34	1	1	1.02	1	77816.13
8-5	-15230	-21730	0.26068	0.198155	1.62	1	0.92	1	0.95	115467.4
8-6	-18616.7	-25866.7	0.147979	0.111111	1.54	0.95	1	1.18	0.82	203407.7
8-7	-20350	-28000	0.093541	0.069767	1.33	0.94	1	1	1	321783.3
8-8	2000	1800	3.5	2.8	1.22	1.06	1	1.05	0.75	8600
8-9	1300	350	1.83871	1.14	0.98	1.22	1.03	1.14	1	16370.18
8-10	366.6667	-1683.33	1.124294	0.663333	0.99	1	0.92	1	0.72	26772.36
8-11	483.3333	-2816.67	1.102837	0.647917	0.95	1	0.95	1.05	0.82	27293.25
8-12	1100	-2500	1.15942	0.761905	0.92	0.96	0.96	1.08	0.92	25961.25
8-13	-2000	-6250	0.771429	0.519231	1.12	0.94	1	1	1	39018.52
8-14	-4095	-9895	0.598529	0.381563	1.32	0.62	1	1	1	50289.93
8-15	-5829.17	-13379.2	0.52415	0.324285	1	0.72	1	1	1	57426.35
8-16	-5250	-13200	0.664537	0.440678	1	0.51	1	1.13	1	45294.71
9-1	-11000	-20200	0.385475	0.254613	1	1.02	1.05	1	1	78085.51
9-2	-15266.7	-24966.7	0.213058	0.142039	1	1.04	1.02	1.18	1	141275.8

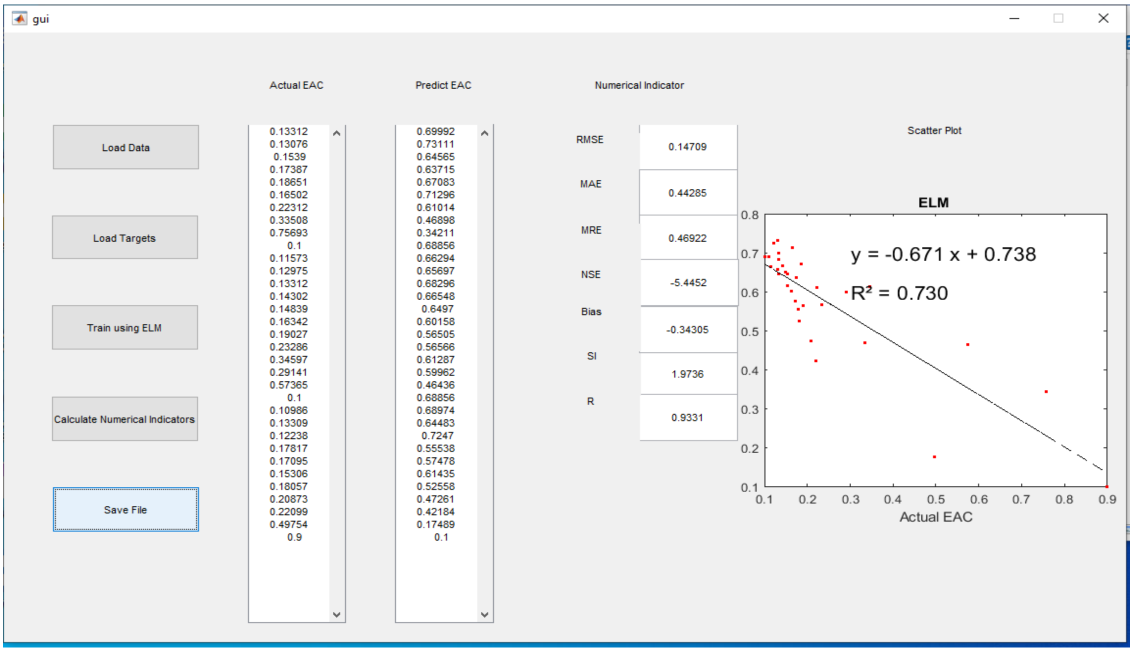
9-3	-18275	-28525	0.079345	0.052326	1	1.05	1.05	1.08	0.95	379355.6
9-4	2500	2500	3.5	3.5	1.47	1	0.99	1	0.96	8600
9-5	1300	600	1.722222	1.24	1.36	1	0.98	1.06	1	17477.42
9-6	658.3333	-791.667	1.185446	0.841667	1.22	1	0.94	1.18	1	25391.29
9-7	550	-2100	1.102804	0.7375	1.26	1.42	1	1.02	1	27294.07
9-8	-600	-4000	0.915493	0.619048	1.38	1.53	1	1	0.82	32878.46
9-9	-1480	-5330	0.838251	0.59	1.42	1.31	1	1	0.62	35908.08
9-10	-3670	-8270	0.67807	0.483125	1.33	1.11	1	1.12	0.71	44390.69
9-11	-6750	-12900	0.505495	0.348485	1.54	1.05	1	1.18	0.82	59545.65
9-12	-9950	-18000	0.360129	0.237288	1.48	0.94	1	1	1	83581.25
9-13	-13330	-23680	0.204179	0.126199	1.24	0.96	0.98	1	0.92	147419.6
10-1	-13836.7	-24286.7	0.258088	0.165407	1.11	0.99	0.92	1	1	116627.1
10-2	-17150	-28000	0.109091	0.069767	1.11	1.41	1.11	1	0.84	275916.7
10-3	2500	2500	3.5	3.5	1.22	1.11	1.02	1.02	1	8600
10-4	2250	1750	2.125	1.7	1	1	0.99	1	0.62	14164.71
10-5	383.3333	-916.667	1.103604	0.816667	1	1	1.05	1.08	1	27274.29
10-6	2800	1500	1.41791	1.1875	1	1	1	1.06	0.92	21228.42
10-7	-3325	-6075	0.570968	0.421429	1	1	1	1.08	0.82	52717.51
10-8	-3545	-7245	0.618817	0.442692	1.23	1	1	1	1	48641.18
10-9	-2640	-6590	0.780913	0.588125	125	0.67	1	1.12	1	38544.63
10-10	-6516.67	-11616.7	0.556689	0.4133	1.48	0.62	1.06	1	0.99	54069.65
10-11	-9800	-16200	0.430233	0.313559	1.62	0.84	1.08	1	1	69962.16
10-12	-12170	-19270	0.3915	0.28893	1.22	0.59	1	1	0.98	76883.78

10-13	-18286.7	-26386.7	0.129206	0.093242	1.32	0.62	0.98	1.05	0.74	232960.7
10-14	-20000	-28700	0.065421	0.046512	1.29	0.82	1	1	0.82	460100

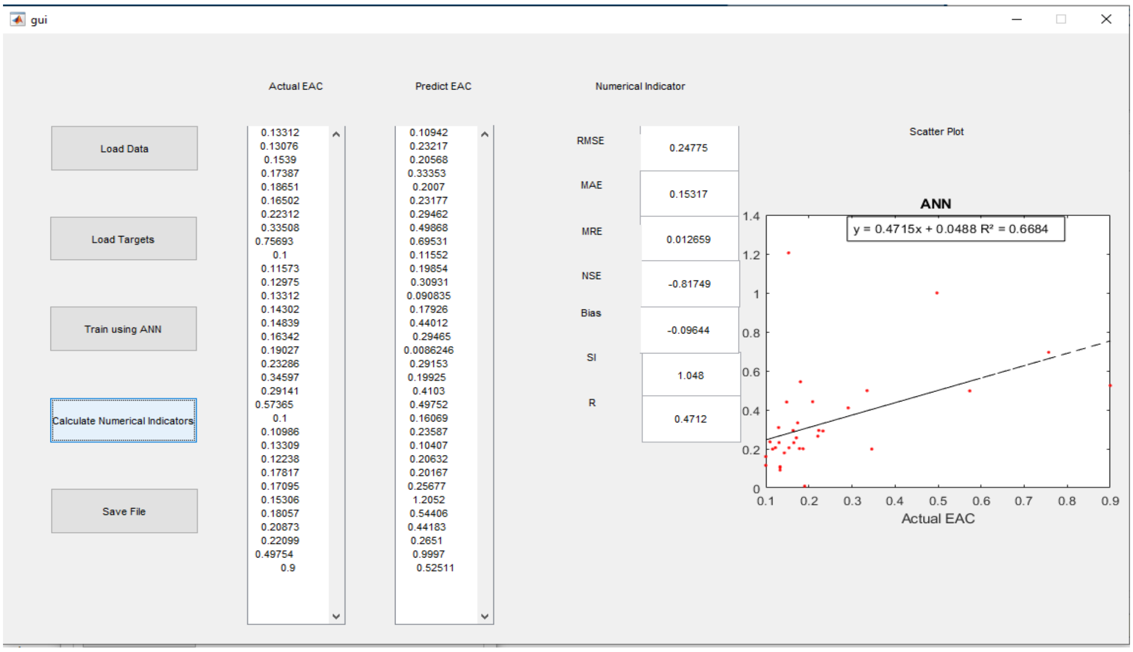
B

The Results of the Prediction

A.) ELM MODEL

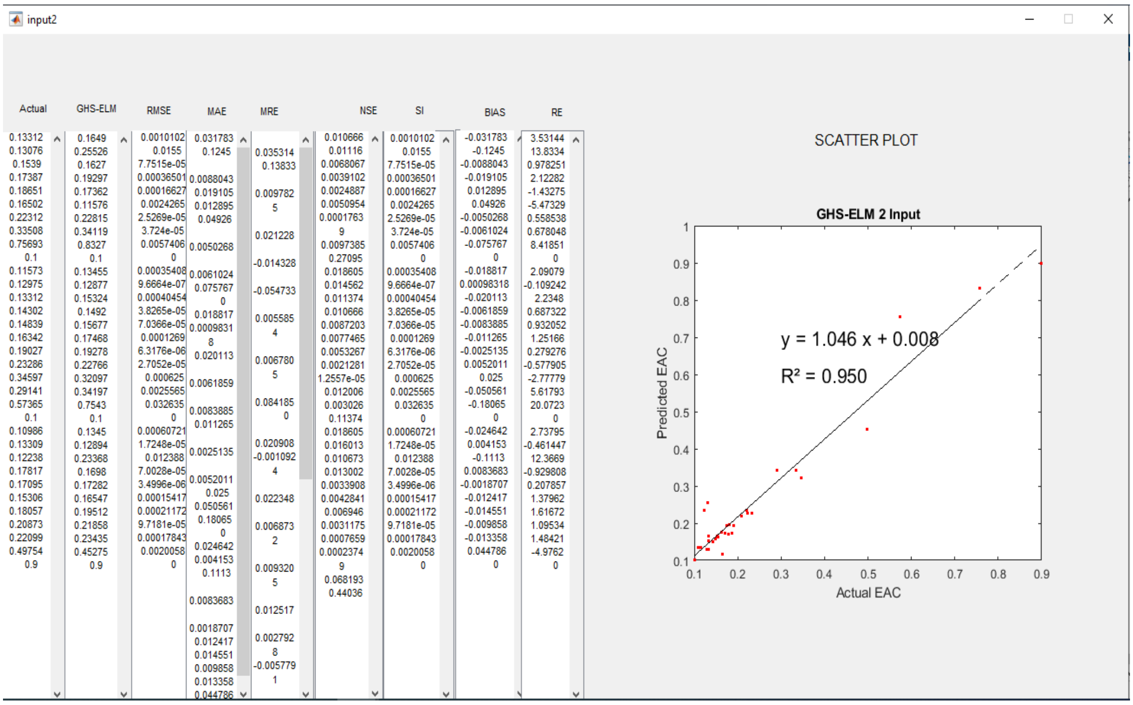


B.) ANN Model


gui
Actual EAC
Predict EAC
Numerical Indicator
Load Data
Load Targets
Train using ANN
Calculate Numerical Indicators
Save File
RMSE 0.24775
MAE 0.15317
MRE 0.012659
NSE -0.81749
Bias -0.09644
SI 1.048
R 0.4712
Scatter Plot
ANN
y = 0.4715x + 0.0488 R² = 0.6684
Actual EAC

C.) GHS-ELM Model

C.1) Model 1 GHS-ELM

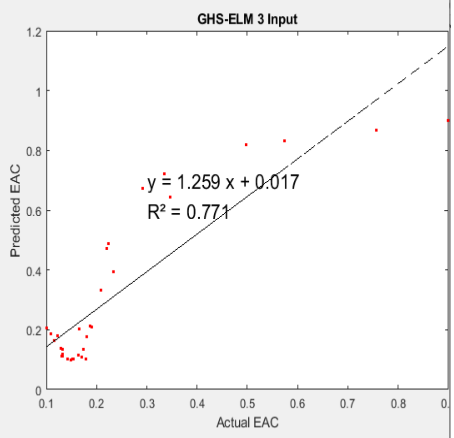


C.2) Model 2 GHS-ELM

input3

Actual	GHS-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.11072	0.0005019	0.022403	-0.024892	0.010666	0.0005019	0.022403	-2.48925
0.13076	0.11251	0.00033321	0.018254	-0.020282	0.01116	0.00033321	0.018254	-2.02823
0.1539	0.10114	0.0027836	0.05276	-0.058622	0.0068067	0.0027836	0.05276	-5.86217
0.17387	0.13618	0.0014201	0.037684	-0.041871	0.0039102	0.0014201	0.037684	-4.18715
0.18651	0.2122	0.00065966	0.025684	0.028538	0.0024887	0.00065966	-0.025684	2.85377
0.16502	0.20244	0.0014005	0.037423	0.041581	0.0050954	0.0014005	-0.037423	4.1581
0.22312	0.48665	0.069448	0.26353	0.29281	0.00017639	0.069448	-0.26353	29.2811
0.33508	0.72118	0.14907	0.38609	0.42899	0.0097385	0.14907	-0.38609	42.8992
0.75693	0.86606	0.011909	0.10913	0.12125	0.27095	0.011909	-0.10913	12.1255
0.1	0.20517	0.011061	0.10517	0.11686	0.018605	0.011061	-0.10517	11.6855
0.11573	0.16268	0.0022046	0.046953	0.05217	0.014562	0.0022046	-0.046953	5.21702
0.12975	0.13795	6.7172e-05	0.0081958	0.0091065	0.011374	6.7172e-05	-0.0081958	0.91065
0.13312	0.11907	0.0001975	0.014054	-0.015615	0.010666	0.0001975	0.014054	-1.56151
0.14302	0.10336	0.001573	0.039661	-0.044067	0.0087203	0.001573	0.039661	-4.40673
0.14839	0.1	0.0023412	0.048386	-0.053763	0.0077465	0.0023412	0.048386	-5.37627
0.16342	0.1164	0.0022102	0.047012	-0.052236	0.0053267	0.0022102	0.047012	-5.22358
0.19027	0.20876	0.00034197	0.018493	0.020547	0.0021281	0.00034197	-0.018493	2.05472
0.23286	0.39515	0.026339	0.16229	0.18032	1.2557e-05	0.026339	-0.16229	18.0324
0.34597	0.64364	0.088607	0.29767	0.33074	0.012006	0.088607	-0.29767	33.0743
0.29141	0.67195	0.14481	0.38054	0.42282	0.003026	0.14481	-0.38054	42.2822
0.57365	0.83351	0.067526	0.25986	0.28873	0.11374	0.067526	-0.25986	28.873
0.1	0.20517	0.011061	0.10517	0.11686	0.018605	0.011061	-0.10517	11.6856
0.10986	0.18715	0.0059736	0.077289	0.085877	0.016013	0.0059736	-0.077289	8.58771
0.13309	0.13608	8.9525e-06	0.0029921	0.0033245	0.010673	8.9525e-06	-0.0029921	0.332452
0.12238	0.18003	0.0033236	0.057651	0.064057	0.013002	0.0033236	-0.057651	6.40566
0.17817	0.10239	0.0057422	0.075777	-0.084197	0.0033908	0.0057422	0.075777	-8.41968
0.17095	0.10829	0.0039255	0.062654	-0.069615	0.0042841	0.0039255	0.062654	-6.96155
0.15306	0.10361	0.0024447	0.049444	-0.054938	0.006946	0.0024447	0.049444	-5.4938
0.18057	0.17763	8.6119e-06	0.0029346	-0.0032607	0.0031175	8.6119e-06	0.0029346	-0.326066
0.20873	0.33108	0.014971	0.12236	0.13595	0.0007659	0.014971	-0.12236	13.5951
0.22099	0.47159	0.062803	0.2506	0.27845	0.00023749	0.062803	-0.2506	27.8449
0.49754	0.81735	0.10228	0.31981	0.35535	0.068193	0.10228	-0.31981	35.5349
0.9	0.9	0	0	0	0.44036	0	0	0

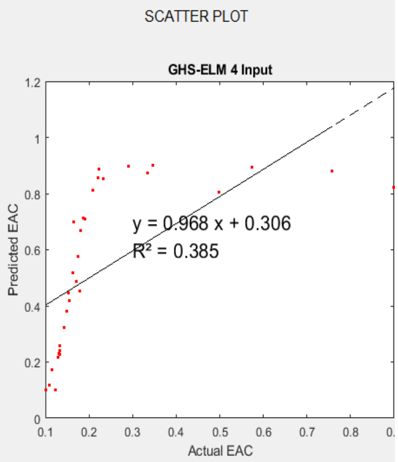
SCATTER PLOT



C.3) Model 3 GHS-ELM

input4

Actual	GHS-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.25907	0.015863	0.12595	0.13994	0.010666	0.015863	-0.12595	13.9943
0.13076	0.2306	0.0099674	0.099837	0.11093	0.01116	0.0099674	-0.099837	11.093
0.1539	0.41913	0.070347	0.26523	0.2947	0.0068067	0.070347	-0.26523	29.4699
0.17387	0.57491	0.16084	0.40104	0.44561	0.0039102	0.16084	-0.40104	44.5605
0.18651	0.71157	0.27569	0.52506	0.5834	0.0024887	0.27569	-0.52506	58.34
0.16502	0.69763	0.28368	0.53261	0.59179	0.0050954	0.28368	-0.53261	59.1792
0.22312	0.88658	0.44019	0.66347	0.73718	0.00017639	0.44019	-0.66347	73.7184
0.33508	0.87362	0.29002	0.53853	0.59837	0.0097385	0.29002	-0.53853	59.8372
0.75693	0.87939	0.014996	0.12246	0.13606	0.27095	0.014996	-0.12246	13.6063
0.1	0.10115	1.3125e-06	0.0011457	0.0012729	0.018605	1.3125e-06	-0.0011457	0.127295
0.11573	0.17097	0.0030518	0.055243	0.061381	0.014562	0.0030518	-0.055243	6.1381
0.12975	0.21589	0.0074197	0.086138	0.095709	0.011374	0.0074197	-0.086138	9.57085
0.13312	0.24273	0.012014	0.10961	0.12179	0.010666	0.012014	-0.10961	12.1789
0.14302	0.32146	0.031841	0.17844	0.19827	0.0087203	0.031841	-0.17844	19.8267
0.14839	0.38055	0.053899	0.23216	0.25796	0.0077465	0.053899	-0.23216	25.7956
0.16342	0.51838	0.126	0.35496	0.3944	0.0053267	0.126	-0.35496	39.4404
0.19027	0.70925	0.26934	0.51898	0.57665	0.0021281	0.26934	-0.51898	57.6649
0.23286	0.85251	0.38398	0.61966	0.68851	1.2557e-05	0.38398	-0.61966	68.8508
0.34597	0.9	0.30695	0.55403	0.61559	0.012006	0.30695	-0.55403	61.5588
0.29141	0.89772	0.36761	0.60631	0.67368	0.003026	0.36761	-0.60631	67.3678
0.57365	0.89288	0.10191	0.31923	0.3547	0.11374	0.10191	-0.31923	35.4699
0.1	0.10115	1.3125e-06	0.0011457	0.0012729	0.018605	1.3125e-06	-0.0011457	0.127295
0.10986	0.11904	8.4338e-05	0.0091836	0.010204	0.016013	8.4338e-05	-0.0091836	1.02039
0.13309	0.22801	0.0090106	0.094924	0.10547	0.010673	0.0090106	-0.094924	10.5471
0.12238	0.1	0.00050068	0.022376	-0.024862	0.013002	0.00050068	0.022376	-2.48622
0.17817	0.45206	0.075014	0.27389	0.30432	0.0033908	0.075014	-0.27389	30.4319
0.17095	0.4875	0.10021	0.31655	0.35173	0.0042841	0.10021	-0.31655	35.1726
0.15306	0.44634	0.086013	0.29328	0.32587	0.006946	0.086013	-0.29328	32.5867
0.18057	0.6692	0.23876	0.48863	0.54293	0.0031175	0.23876	-0.48863	54.2927
0.20873	0.81235	0.36437	0.60363	0.6707	0.0007659	0.36437	-0.60363	67.0697
0.22099	0.8562	0.40349	0.63521	0.70579	0.00023749	0.40349	-0.63521	70.5789
0.49754	0.80541	0.094782	0.30787	0.34208	0.068193	0.094782	-0.30787	34.2075
0.9	0.82323	0.0058941	0.076773	-0.085303	0.44036	0.0058941	0.076773	-8.53033

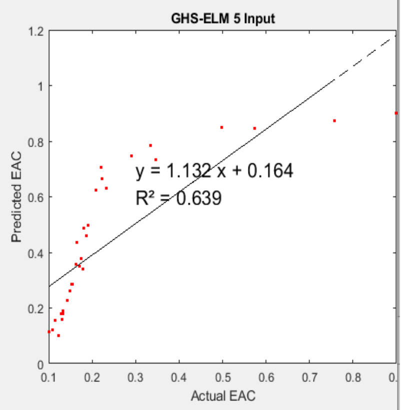


C.4) Model 4 GHS-ELM

input5

Actual	GHS-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.18261	0.0024492	0.04949	0.054988	0.010666	0.0024492	-0.04949	5.49884
0.13076	0.1587	0.00078059	0.027939	0.031043	0.01116	0.00078059	-0.027939	3.10434
0.1539	0.28443	0.017038	0.13053	0.14503	0.0068067	0.017038	-0.13053	14.5033
0.17387	0.37887	0.042027	0.20501	0.22778	0.0039102	0.042027	-0.20501	22.7784
0.18651	0.4604	0.075014	0.27389	0.30432	0.0024887	0.075014	-0.27389	30.4319
0.16502	0.43554	0.07318	0.27052	0.30058	0.0050954	0.07318	-0.27052	30.0576
0.22312	0.66474	0.19503	0.44162	0.49069	0.00017639	0.19503	-0.44162	49.069
0.33508	0.78578	0.20312	0.45069	0.50077	0.0097385	0.20312	-0.45069	50.0769
0.75693	0.87509	0.013962	0.11816	0.13129	0.27095	0.013962	-0.11816	13.1288
0.1	0.11535	0.0002357	0.015353	0.017058	0.018605	0.0002357	-0.015353	1.70583
0.11573	0.15645	0.0016581	0.040719	0.045244	0.014562	0.0016581	-0.040719	4.52436
0.12975	0.17865	0.0023906	0.048894	0.054327	0.011374	0.0023906	-0.048894	5.43268
0.13312	0.18064	0.0022575	0.047514	0.052793	0.010666	0.0022575	-0.047514	5.2793
0.14302	0.22574	0.0068427	0.08272	0.091912	0.0087203	0.0068427	-0.08272	9.19115
0.14839	0.26213	0.012937	0.11374	0.12638	0.0077465	0.012937	-0.11374	12.638
0.16342	0.35787	0.037813	0.19446	0.21606	0.0053267	0.037813	-0.19446	21.6062
0.19027	0.49852	0.095019	0.30825	0.3425	0.0021281	0.095019	-0.30825	34.2502
0.23286	0.62948	0.15731	0.39663	0.4407	1.2557e-05	0.15731	-0.39663	44.0697
0.34597	0.73408	0.15063	0.38811	0.43123	0.012006	0.15063	-0.38811	43.1228
0.29141	0.74863	0.20905	0.45722	0.50803	0.003026	0.20905	-0.45722	50.8028
0.57365	0.8477	0.075101	0.27405	0.3045	0.11374	0.075101	-0.27405	30.4496
0.1	0.11535	0.00023566	0.015351	0.017057	0.018605	0.00023566	-0.015351	1.7057
0.10986	0.1222	0.00015235	0.012343	0.013715	0.016013	0.00015235	-0.012343	1.37146
0.13309	0.18965	0.0031991	0.05656	0.062845	0.010673	0.0031991	-0.05656	6.28449
0.12238	0.1	0.00050068	0.022376	-0.024862	0.013002	0.00050068	0.022376	-2.48622
0.17817	0.34092	0.026487	0.16275	0.18083	0.0033908	0.026487	-0.16275	18.0831
0.17095	0.35123	0.032503	0.18028	0.20032	0.0042841	0.032503	-0.18028	20.0316
0.15306	0.28619	0.017725	0.13313	0.14793	0.006946	0.017725	-0.13313	14.7928
0.18057	0.4865	0.093595	0.30593	0.33993	0.0031175	0.093595	-0.30593	33.9926
0.20873	0.62486	0.17317	0.41614	0.46237	0.0007659	0.17317	-0.41614	46.2373
0.22099	0.7052	0.23446	0.48421	0.53801	0.00023749	0.23446	-0.48421	53.8015
0.49754	0.84979	0.12408	0.35225	0.39139	0.068193	0.12408	-0.35225	39.1389
0.9	0.9	0	0	0	0.44036	0	0	0

SCATTER PLOT

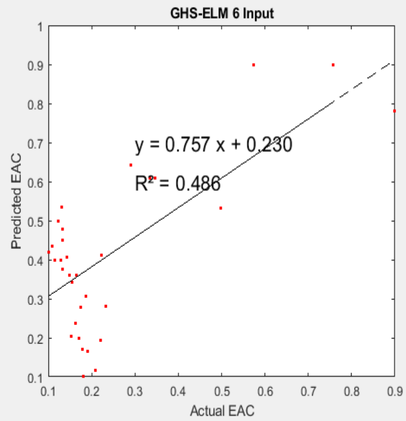


C.5) Model 5 GHS-ELM

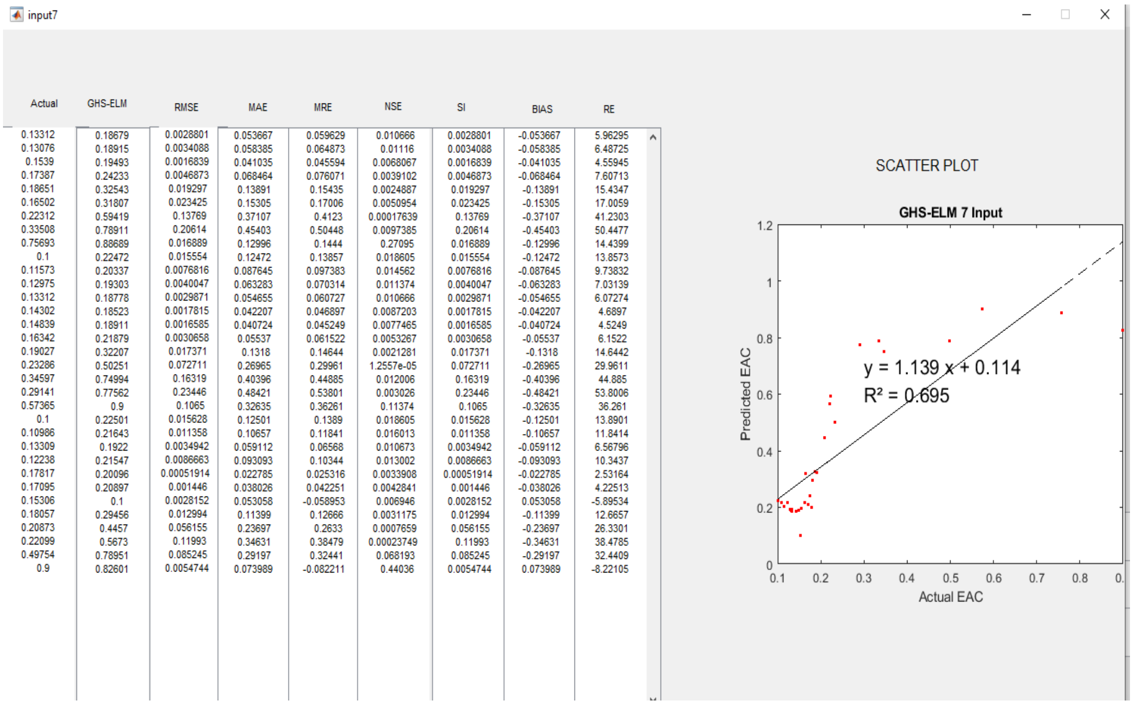
input6

Actual	GHS-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.47843	0.11924	0.34531	0.38367	0.010666	0.11924	-0.34531	38.3673
0.13076	0.53578	0.16404	0.40502	0.45002	0.01116	0.16404	-0.40502	45.0021
0.1539	0.34104	0.035022	0.18714	0.20794	0.0068067	0.035022	-0.18714	20.7936
0.17387	0.27704	0.010645	0.10317	0.11464	0.0039102	0.010645	-0.10317	11.4637
0.18651	0.30706	0.014532	0.12055	0.13394	0.0024887	0.014532	-0.12055	13.3944
0.16502	0.36027	0.038124	0.19525	0.21695	0.0050954	0.038124	-0.19525	21.6949
0.22312	0.41197	0.035663	0.18885	0.20983	0.00017639	0.035663	-0.18885	20.9829
0.33508	0.60823	0.074609	0.27315	0.3035	0.0097385	0.074609	-0.27315	30.3496
0.75693	0.9	0.020469	0.14307	0.15897	0.27095	0.020469	-0.14307	15.8965
0.1	0.41903	0.10178	0.31903	0.35448	0.018605	0.10178	-0.31903	35.4477
0.11573	0.39921	0.080362	0.28348	0.31498	0.014562	0.080362	-0.28348	31.498
0.12975	0.39852	0.072239	0.26877	0.29864	0.011374	0.072239	-0.26877	29.8636
0.13312	0.44991	0.10035	0.31679	0.35198	0.010666	0.10035	-0.31679	35.1985
0.14302	0.40534	0.068812	0.26232	0.29147	0.0087203	0.068812	-0.26232	29.1468
0.14839	0.36076	0.045104	0.21238	0.23597	0.0077465	0.045104	-0.21238	23.5974
0.16342	0.23632	0.0053155	0.072907	0.081008	0.0053267	0.0053155	-0.072907	8.10081
0.19027	0.16558	0.00060979	0.024694	-0.027438	0.0021281	0.00060979	0.024694	-2.74377
0.23286	0.28007	0.0022287	0.047209	0.052454	1.2557e-05	0.0022287	-0.047209	5.24541
0.34597	0.60871	0.06903	0.26273	0.29193	0.012006	0.06903	-0.26273	29.1928
0.29141	0.64171	0.12271	0.3503	0.38922	0.003026	0.12271	-0.3503	38.9223
0.57365	0.89874	0.10568	0.32509	0.36121	0.11374	0.10568	-0.32509	36.1206
0.1	0.41918	0.10187	0.31918	0.35464	0.018605	0.10187	-0.31918	35.464
0.10986	0.43381	0.10494	0.32395	0.35995	0.016013	0.10494	-0.32395	35.9947
0.13309	0.37478	0.058416	0.24169	0.26855	0.010673	0.058416	-0.24169	26.8548
0.12238	0.49836	0.14136	0.37598	0.41776	0.013002	0.14136	-0.37598	41.7758
0.17817	0.17025	6.2698e-05	0.0079182	-0.008798	0.0033908	6.2698e-05	0.0079182	-0.879804
0.17095	0.19861	0.000765	0.027659	0.030732	0.0042841	0.000765	-0.027659	3.07318
0.15306	0.20479	0.002676	0.05173	0.057478	0.006946	0.002676	-0.05173	5.74778
0.18057	0.1	0.0064909	0.080566	-0.089518	0.0031175	0.0064909	0.080566	-8.95182
0.20873	0.11731	0.0083566	0.091415	-0.10157	0.0007659	0.0083566	0.091415	-10.1572
0.22099	0.19396	0.00073067	0.027031	-0.030034	0.00023749	0.00073067	0.027031	-3.00343
0.49754	0.53154	0.0011559	0.033999	0.037776	0.068193	0.0011559	-0.033999	3.77764
0.9	0.78127	0.014096	0.11873	-0.13192	0.44036	0.014096	0.11873	-13.192

SCATTER PLOT



C.6) Model 6 GHS-ELM



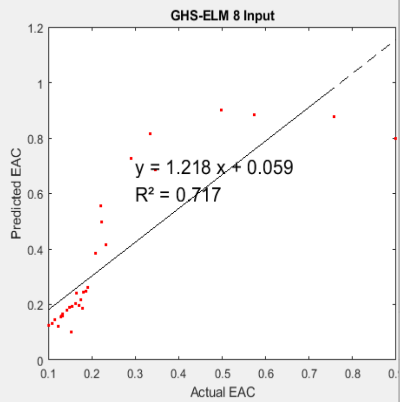
Actual	GHS-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.18679	0.0028801	0.053667	0.059629	0.010666	0.0028801	-0.053667	5.96295
0.13076	0.18915	0.0034088	0.058385	0.064873	0.01116	0.0034088	-0.058385	6.48725
0.1539	0.19493	0.0016839	0.041035	0.045594	0.0068067	0.0016839	-0.041035	4.55945
0.17387	0.24233	0.0046873	0.068464	0.076071	0.0039102	0.0046873	-0.068464	7.60713
0.18651	0.32543	0.019297	0.13891	0.15435	0.0024887	0.019297	-0.13891	15.4347
0.16502	0.31807	0.023425	0.15305	0.17006	0.0050954	0.023425	-0.15305	17.0059
0.22312	0.59419	0.13769	0.37107	0.4123	0.00017639	0.13769	-0.37107	41.2303
0.33508	0.78911	0.20614	0.45403	0.50448	0.0097385	0.20614	-0.45403	50.4477
0.75693	0.88689	0.016889	0.12996	0.1444	0.27095	0.016889	-0.12996	14.4399
0.1	0.22472	0.015554	0.12472	0.13857	0.018605	0.015554	-0.12472	13.8573
0.11573	0.20337	0.0076816	0.087645	0.097383	0.014562	0.0076816	-0.087645	9.73832
0.12975	0.19303	0.0040047	0.063283	0.070314	0.011374	0.0040047	-0.063283	7.03139
0.13312	0.18778	0.0029871	0.054655	0.060727	0.010666	0.0029871	-0.054655	6.07274
0.14302	0.18523	0.0017815	0.042207	0.046897	0.0087203	0.0017815	-0.042207	4.6897
0.14839	0.18911	0.0016585	0.040724	0.045249	0.0077465	0.0016585	-0.040724	4.5249
0.16342	0.21879	0.0030658	0.05537	0.061522	0.0053267	0.0030658	-0.05537	6.1522
0.19027	0.32207	0.017371	0.1318	0.14644	0.0021281	0.017371	-0.1318	14.6442
0.23286	0.50251	0.072711	0.26965	0.29961	1.2557e-05	0.072711	-0.26965	29.9611
0.34597	0.74994	0.16319	0.40396	0.44885	0.012006	0.16319	-0.40396	44.885
0.29141	0.77562	0.23446	0.48421	0.53801	0.003026	0.23446	-0.48421	53.8006
0.57365	0.9	0.1065	0.32635	0.36261	0.11374	0.1065	-0.32635	36.261
0.1	0.22501	0.015628	0.12501	0.1389	0.018605	0.015628	-0.12501	13.8901
0.10986	0.21643	0.011358	0.10657	0.11841	0.016013	0.011358	-0.10657	11.8414
0.13309	0.1922	0.0034942	0.059112	0.06568	0.010673	0.0034942	-0.059112	6.56796
0.12238	0.21547	0.0086663	0.093093	0.10344	0.013002	0.0086663	-0.093093	10.3437
0.17817	0.20096	0.00051914	0.022785	0.025316	0.0033908	0.00051914	-0.022785	2.53164
0.17095	0.20897	0.001446	0.038026	0.042251	0.0042841	0.001446	-0.038026	4.22513
0.15306	0.1	0.0028152	0.053058	-0.058953	0.006946	0.0028152	0.053058	-5.89534
0.18057	0.29456	0.012994	0.11399	0.12666	0.0031175	0.012994	-0.11399	12.6657
0.20873	0.4457	0.056155	0.23697	0.2633	0.0007659	0.056155	-0.23697	26.3301
0.22099	0.5673	0.11993	0.34631	0.38479	0.00023749	0.11993	-0.34631	38.4785
0.49754	0.78951	0.085245	0.29197	0.32441	0.068193	0.085245	-0.29197	32.4409
0.9	0.82601	0.0054744	0.073989	-0.082211	0.44036	0.0054744	0.073989	-8.22105

C.7) Model 7 GHS-ELM

input8

Actual	GHS-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.16744	0.001178	0.034322	0.038136	0.010666	0.001178	-0.034322	3.81356
0.13076	0.15833	0.00076024	0.027572	0.030636	0.01116	0.00076024	-0.027572	3.06361
0.1539	0.19358	0.0015748	0.039684	0.044093	0.0068067	0.0015748	-0.039684	4.4093
0.17387	0.21562	0.001743	0.041749	0.046387	0.0039102	0.001743	-0.041749	4.63875
0.18651	0.24942	0.0039574	0.062908	0.069898	0.0024887	0.0039574	-0.062908	6.98978
0.16502	0.23982	0.0055946	0.074797	0.083108	0.0050954	0.0055946	-0.074797	8.31078
0.22312	0.49851	0.075839	0.27539	0.30599	0.00017639	0.075839	-0.27539	30.5988
0.33508	0.81659	0.23185	0.4815	0.53501	0.0097385	0.23185	-0.4815	53.5005
0.75693	0.87646	0.014286	0.11952	0.1328	0.27095	0.014286	-0.11952	13.2805
0.1	0.12413	0.00058221	0.024129	0.02681	0.018605	0.00058221	-0.024129	2.681
0.11573	0.14418	0.00080916	0.028446	0.031606	0.014562	0.00080916	-0.028446	3.16063
0.12975	0.15597	0.00068757	0.026222	0.029135	0.011374	0.00068757	-0.026222	2.91351
0.13312	0.16369	0.00093411	0.030563	0.033959	0.010666	0.00093411	-0.030563	3.39592
0.14302	0.17944	0.0013267	0.036424	0.040471	0.0087203	0.0013267	-0.036424	4.0471
0.14839	0.1881	0.0015772	0.039713	0.044126	0.0077465	0.0015772	-0.039713	4.41261
0.16342	0.20416	0.0016597	0.040739	0.045266	0.0053267	0.0016597	-0.040739	4.52659
0.19027	0.26013	0.0048802	0.069859	0.077621	0.0021281	0.0048802	-0.069859	7.76207
0.23286	0.41666	0.033785	0.18381	0.20423	1.2557e-05	0.033785	-0.18381	20.4229
0.34597	0.68643	0.11591	0.34046	0.37828	0.012006	0.11591	-0.34046	37.8284
0.29141	0.72539	0.18834	0.43398	0.4822	0.003026	0.18834	-0.43398	48.2197
0.57365	0.88398	0.096302	0.31033	0.34481	0.11374	0.096302	-0.31033	34.4806
0.1	0.12425	0.00058797	0.024248	0.026942	0.018605	0.00058797	-0.024248	2.69423
0.10986	0.12999	0.00040515	0.020128	0.022365	0.016013	0.00040515	-0.020128	2.23648
0.13309	0.15767	0.00060407	0.024578	0.027309	0.010673	0.00060407	-0.024578	2.73087
0.12238	0.12013	5.0405e-06	0.0022451	-0.0024946	0.013002	5.0405e-06	0.0022451	-0.249457
0.17817	0.18487	4.4949e-05	0.0067044	0.0074494	0.0033908	4.4949e-05	-0.0067044	0.744936
0.17095	0.1955	0.00060273	0.02455	0.027278	0.0042841	0.00060273	-0.02455	2.72783
0.15306	0.1	0.0028152	0.053058	-0.058953	0.006946	0.0028152	0.053058	-5.89534
0.18057	0.24286	0.0038803	0.062292	0.069214	0.0031175	0.0038803	-0.062292	6.92135
0.20873	0.38501	0.031075	0.17628	0.19587	0.0007659	0.031075	-0.17628	19.5869
0.22099	0.55415	0.111	0.33316	0.37018	0.00023749	0.111	-0.33316	37.0183
0.49754	0.9	0.16198	0.40246	0.44718	0.068193	0.16198	-0.40246	44.718
0.9	0.79766	0.010473	0.10234	-0.11371	0.44036	0.010473	0.10234	-11.3708

SCATTER PLOT



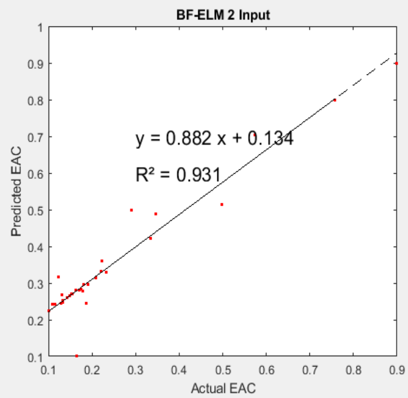
D.) BF-ELM Models

D.1) Model 1 BF-ELM

input2

Actual	BF-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.25302	0.014375	0.1199	0.13322	0.010666	0.014375	-0.1199	13.3217
0.13076	0.2685	0.018971	0.13774	0.15304	0.01116	0.018971	-0.13774	15.304
0.1539	0.26948	0.013358	0.11558	0.12842	0.0068067	0.013358	-0.11558	12.8419
0.17387	0.28332	0.01198	0.10945	0.12161	0.0039102	0.01198	-0.10945	12.1613
0.18651	0.2442	0.0033271	0.057681	0.06409	0.0024887	0.0033271	-0.057681	6.40901
0.16502	0.1	0.0042274	0.065018	-0.072243	0.0050954	0.0042274	0.065018	-7.22426
0.22312	0.36096	0.019001	0.13784	0.15316	0.00017639	0.019001	-0.13784	15.3161
0.33508	0.42156	0.0074779	0.086475	0.096083	0.0097385	0.0074779	-0.086475	9.60831
0.75693	0.79854	0.0017314	0.04161	0.046234	0.27095	0.0017314	-0.04161	4.62336
0.1	0.22488	0.015596	0.12488	0.13876	0.018605	0.015596	-0.12488	13.8759
0.11573	0.24174	0.015879	0.12601	0.14001	0.014562	0.015879	-0.12601	14.0012
0.12975	0.24529	0.013349	0.11554	0.12837	0.011374	0.013349	-0.11554	12.8374
0.13312	0.24904	0.013436	0.11591	0.12879	0.010666	0.013436	-0.11591	12.8791
0.14302	0.26028	0.01375	0.11726	0.13029	0.0087203	0.01375	-0.11726	13.0288
0.14839	0.26578	0.013782	0.1174	0.13044	0.0077465	0.013782	-0.1174	13.0441
0.16342	0.28038	0.013681	0.11697	0.12996	0.0053267	0.013681	-0.11697	12.9962
0.19027	0.29693	0.011377	0.10666	0.11851	0.0021281	0.011377	-0.10666	11.8514
0.23286	0.32854	0.0091557	0.095686	0.10632	1.2557e-05	0.0091557	-0.095686	10.6317
0.34597	0.48755	0.020043	0.14157	0.15731	0.012006	0.020043	-0.14157	15.7305
0.29141	0.49855	0.042905	0.20714	0.23015	0.003026	0.042905	-0.20714	23.0151
0.57365	0.70299	0.016729	0.12934	0.14371	0.11374	0.016729	-0.12934	14.3713
0.1	0.22488	0.015596	0.12488	0.13876	0.018605	0.015596	-0.12488	13.8759
0.10986	0.24131	0.01728	0.13145	0.14606	0.016013	0.01728	-0.13145	14.606
0.13309	0.24661	0.012887	0.11352	0.12613	0.010673	0.012887	-0.11352	12.6133
0.12238	0.31648	0.037678	0.19411	0.21568	0.013002	0.037678	-0.19411	21.5676
0.17817	0.2793	0.010228	0.10113	0.11237	0.0033908	0.010228	-0.10113	11.2372
0.17095	0.27961	0.011808	0.10867	0.12074	0.0042841	0.011808	-0.10867	12.074
0.15306	0.27127	0.013974	0.11821	0.13135	0.006946	0.013974	-0.11821	13.1348
0.18057	0.29593	0.013309	0.11536	0.12818	0.0031175	0.013309	-0.11536	12.8181
0.20873	0.31462	0.011213	0.10589	0.11766	0.0007659	0.011213	-0.10589	11.7656
0.22099	0.33245	0.012424	0.11146	0.12385	0.00023749	0.012424	-0.11146	12.3849
0.49754	0.51441	0.0002847	0.016873	0.018748	0.068193	0.0002847	-0.016873	1.8748
0.9	0.9	0	0	0	0.44036	0	0	0

SCATTER PLOT

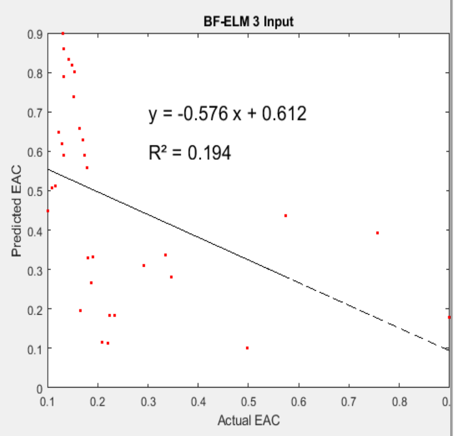


D.2) Model 2 BF-ELM

input3

Actual	BF-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.85958	0.52774	0.72646	0.80717	0.010666	0.52774	-0.72646	80.7175
0.13076	0.9	0.59173	0.76924	0.85471	0.01116	0.59173	-0.76924	85.4709
0.1539	0.80126	0.41908	0.64736	0.71929	0.0068067	0.41908	-0.64736	71.9294
0.17387	0.58967	0.17289	0.4158	0.462	0.0039102	0.17289	-0.4158	46.1998
0.18651	0.26576	0.0062806	0.07925	0.088056	0.0024887	0.0062806	-0.07925	8.8056
0.16502	0.19605	0.00096318	0.031035	0.034483	0.0050954	0.00096318	-0.031035	3.44834
0.22312	0.18255	0.0016461	0.040573	-0.045081	0.00017639	0.0016461	0.040573	-4.50806
0.33508	0.33651	2.0298e-06	0.0014247	0.001583	0.0097385	2.0298e-06	-0.0014247	0.1583
0.75693	0.39258	0.13275	0.36435	-0.40484	0.27095	0.13275	0.36435	-40.4837
0.1	0.44994	0.12246	0.34994	0.38882	0.018605	0.12246	-0.34994	38.8823
0.11573	0.51201	0.15704	0.39629	0.44032	0.014562	0.15704	-0.39629	44.0317
0.12975	0.61873	0.2391	0.48898	0.54331	0.011374	0.2391	-0.48898	54.3313
0.13312	0.78939	0.43068	0.65626	0.72918	0.010666	0.43068	-0.65626	72.9182
0.14302	0.83358	0.47687	0.69056	0.76729	0.0087203	0.47687	-0.69056	76.729
0.14839	0.81957	0.45048	0.67118	0.74576	0.0077465	0.45048	-0.67118	74.5755
0.16342	0.65899	0.24559	0.49557	0.55064	0.0053267	0.24559	-0.49557	55.0637
0.19027	0.33241	0.020205	0.14214	0.15794	0.0021281	0.020205	-0.14214	15.7939
0.23286	0.18385	0.0024019	0.049009	-0.054454	1.2557e-05	0.0024019	0.049009	-5.44541
0.34597	0.28176	0.0041228	0.064209	-0.071344	0.012006	0.0041228	0.064209	-7.13436
0.29141	0.30964	0.00033228	0.018228	0.020254	0.003026	0.00033228	-0.018228	2.02539
0.57365	0.43755	0.018525	0.13611	-0.15123	0.11374	0.018525	0.13611	-15.1228
0.1	0.4499	0.12243	0.3499	0.38878	0.018605	0.12243	-0.3499	38.8781
0.10986	0.50666	0.15745	0.3968	0.44089	0.016013	0.15745	-0.3968	44.0889
0.13309	0.59013	0.20889	0.45704	0.50783	0.010673	0.20889	-0.45704	50.7827
0.12238	0.64942	0.27777	0.52704	0.5856	0.013002	0.27777	-0.52704	58.5602
0.17817	0.55791	0.1442	0.37974	0.42193	0.0033908	0.1442	-0.37974	42.1932
0.17095	0.62799	0.20889	0.45704	0.50782	0.0042841	0.20889	-0.45704	50.7823
0.15306	0.73734	0.34139	0.58428	0.6492	0.006946	0.34139	-0.58428	64.9202
0.18057	0.33033	0.022429	0.14976	0.1664	0.0031175	0.022429	-0.14976	16.6403
0.20873	0.11492	0.0087996	0.093806	-0.10423	0.0007659	0.0087996	0.093806	-10.4229
0.22099	0.11265	0.011737	0.10834	-0.12037	0.00023749	0.011737	0.10834	-12.0374
0.49754	0.1	0.15804	0.39754	-0.44171	0.068193	0.15804	0.39754	-44.1709
0.9	0.17903	0.5198	0.72097	-0.80108	0.44036	0.5198	0.72097	-80.1083

SCATTER PLOT

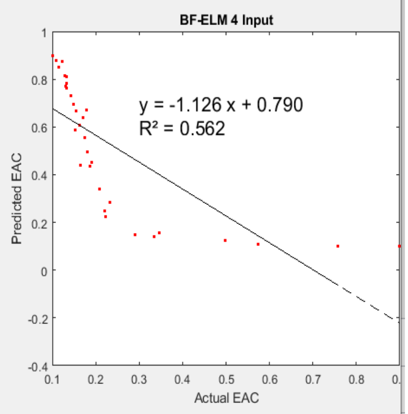


D.3) Model 3 BF-ELM

input4

Actual	BF-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.76234	0.39591	0.62921	0.69913	0.010666	0.39591	-0.62921	69.9126
0.13076	0.77062	0.40942	0.63986	0.71095	0.01116	0.40942	-0.63986	71.0954
0.1539	0.66749	0.26378	0.51359	0.57066	0.0068067	0.26378	-0.51359	57.066
0.17387	0.55341	0.14405	0.37954	0.42171	0.0039102	0.14405	-0.37954	42.1713
0.18651	0.43513	0.061811	0.24862	0.27624	0.0024887	0.061811	-0.24862	27.6241
0.16502	0.44132	0.076341	0.2763	0.307	0.0050954	0.076341	-0.2763	30.6999
0.22312	0.22607	8.7219e-06	0.0029533	0.0032814	0.00017639	8.7219e-06	-0.0029533	0.328143
0.33508	0.13993	0.038087	0.19516	-0.21684	0.0097385	0.038087	0.19516	-21.6844
0.75693	0.10213	0.42877	0.6548	-0.72756	0.27095	0.42877	0.6548	-72.7561
0.1	0.89993	0.63988	0.79993	0.88881	0.018605	0.63988	-0.79993	88.8808
0.11573	0.84999	0.53914	0.73426	0.81584	0.014562	0.53914	-0.73426	81.5843
0.12975	0.81437	0.4687	0.68462	0.76069	0.011374	0.4687	-0.68462	76.0685
0.13312	0.78082	0.41951	0.64769	0.71966	0.010666	0.41951	-0.64769	71.966
0.14302	0.73062	0.34528	0.58761	0.6529	0.0087203	0.34528	-0.58761	65.2896
0.14839	0.69382	0.2975	0.54543	0.60604	0.0077465	0.2975	-0.54543	60.6038
0.16342	0.60595	0.19584	0.44253	0.49171	0.0053267	0.19584	-0.44253	49.1705
0.19027	0.45121	0.068092	0.26094	0.28994	0.0021281	0.068092	-0.26094	28.9938
0.23286	0.28468	0.0026853	0.05182	0.057577	1.2557e-05	0.0026853	-0.05182	5.75774
0.34597	0.15744	0.035542	0.18853	-0.20947	0.012006	0.035542	0.18853	-20.9474
0.29141	0.14875	0.020351	0.14266	-0.15851	0.003026	0.020351	0.14266	-15.8506
0.57365	0.10746	0.21733	0.46619	-0.51799	0.11374	0.21733	0.46619	-51.7989
0.1	0.9	0.64	0.8	0.88889	0.018605	0.64	-0.8	88.8889
0.10986	0.87995	0.59304	0.77009	0.85566	0.016013	0.59304	-0.77009	85.5659
0.13309	0.81124	0.45989	0.67815	0.7535	0.010673	0.45989	-0.67815	75.3505
0.12238	0.87324	0.5638	0.75087	0.8343	0.013002	0.5638	-0.75087	83.4297
0.17817	0.6726	0.24446	0.49443	0.54937	0.0033908	0.24446	-0.49443	54.9365
0.17095	0.63771	0.21787	0.46677	0.51863	0.0042841	0.21787	-0.46677	51.8629
0.15306	0.58874	0.18982	0.43568	0.48409	0.006946	0.18982	-0.43568	48.4089
0.18057	0.49532	0.099068	0.31475	0.34972	0.0031175	0.099068	-0.31475	34.9722
0.20873	0.34006	0.017248	0.13133	0.14592	0.0007659	0.017248	-0.13133	14.5922
0.22099	0.24947	0.00081135	0.028484	0.031649	0.00023749	0.00081135	-0.028484	3.1649
0.49754	0.12354	0.13987	0.374	-0.41555	0.068193	0.13987	0.374	-41.5552
0.9	0.1	0.64	0.8	-0.88889	0.44036	0.64	0.8	-88.8889

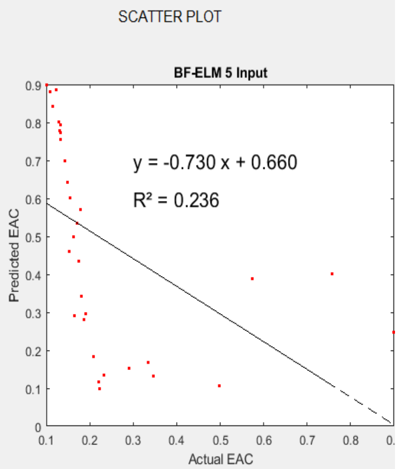
SCATTER PLOT



D.4) Model 4 BF-ELM

input5

Actual	BF-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.75624	0.38828	0.62312	0.69235	0.010666	0.38828	-0.62312	69.2353
0.13076	0.77719	0.41787	0.64643	0.71825	0.01116	0.41787	-0.64643	71.8251
0.1539	0.60143	0.20029	0.44754	0.49726	0.0068067	0.20029	-0.44754	49.7261
0.17387	0.43471	0.068038	0.26084	0.28982	0.0039102	0.068038	-0.26084	28.9824
0.18651	0.2813	0.0089846	0.094787	0.10532	0.0024887	0.0089846	-0.094787	10.5319
0.16502	0.2911	0.015897	0.12609	0.14009	0.0050954	0.015897	-0.12609	14.0094
0.22312	0.1	0.015158	0.12312	-0.1368	0.00017639	0.015158	0.12312	-13.6799
0.33508	0.16856	0.027731	0.16653	-0.18503	0.0097385	0.027731	0.16653	-18.503
0.75693	0.4022	0.12584	0.35474	-0.39415	0.27095	0.12584	0.35474	-39.415
0.1	0.89977	0.63963	0.79977	0.88863	0.018605	0.63963	-0.79977	88.8629
0.11573	0.84235	0.52797	0.72662	0.80735	0.014562	0.52797	-0.72662	80.7351
0.12975	0.80233	0.45237	0.67258	0.74731	0.011374	0.45237	-0.67258	74.7314
0.13312	0.77391	0.4106	0.64078	0.71198	0.010666	0.4106	-0.64078	71.198
0.14302	0.6997	0.3099	0.55668	0.61854	0.0087203	0.3099	-0.55668	61.8537
0.14839	0.64115	0.24281	0.49276	0.54751	0.0077465	0.24281	-0.49276	54.7513
0.16342	0.49913	0.1127	0.33571	0.37302	0.0053267	0.1127	-0.33571	37.3016
0.19027	0.29524	0.011018	0.10497	0.11663	0.0021281	0.011018	-0.10497	11.6632
0.23286	0.13499	0.0095786	0.09787	-0.10874	1.2557e-05	0.0095786	0.09787	-10.8745
0.34597	0.1321	0.045741	0.21387	-0.23764	0.012006	0.045741	0.21387	-23.7636
0.29141	0.15236	0.019335	0.13905	-0.1545	0.003026	0.019335	0.13905	-15.4502
0.57365	0.38961	0.033872	0.18404	-0.20449	0.11374	0.033872	0.18404	-20.4494
0.1	0.9	0.64	0.8	0.88889	0.018605	0.64	-0.8	88.8889
0.10986	0.88158	0.59556	0.77172	0.85747	0.016013	0.59556	-0.77172	85.7472
0.13309	0.79265	0.43502	0.65956	0.73285	0.010673	0.43502	-0.65956	73.2847
0.12238	0.88587	0.58293	0.7635	0.84833	0.013002	0.58293	-0.7635	84.833
0.17817	0.57143	0.15465	0.39326	0.43696	0.0033908	0.15465	-0.39326	43.6957
0.17095	0.53354	0.13148	0.3626	0.40288	0.0042841	0.13148	-0.3626	40.2884
0.15306	0.45997	0.094197	0.30691	0.34102	0.006946	0.094197	-0.30691	34.1016
0.18057	0.34209	0.02609	0.16153	0.17947	0.0031175	0.02609	-0.16153	17.9473
0.20873	0.18371	0.00062585	0.025017	-0.027797	0.0007659	0.00062585	0.025017	-2.77966
0.22099	0.1169	0.010834	0.10409	-0.11565	0.00023749	0.010834	0.10409	-11.5652
0.49754	0.10536	0.15381	0.39218	-0.43576	0.068193	0.15381	0.39218	-43.5759
0.9	0.24748	0.42578	0.65252	-0.72502	0.44036	0.42578	0.65252	-72.5023

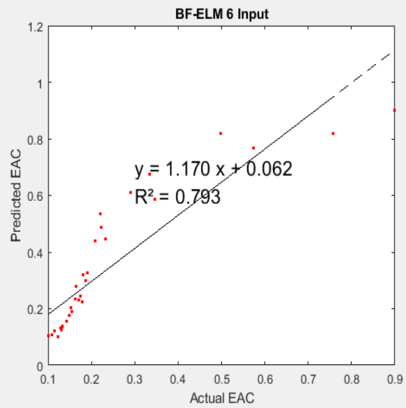


D.5) Model 5 BF-ELM

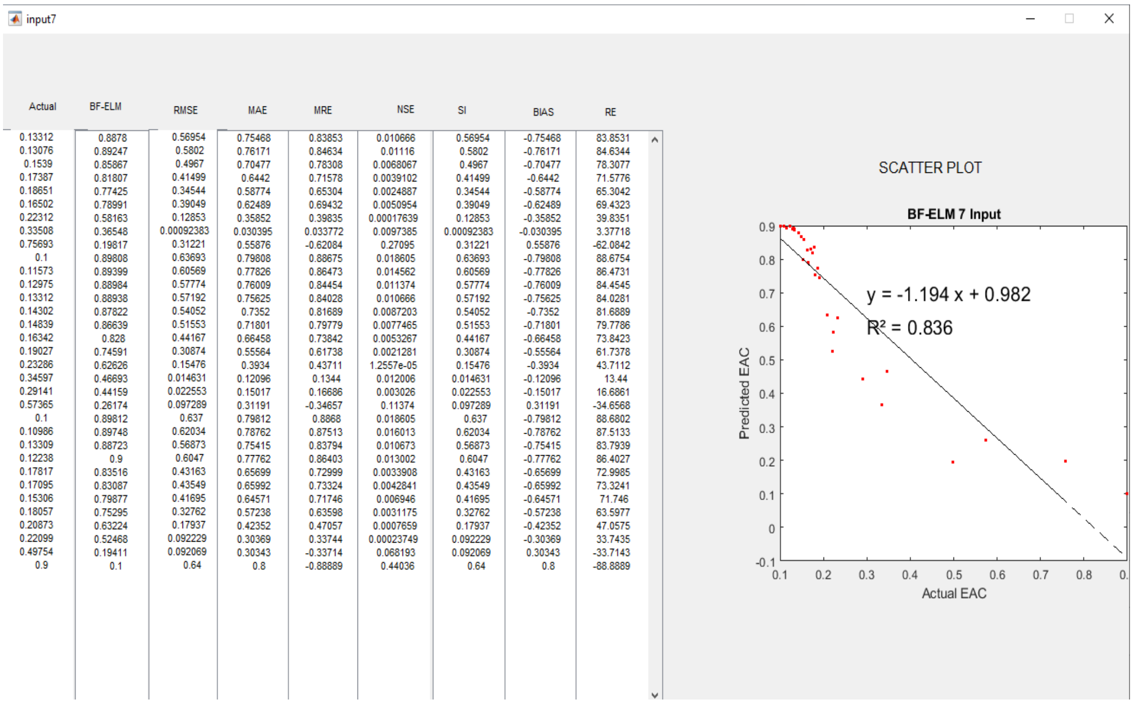
input6

Actual	BF-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.13551	5.7086e-06	0.0023893	0.0026547	0.010666	5.7086e-06	-0.0023893	0.265473
0.13076	0.1246	3.7996e-05	0.0061641	-0.006849	0.01116	3.7996e-05	0.0061641	-0.684899
0.1539	0.18908	0.0012377	0.03518	0.039089	0.0068067	0.0012377	-0.03518	3.90892
0.17387	0.24478	0.0050279	0.070907	0.078786	0.0039102	0.0050279	-0.070907	7.87859
0.18651	0.29764	0.01235	0.11113	0.12348	0.0024887	0.01235	-0.11113	12.3476
0.16502	0.27887	0.012963	0.11386	0.12651	0.0050954	0.012963	-0.11386	12.6507
0.22312	0.48781	0.070064	0.2647	0.29411	0.00017639	0.070064	-0.2647	29.4106
0.33508	0.67607	0.11627	0.34098	0.37887	0.0097385	0.11627	-0.34098	37.8868
0.75693	0.81911	0.0038668	0.062184	0.069093	0.27095	0.0038668	-0.062184	6.9093
0.1	0.10355	1.2595e-05	0.003549	0.0039433	0.018605	1.2595e-05	-0.003549	0.394332
0.11573	0.12117	2.9547e-05	0.0054357	0.0060397	0.014562	2.9547e-05	-0.0054357	0.603972
0.12975	0.13212	5.5842e-06	0.0023631	0.0026256	0.011374	5.5842e-06	-0.0023631	0.262565
0.13312	0.13417	1.1019e-06	0.0010497	0.0011664	0.010666	1.1019e-06	-0.0010497	0.116635
0.14302	0.15699	0.00019523	0.013973	0.015525	0.0087203	0.00019523	-0.013973	1.5525
0.14839	0.17658	0.00079481	0.028192	0.031325	0.0077465	0.00079481	-0.028192	3.13249
0.16342	0.23261	0.0047877	0.069193	0.076881	0.0053267	0.0047877	-0.069193	7.68814
0.19027	0.32792	0.018947	0.13765	0.15294	0.0021281	0.018947	-0.13765	15.2942
0.23286	0.44555	0.04524	0.2127	0.23633	1.2557e-05	0.04524	-0.2127	23.6329
0.34597	0.58784	0.058502	0.24187	0.26875	0.012006	0.058502	-0.24187	26.8747
0.29141	0.61074	0.10197	0.31933	0.35481	0.003026	0.10197	-0.31933	35.4807
0.57365	0.76624	0.03709	0.19259	0.21399	0.11374	0.03709	-0.19259	21.3987
0.1	0.10341	1.1618e-05	0.0034085	0.0037872	0.018605	1.1618e-05	-0.0034085	0.378724
0.10986	0.10698	8.3074e-06	0.0028823	-0.0032025	0.016013	8.3074e-06	0.0028823	-0.32025
0.13309	0.13722	1.7083e-05	0.0041331	0.0045923	0.010673	1.7083e-05	-0.0041331	0.459234
0.12238	0.1	0.00050068	0.022376	-0.024862	0.013002	0.00050068	0.022376	-2.48622
0.17817	0.22322	0.0020293	0.045048	0.050054	0.0033908	0.0020293	-0.045048	5.00536
0.17095	0.22944	0.0034212	0.058491	0.06499	0.0042841	0.0034212	-0.058491	6.49904
0.15306	0.20483	0.0026806	0.051774	0.057527	0.006946	0.0026806	-0.051774	5.75271
0.18057	0.31989	0.019411	0.13932	0.1548	0.0031175	0.019411	-0.13932	15.4802
0.20873	0.43927	0.053152	0.23055	0.25616	0.0007659	0.053152	-0.23055	25.6163
0.22099	0.53619	0.09935	0.3152	0.35022	0.00023749	0.09935	-0.3152	35.0221
0.49754	0.81855	0.10305	0.32101	0.35668	0.068193	0.10305	-0.32101	35.6676
0.9	0.9	0	0	0	0.44036	0	0	0

SCATTER PLOT



D.6) Model 6 BF-ELM



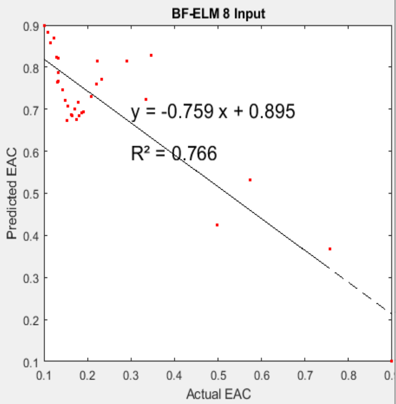
Actual	BF-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.8878	0.56954	0.75468	0.83853	0.010666	0.56954	-0.75468	83.8531
0.13076	0.89247	0.5802	0.76171	0.84634	0.01116	0.5802	-0.76171	84.6344
0.1539	0.85867	0.4967	0.70477	0.78308	0.0068067	0.4967	-0.70477	78.3077
0.17387	0.81807	0.41499	0.6442	0.71578	0.0039102	0.41499	-0.6442	71.5776
0.18651	0.77425	0.34544	0.58774	0.65304	0.0024887	0.34544	-0.58774	65.3042
0.16502	0.78991	0.39049	0.62489	0.69432	0.0050954	0.39049	-0.62489	69.4323
0.22312	0.58163	0.12853	0.35852	0.39835	0.00017639	0.12853	-0.35852	39.8351
0.33508	0.36548	0.00092383	0.030395	0.033772	0.0097385	0.00092383	-0.030395	3.37718
0.75693	0.19817	0.31221	0.55876	-0.62084	0.27095	0.31221	0.55876	-62.0842
0.1	0.89808	0.63693	0.79808	0.88675	0.018605	0.63693	-0.79808	88.6754
0.11573	0.89399	0.60569	0.77826	0.86473	0.014562	0.60569	-0.77826	86.4731
0.12975	0.88984	0.57774	0.76009	0.84454	0.011374	0.57774	-0.76009	84.4545
0.13312	0.88938	0.57192	0.75625	0.84028	0.010666	0.57192	-0.75625	84.0281
0.14302	0.87822	0.54052	0.7352	0.81689	0.0087203	0.54052	-0.7352	81.6889
0.14839	0.86639	0.51553	0.71801	0.79779	0.0077465	0.51553	-0.71801	79.7786
0.16342	0.828	0.44167	0.66458	0.73842	0.0053267	0.44167	-0.66458	73.8423
0.19027	0.74591	0.30874	0.55564	0.61738	0.0021281	0.30874	-0.55564	61.7378
0.23286	0.62626	0.15476	0.3934	0.43711	1.2557e-05	0.15476	-0.3934	43.7112
0.34597	0.46693	0.014631	0.12096	0.1344	0.012006	0.014631	-0.12096	13.44
0.29141	0.44159	0.022553	0.15017	0.16686	0.003026	0.022553	-0.15017	16.6861
0.57365	0.26174	0.097289	0.31191	-0.34657	0.11374	0.097289	0.31191	-34.6568
0.1	0.89812	0.637	0.79812	0.8868	0.018605	0.637	-0.79812	88.6802
0.10986	0.89748	0.62034	0.78762	0.87513	0.016013	0.62034	-0.78762	87.5133
0.13309	0.88723	0.56873	0.75415	0.83794	0.010673	0.56873	-0.75415	83.7939
0.12238	0.9	0.6047	0.77762	0.86403	0.013002	0.6047	-0.77762	86.4027
0.17817	0.83516	0.43163	0.65699	0.72999	0.0033908	0.43163	-0.65699	72.9985
0.17095	0.83087	0.43549	0.65992	0.73324	0.0042841	0.43549	-0.65992	73.3241
0.15306	0.79877	0.41695	0.64571	0.71746	0.006946	0.41695	-0.64571	71.746
0.18057	0.75295	0.32762	0.57238	0.63598	0.0031175	0.32762	-0.57238	63.5977
0.20873	0.63224	0.17937	0.42352	0.47057	0.0007659	0.17937	-0.42352	47.0575
0.22099	0.52468	0.092229	0.30369	0.33744	0.00023749	0.092229	-0.30369	33.7435
0.49754	0.19411	0.092069	0.30343	-0.33714	0.068193	0.092069	0.30343	-33.7143
0.9	0.1	0.64	0.8	-0.88889	0.44036	0.64	0.8	-88.8889

D.7) Model 7 BF-ELM

input8

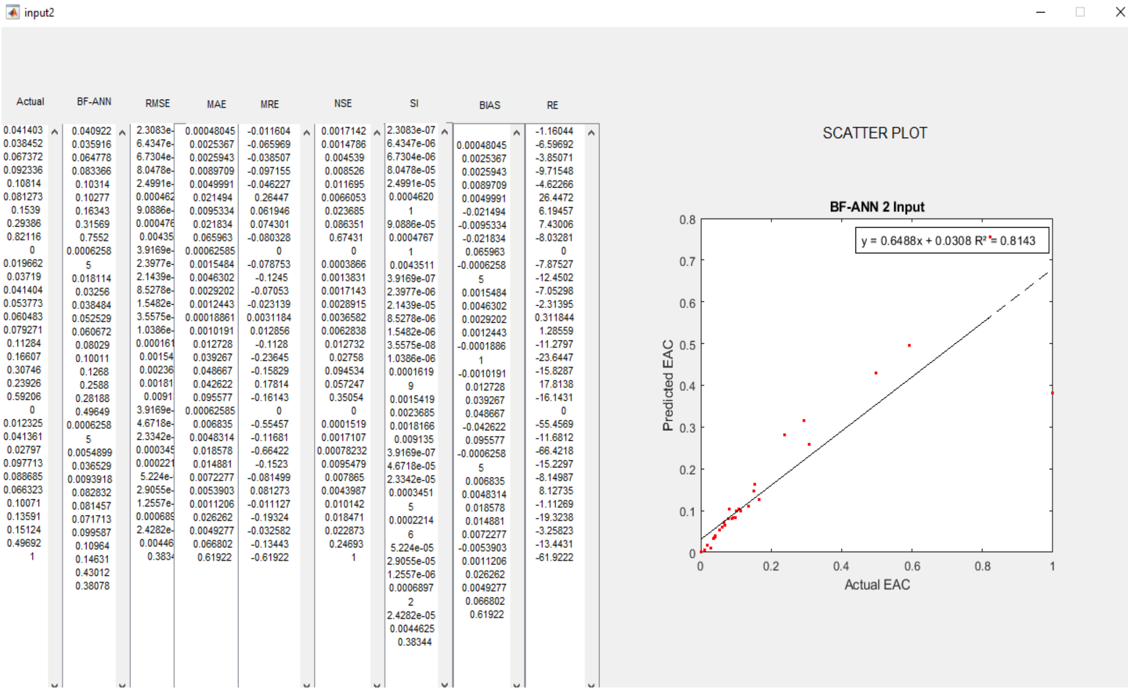
Actual	BF-ELM	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.13312	0.76583	0.40032	0.63271	0.70301	0.010666	0.40032	-0.63271	70.3012
0.13076	0.76529	0.40262	0.63452	0.70503	0.01116	0.40262	-0.63452	70.5026
0.1539	0.70641	0.30527	0.55251	0.6139	0.0068067	0.30527	-0.55251	61.3905
0.17387	0.6753	0.25143	0.50143	0.55714	0.0039102	0.25143	-0.50143	55.7141
0.18651	0.69222	0.25574	0.50571	0.5619	0.0024887	0.25574	-0.50571	56.1898
0.16502	0.68549	0.27089	0.52047	0.5783	0.0050954	0.27089	-0.52047	57.8302
0.22312	0.81466	0.34992	0.59154	0.65727	0.00017639	0.34992	-0.59154	65.727
0.33508	0.7234	0.15079	0.38832	0.43147	0.0097385	0.15079	-0.38832	43.1467
0.75693	0.36798	0.15128	0.38895	-0.43216	0.27095	0.15128	0.38895	-43.2163
0.1	0.89994	0.63991	0.79994	0.88882	0.018605	0.63991	-0.79994	88.8823
0.11573	0.85717	0.54973	0.74144	0.82382	0.014562	0.54973	-0.74144	82.382
0.12975	0.82348	0.48126	0.69373	0.77081	0.011374	0.48126	-0.69373	77.0813
0.13312	0.78701	0.42756	0.65388	0.72654	0.010666	0.42756	-0.65388	72.6538
0.14302	0.74554	0.36304	0.60252	0.66947	0.0087203	0.36304	-0.60252	66.9471
0.14839	0.72149	0.32844	0.5731	0.63678	0.0077465	0.32844	-0.5731	63.6778
0.16342	0.68766	0.27483	0.52424	0.58249	0.0053267	0.27483	-0.52424	58.2494
0.19027	0.69271	0.25245	0.50244	0.55827	0.0021281	0.25245	-0.50244	55.827
0.23286	0.7706	0.28917	0.53775	0.5975	1.2557e-05	0.28917	-0.53775	59.7495
0.34597	0.82845	0.23279	0.48248	0.53609	0.012006	0.23279	-0.48248	53.6087
0.29141	0.81344	0.27251	0.52203	0.58003	0.003026	0.27251	-0.52203	58.0028
0.57365	0.53145	0.001781	0.042201	-0.04689	0.11374	0.001781	0.042201	-4.68904
0.1	0.9	0.64	0.8	0.88889	0.018605	0.64	-0.8	88.8889
0.10986	0.88261	0.59714	0.77275	0.85861	0.016013	0.59714	-0.77275	85.8611
0.13309	0.82138	0.47374	0.68829	0.76477	0.010673	0.47374	-0.68829	76.4766
0.12238	0.87026	0.55933	0.74789	0.83099	0.013002	0.55933	-0.74789	83.0985
0.17817	0.71601	0.28927	0.53784	0.5976	0.0033908	0.28927	-0.53784	59.7598
0.17095	0.69994	0.27983	0.52899	0.58777	0.0042841	0.27983	-0.52899	58.7769
0.15306	0.67372	0.27109	0.52066	0.57851	0.006946	0.27109	-0.52066	57.8513
0.18057	0.68451	0.25396	0.50394	0.55994	0.0031175	0.25396	-0.50394	55.9935
0.20873	0.72995	0.27167	0.52122	0.57913	0.0007659	0.27167	-0.52122	57.9133
0.22099	0.75896	0.28941	0.53797	0.59774	0.00023749	0.28941	-0.53797	59.774
0.49754	0.42473	0.0053017	0.072813	-0.080903	0.068193	0.0053017	0.072813	-8.09031
0.9	0.1	0.64	0.8	-0.88889	0.44036	0.64	0.8	-88.8889

SCATTER PLOT



E.) BF-ANN

E.1) Model 1 BF-ANN

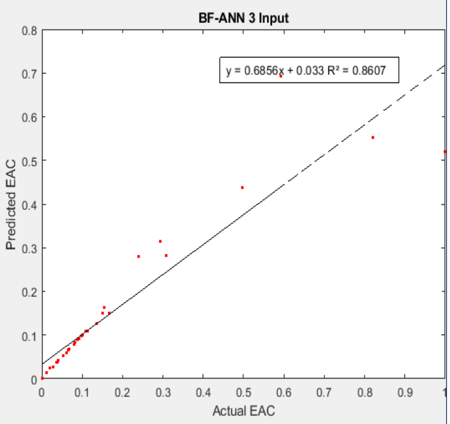


E.2) Model 2 BF-ANN

input3

Actual	BF-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.041296	1.1402e-08	0.00010678	-0.0025791	0.0017142	1.1402e-08	0.00010678	-0.257906
0.038452	0.038664	4.4952e-08	0.00021202	0.0055138	0.0014786	4.4952e-08	-0.00021202	0.551378
0.067372	0.06761	5.6685e-08	0.00023809	0.0035339	0.004539	5.6685e-08	-0.00023809	0.353389
0.092336	0.092915	3.3501e-07	0.0005788	0.0062684	0.008526	3.3501e-07	-0.0005788	0.626841
0.10814	0.10863	2.3868e-07	0.00048855	0.0045176	0.011695	2.3868e-07	-0.00048855	0.451764
0.081273	0.083496	4.9406e-06	0.0022228	0.027349	0.0066053	4.9406e-06	-0.0022228	2.73493
0.1539	0.16366	9.5306e-05	0.0097625	0.063434	0.023685	9.5306e-05	-0.0097625	6.34343
0.29386	0.31454	0.00042792	0.020686	0.070396	0.086351	0.00042792	-0.020686	7.0396
0.82116	0.55347	0.07166	0.26769	-0.32599	0.67431	0.07166	0.26769	-32.5993
0	0.00092075	8.4779e-07	0.00092075	0	0	8.4779e-07	-0.00092075	0
0.019662	0.024638	2.476e-05	0.0049759	0.25307	0.0003866	2.476e-05	-0.0049759	25.3072
0.03719	0.037366	3.1093e-08	0.00017633	0.0047414	0.0013831	3.1093e-08	-0.00017633	0.474141
0.041404	0.041142	6.8982e-08	0.00026264	-0.0063434	0.0017143	6.8982e-08	0.00026264	-0.634341
0.053773	0.053872	9.863e-09	9.9313e-05	0.0018469	0.0028915	9.863e-09	-9.9313e-05	0.184689
0.060483	0.060344	1.9388e-08	0.00013924	-0.0023022	0.0036582	1.9388e-08	0.00013924	-0.230215
0.079271	0.079305	1.1868e-09	3.445e-05	0.00043459	0.0062838	1.1868e-09	-3.445e-05	0.0434587
0.11284	0.11007	7.6798e-06	0.0027712	-0.02456	0.012732	7.6798e-06	0.0027712	-2.45599
0.16607	0.1494	0.00027789	0.01667	-0.10038	0.02758	0.00027789	0.01667	-10.0378
0.30746	0.28225	0.00063561	0.025211	-0.081998	0.094534	0.00063561	0.025211	-8.1998
0.23926	0.2801	0.0016677	0.040837	0.17068	0.057247	0.0016677	-0.040837	17.068
0.59206	0.69363	0.010316	0.10157	0.17155	0.35054	0.010316	-0.10157	17.1547
0	0.00092075	8.4779e-07	0.00092075	0	0	8.4779e-07	-0.00092075	0
0.012325	0.01312	6.3254e-07	0.00079532	0.06453	0.0001519	6.3254e-07	-0.00079532	6.45295
0.041361	0.04137	8.6768e-11	9.315e-06	0.00022521	0.0017107	8.6768e-11	-9.315e-06	0.0225214
0.02797	0.02704	8.6562e-07	0.00093039	-0.033264	0.00078232	8.6562e-07	0.00093039	-3.32639
0.097713	0.097541	2.9495e-08	0.00017174	-0.0017576	0.0095479	2.9495e-08	0.00017174	-0.175761
0.088685	0.089578	7.9779e-07	0.00089319	0.010072	0.007865	7.9779e-07	-0.00089319	1.00715
0.066323	0.065507	6.6477e-07	0.00081533	-0.012293	0.0043987	6.6477e-07	0.00081533	-1.22934
0.10071	0.10044	7.2392e-08	0.00026906	-0.0026717	0.010142	7.2392e-08	0.00026906	-0.267167
0.13591	0.12555	0.00010732	0.01036	-0.076225	0.018471	0.00010732	0.01036	-7.6225
0.15124	0.15105	3.6466e-08	0.00019096	-0.0012627	0.022873	3.6466e-08	0.00019096	-0.126266
0.49692	0.43705	0.0035847	0.059872	-0.12049	0.24693	0.0035847	0.059872	-12.0486
1	0.52068	0.22975	0.47932	-0.47932	1	0.22975	0.47932	-47.9323

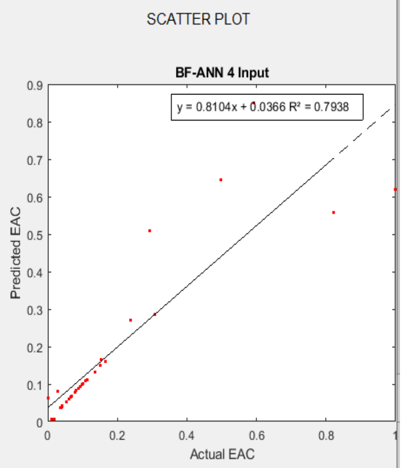
SCATTER PLOT



E.3) Model 3 BF-ANN

input4

Actual	BF-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.040475	8.6119e-07	0.000928	-0.022414	0.0017142	8.6119e-07	0.000928	-2.241419
0.038452	0.037161	1.6675e-06	0.0012913	-0.033582	0.0014786	1.6675e-06	0.0012913	-3.358182
0.067372	0.066828	2.9642e-07	0.00054444	-0.0080811	0.004539	2.9642e-07	0.00054444	-0.8081093
0.092336	0.092674	1.1358e-07	0.00033702	0.0036499	0.008526	1.1358e-07	-0.00033702	0.3649898
0.10814	0.10941	1.6021e-06	0.0012658	0.011704	0.011695	1.6021e-06	-0.0012658	1.170447
0.081273	0.083066	3.2155e-06	0.0017932	0.022064	0.0066053	3.2155e-06	-0.0017932	2.206373
0.1539	0.16488	0.0001206	0.010982	0.071357	0.023685	0.0001206	-0.010982	7.135677
0.29386	0.50806	0.045882	0.2142	0.72894	0.086351	0.045882	-0.2142	72.89354
0.82116	0.55725	0.069649	0.26391	-0.32139	0.67431	0.069649	0.26391	-32.13873
0	0.062115	0.0038583	0.062115	0	0	0.0038583	-0.062115	0
0.019662	0.0061271	0.00018319	0.013535	-0.68838	0.0003866	0.00018319	0.013535	-68.83779
0.03719	0.036827	1.3186e-07	0.00036313	-0.0097642	0.0013831	1.3186e-07	0.00036313	-0.9764225
0.041404	0.040585	6.7104e-07	0.00081917	-0.019785	0.0017143	6.7104e-07	0.00081917	-1.978459
0.053773	0.053826	2.8068e-09	5.2979e-05	0.00098524	0.0028915	2.8068e-09	-5.2979e-05	0.09852368
0.060483	0.059938	2.9665e-07	0.00054466	-0.0090051	0.0036582	2.9665e-07	0.00054466	-0.9005092
0.079271	0.078649	3.8672e-07	0.00062187	-0.0078449	0.0062838	3.8672e-07	0.00062187	-0.7844876
0.11284	0.1125	1.118e-07	0.00033436	-0.0029632	0.012732	1.118e-07	0.00033436	-0.2963243
0.16607	0.16023	3.4127e-05	0.0058418	-0.035177	0.02758	3.4127e-05	0.0058418	-3.517662
0.30746	0.28544	0.00048504	0.022024	-0.07163	0.094534	0.00048504	0.022024	-7.162985
0.23926	0.27041	0.00097012	0.031147	0.13018	0.057247	0.00097012	-0.031147	13.01781
0.59206	0.8495	0.066274	0.25744	0.43482	0.35054	0.066274	-0.25744	43.48151
0	0.062115	0.0038583	0.062115	0	0	0.0038583	-0.062115	0
0.012325	0.0075232	2.3057e-05	0.0048017	-0.3896	0.0001519	2.3057e-05	0.0048017	-38.95957
0.041361	0.04186	2.497e-07	0.0004997	0.012082	0.0017107	2.497e-07	-0.0004997	1.208156
0.02797	0.080129	0.0027206	0.052159	1.8648	0.00078232	0.0027206	-0.052159	186.4826
0.097713	0.097663	2.5558e-09	5.0554e-05	-0.00051738	0.0095479	2.5558e-09	5.0554e-05	-0.05173762
0.088685	0.088878	3.7522e-08	0.00019371	0.0021842	0.007865	3.7522e-08	-0.00019371	0.2184202
0.066323	0.065086	1.53e-06	0.0012369	-0.01865	0.0043987	1.53e-06	0.0012369	-1.865
0.10071	0.10159	7.8081e-07	0.00088364	0.0087742	0.010142	7.8081e-07	-0.00088364	0.8774246
0.13591	0.13092	2.4917e-05	0.0049917	-0.036729	0.018471	2.4917e-05	0.0049917	-3.672864
0.15124	0.15016	1.1653e-06	0.0010795	-0.0071378	0.022873	1.1653e-06	0.0010795	-0.7137824
0.49692	0.64439	0.021747	0.14747	0.29676	0.24693	0.021747	-0.14747	29.6764
1	0.61991	0.14447	0.38009	-0.38009	1	0.14447	0.38009	-38.00864

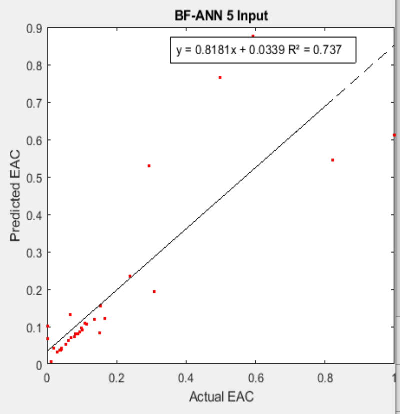


E.4) Model 4 BF-ANN

input5

Actual	BF-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.039678	2.9749e-06	0.0017248	-0.041659	0.0017142	2.9749e-06	0.0017248	-4.165888
0.038452	0.037726	5.2747e-07	0.00072627	-0.018888	0.0014786	5.2747e-07	0.00072627	-1.888763
0.067372	0.06961	5.0087e-06	0.002238	0.033219	0.004539	5.0087e-06	-0.002238	3.321878
0.092336	0.085076	5.2712e-05	0.0072603	-0.078629	0.008526	5.2712e-05	0.0072603	-7.86289
0.10814	0.10905	8.1696e-07	0.00090386	0.008358	0.011695	8.1696e-07	-0.00090386	0.8358044
0.081273	0.079583	2.8554e-06	0.0016898	-0.020792	0.0066053	2.8554e-06	0.0016898	-2.079156
0.1539	0.15386	1.844e-09	4.2942e-05	-0.00027903	0.023685	1.844e-09	4.2942e-05	-0.02790258
0.29386	0.5291	0.055342	0.23525	0.80056	0.086351	0.055342	-0.23525	80.05592
0.82116	0.54591	0.075766	0.27526	-0.3352	0.67431	0.075766	0.27526	-33.52035
0	0.10077	0.010154	0.10077	0	0	0.010154	-0.10077	0
0.019662	0.042944	0.00054205	0.023282	1.1841	0.0003866	0.00054205	-0.023282	118.411
0.03719	0.036723	2.1774e-07	0.00046662	-0.012547	0.0013831	2.1774e-07	0.00046662	-1.254701
0.041404	0.043423	4.0766e-06	0.002019	0.048764	0.0017143	4.0766e-06	-0.002019	4.876416
0.053773	0.052548	1.5003e-06	0.0012249	-0.022778	0.0028915	1.5003e-06	0.0012249	-2.277831
0.060483	0.062617	4.5523e-06	0.0021336	0.035276	0.0036582	4.5523e-06	-0.0021336	3.527633
0.079271	0.073399	3.4478e-05	0.0058718	-0.074073	0.0062838	3.4478e-05	0.0058718	-7.407333
0.11284	0.10738	2.9724e-05	0.0054519	-0.048317	0.012732	2.9724e-05	0.0054519	-4.831721
0.16607	0.12213	0.0019307	0.04394	-0.26458	0.02758	0.0019307	0.04394	-26.45848
0.30746	0.19484	0.012684	0.11263	-0.3663	0.094534	0.012684	0.11263	-36.63045
0.23926	0.23355	3.2644e-05	0.0057135	-0.02388	0.057247	3.2644e-05	0.0057135	-2.387958
0.59206	0.87501	0.080057	0.28294	0.47789	0.35054	0.080057	-0.28294	47.78931
0	0.068881	0.0047446	0.068881	0	0	0.0047446	-0.068881	0
0.012325	0.0071888	2.638e-05	0.0051362	-0.41673	0.0001519	2.638e-05	0.0051362	-41.67293
0.041361	0.039789	2.4687e-06	0.0015712	-0.037988	0.0017107	2.4687e-06	0.0015712	-3.798832
0.02797	0.032766	2.3007e-05	0.0047965	0.17149	0.00078232	2.3007e-05	-0.0047965	17.1489
0.097713	0.097157	3.0946e-07	0.00055629	-0.0056931	0.0095479	3.0946e-07	0.00055629	-0.5693058
0.088685	0.081877	4.6348e-05	0.0068079	-0.076765	0.007865	4.6348e-05	0.0068079	-7.676529
0.066323	0.13079	0.0041562	0.064468	0.97204	0.0043987	0.0041562	-0.064468	97.20435
0.10071	0.09223	7.1873e-05	0.0084778	-0.084182	0.010142	7.1873e-05	0.0084778	-8.418212
0.13591	0.11843	0.0003053	0.017473	-0.12857	0.018471	0.0003053	0.017473	-12.85651
0.15124	0.08435	0.0044739	0.066887	-0.44227	0.022873	0.0044739	0.066887	-44.22674
0.49692	0.76437	0.071527	0.26745	0.5382	0.24693	0.071527	-0.26745	53.82033
1	0.61045	0.15175	0.38955	-0.38955	1	0.15175	0.38955	-38.95494

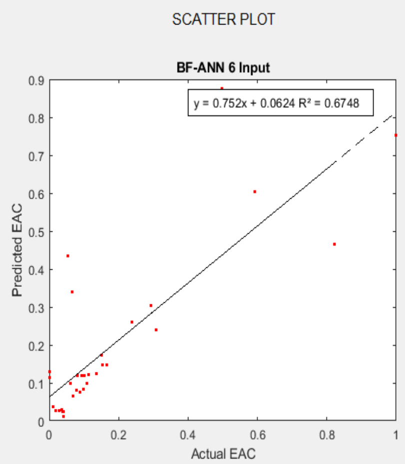
SCATTER PLOT



E.5) Model 5 BF-ANN

input6

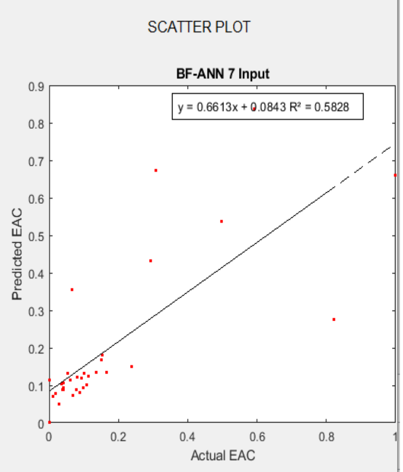
Actual	BF-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.024192	0.00029621	0.017211	-0.41569	0.0017142	0.00029621	0.017211	-41.56906
0.038452	0.024156	0.00020437	0.014296	-0.37178	0.0014786	0.00020437	0.014296	-37.1782
0.067372	0.064871	6.2559e-06	0.0025012	-0.037125	0.004539	6.2559e-06	0.0025012	-3.712483
0.092336	0.1185	0.00068465	0.026166	0.28337	0.008526	0.00068465	-0.026166	28.33747
0.10814	0.097479	0.00011371	0.010663	-0.098605	0.011695	0.00011371	0.010663	-9.860463
0.081273	0.11847	0.0013839	0.037201	0.45774	0.0066053	0.0013839	-0.037201	45.77353
0.1539	0.14783	3.6814e-05	0.0060674	-0.039425	0.023685	3.6814e-05	0.0060674	-3.942479
0.29386	0.30504	0.00012509	0.011184	0.03806	0.086351	0.00012509	-0.011184	3.806016
0.82116	0.46524	0.12668	0.35592	-0.43344	0.67431	0.12668	0.35592	-43.34393
0	0.12948	0.016764	0.12948	0	0	0.016764	-0.12948	0
0.019662	0.02664	4.8687e-05	0.0069776	0.35488	0.0003866	4.8687e-05	-0.0069776	35.48777
0.03719	0.028318	7.8707e-05	0.0088717	-0.23855	0.0013831	7.8707e-05	0.0088717	-23.8551
0.041404	0.010434	0.00095917	0.03097	-0.748	0.0017143	0.00095917	0.03097	-74.80003
0.053773	0.43362	0.14428	0.37985	7.0639	0.0028915	0.14428	-0.37985	706.392
0.060483	0.098702	0.0014607	0.038219	0.63189	0.0036582	0.0014607	-0.038219	63.1891
0.079271	0.080228	9.157e-07	0.00095692	0.012072	0.0062838	9.157e-07	-0.00095692	1.207161
0.11284	0.12157	7.6327e-05	0.0087365	0.077426	0.012732	7.6327e-05	-0.0087365	7.742632
0.16607	0.14772	0.00033691	0.018355	-0.11052	0.02758	0.00033691	0.018355	-11.05247
0.30746	0.23995	0.0045576	0.06751	-0.21957	0.094534	0.0045576	0.06751	-21.95705
0.23926	0.25916	0.00039597	0.019899	0.083168	0.057247	0.00039597	-0.019899	8.316768
0.59206	0.60269	0.0001129	0.010626	0.017947	0.35054	0.0001129	-0.010626	1.794658
0	0.11447	0.013104	0.11447	0	0	0.013104	-0.11447	0
0.012325	0.038111	0.00066492	0.025786	2.0922	0.0001519	0.00066492	-0.025786	209.219
0.041361	0.024137	0.00029665	0.017224	-0.41643	0.0017107	0.00029665	0.017224	-41.64274
0.02797	0.025644	5.4085e-06	0.0023256	-0.083147	0.00078232	5.4085e-06	0.0023256	-8.314744
0.097713	0.082861	0.00022059	0.014852	-0.152	0.0095479	0.00022059	0.014852	-15.19987
0.088685	0.074418	0.00020355	0.014267	-0.16087	0.007865	0.00020355	0.014267	-16.08744
0.066323	0.34032	0.075077	0.274	4.1314	0.0043987	0.075077	-0.274	413.1353
0.10071	0.12035	0.000386	0.019647	0.19509	0.010142	0.000386	-0.019647	19.50879
0.13591	0.12389	0.00014447	0.01202	-0.08844	0.018471	0.00014447	0.01202	-8.844043
0.15124	0.17312	0.00047877	0.021881	0.14468	0.022873	0.00047877	-0.021881	14.46787
0.49692	0.87654	0.14411	0.37962	0.76394	0.24693	0.14411	-0.37962	76.39411
1	0.75148	0.061763	0.24852	-0.24852	1	0.061763	0.24852	-24.85211



E.6) Model 6 BF-ANN

input7

Actual	BF-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.094338	0.0028021	0.052935	1.2785	0.0017142	0.0028021	-0.052935	127.8548
0.038452	0.087211	0.0023774	0.048758	1.268	0.0014786	0.0023774	-0.048758	126.8014
0.067372	0.073348	3.5707e-05	0.0059755	0.088694	0.004539	3.5707e-05	-0.0059755	8.869389
0.092336	0.11852	0.00068567	0.026185	0.28359	0.008526	0.00068567	-0.026185	28.35865
0.10814	0.10053	5.7935e-05	0.0076115	-0.070384	0.011695	5.7935e-05	0.0076115	-7.038422
0.081273	0.12068	0.0015527	0.039405	0.48485	0.0066053	0.0015527	-0.039405	48.48464
0.1539	0.18089	0.0007285	0.026991	0.17538	0.023685	0.0007285	-0.026991	17.53799
0.29386	0.43329	0.019443	0.13944	0.47452	0.086351	0.019443	-0.13944	47.45163
0.82116	0.27479	0.29852	0.54637	-0.66536	0.67431	0.29852	0.54637	-66.53607
0	0.00012599	1.5874e-08	0.00012599	0	0	1.5874e-08	-0.00012599	0
0.019662	0.077594	0.0033561	0.057932	2.9464	0.0003866	0.0033561	-0.057932	294.6376
0.03719	0.10278	0.004302	0.065589	1.7636	0.0013831	0.004302	-0.065589	176.3629
0.041404	0.10629	0.0042097	0.064882	1.567	0.0017143	0.0042097	-0.064882	156.7036
0.053773	0.13169	0.0060709	0.077916	1.449	0.0028915	0.0060709	-0.077916	144.8984
0.060483	0.11284	0.0027409	0.052353	0.86559	0.0036582	0.0027409	-0.052353	86.55892
0.079271	0.089184	9.8273e-05	0.0099133	0.12506	0.0062838	9.8273e-05	-0.0099133	12.50562
0.11284	0.12405	0.00012569	0.011211	0.099357	0.012732	0.00012569	-0.011211	9.935718
0.16607	0.13353	0.0010588	0.03254	-0.19594	0.02758	0.0010588	0.03254	-19.59386
0.30746	0.67228	0.13309	0.36481	1.1865	0.094534	0.13309	-0.36481	118.6528
0.23926	0.14941	0.0080736	0.089853	-0.37554	0.057247	0.0080736	0.089853	-37.55428
0.59206	0.83628	0.059643	0.24422	0.41249	0.35054	0.059643	-0.24422	41.24867
0	0.11317	0.012807	0.11317	0	0	0.012807	-0.11317	0
0.012325	0.069268	0.0032425	0.056943	4.6202	0.0001519	0.0032425	-0.056943	462.0151
0.041361	0.08829	0.0022023	0.046929	1.1346	0.0017107	0.0022023	-0.046929	113.4633
0.02797	0.050079	0.00048883	0.022109	0.79047	0.00078232	0.00048883	-0.022109	79.04715
0.097713	0.093194	2.0421e-05	0.004519	-0.046247	0.0095479	2.0421e-05	0.004519	-4.624731
0.088685	0.080292	7.044e-05	0.0083929	-0.094637	0.007865	7.044e-05	0.0083929	-9.463717
0.066323	0.35397	0.082739	0.28764	4.3371	0.0043987	0.082739	-0.28764	433.7056
0.10071	0.1326	0.0010171	0.031891	0.31667	0.010142	0.0010171	-0.031891	31.66729
0.13591	0.13542	2.4005e-07	0.00048995	-0.003605	0.018471	2.4005e-07	0.00048995	-0.3605032
0.15124	0.16699	0.00024816	0.015753	0.10416	0.022873	0.00024816	-0.015753	10.41606
0.49692	0.53723	0.0016249	0.04031	0.08112	0.24693	0.0016249	-0.04031	8.11198
1	0.66144	0.11462	0.33856	-0.33856	1	0.11462	0.33856	-33.85585

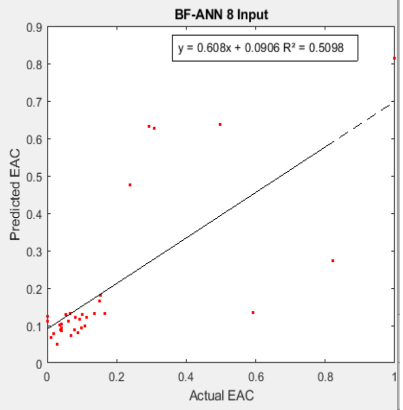


E.7) Model 7 BF-ANN

input8

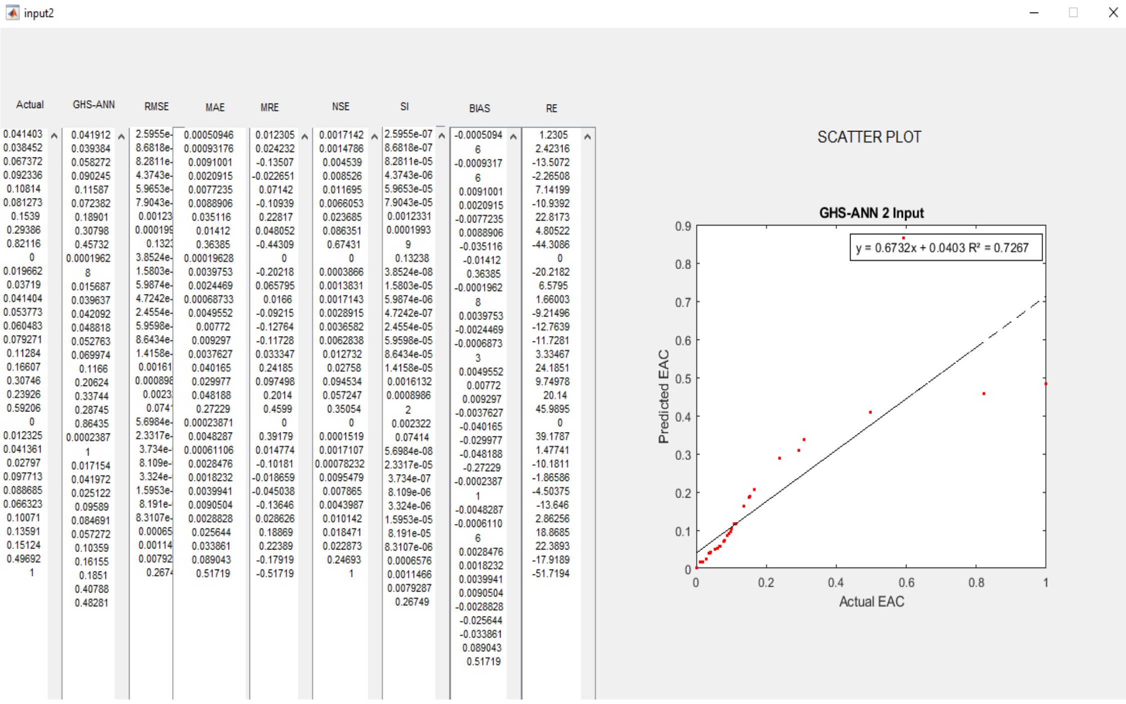
Actual	BF-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.094156	0.0027829	0.052754	1.2742	0.0017142	0.0027829	-0.052754	127.4162
0.038452	0.087394	0.0023953	0.048941	1.2728	0.0014786	0.0023953	-0.048941	127.2778
0.067372	0.073051	3.2245e-05	0.0056785	0.084286	0.004539	3.2245e-05	-0.0056785	8.428561
0.092336	0.11673	0.00059489	0.02439	0.26415	0.008526	0.00059489	-0.02439	26.41471
0.10814	0.09991	6.7769e-05	0.0082322	-0.076124	0.011695	6.7769e-05	0.0082322	-7.612358
0.081273	0.12053	0.0015411	0.039256	0.48302	0.0066053	0.0015411	-0.039256	48.30181
0.1539	0.17951	0.00065586	0.02561	0.16641	0.023685	0.00065586	-0.02561	16.64058
0.29386	0.63245	0.11464	0.33859	1.1522	0.086351	0.11464	-0.33859	115.2237
0.82116	0.27318	0.30029	0.54798	-0.66732	0.67431	0.30029	0.54798	-66.73244
0	0.12411	0.015403	0.12411	0	0	0.015403	-0.12411	0
0.019662	0.07708	0.0032968	0.057418	2.9202	0.0003866	0.0032968	-0.057418	292.0238
0.03719	0.10178	0.0041716	0.064588	1.7367	0.0013831	0.0041716	-0.064588	173.6698
0.041404	0.10451	0.0039827	0.063109	1.5242	0.0017143	0.0039827	-0.063109	152.4203
0.053773	0.12951	0.0057361	0.075737	1.4085	0.0028915	0.0057361	-0.075737	140.8459
0.060483	0.11114	0.0025663	0.050659	0.83758	0.0036582	0.0025663	-0.050659	83.75762
0.079271	0.088591	8.6868e-05	0.0093203	0.11758	0.0062838	8.6868e-05	-0.0093203	11.75759
0.11284	0.12267	9.6638e-05	0.0098305	0.087121	0.012732	9.6638e-05	-0.0098305	8.712145
0.16607	0.13309	0.001088	0.032986	-0.19862	0.02758	0.001088	0.032986	-19.86224
0.30746	0.62719	0.10223	0.31973	1.0399	0.094534	0.10223	-0.31973	103.9888
0.23926	0.47523	0.05568	0.23597	0.98622	0.057247	0.05568	-0.23597	98.62216
0.59206	0.13404	0.20978	0.45802	-0.7736	0.35054	0.20978	0.45802	-77.35999
0	0.11153	0.012438	0.11153	0	0	0.012438	-0.11153	0
0.012325	0.067462	0.0030401	0.055137	4.4737	0.0001519	0.0030401	-0.055137	447.3652
0.041361	0.086749	0.0020601	0.045388	1.0974	0.0017107	0.0020601	-0.045388	109.7375
0.02797	0.05091	0.00052625	0.02294	0.82017	0.00078232	0.00052625	-0.02294	82.01718
0.097713	0.09304	2.1843e-05	0.0046736	-0.04783	0.0095479	2.1843e-05	0.0046736	-4.782986
0.088685	0.079872	7.7658e-05	0.0088124	-0.099367	0.007865	7.7658e-05	0.0088124	-9.93673
0.066323	0.13314	0.0044647	0.066818	1.0075	0.0043987	0.0044647	-0.066818	100.7476
0.10071	0.13042	0.0008831	0.029717	0.29508	0.010142	0.0008831	-0.029717	29.50803
0.13591	0.13318	7.4477e-06	0.002729	-0.02008	0.018471	7.4477e-06	0.002729	-2.008015
0.15124	0.16555	0.00020474	0.014309	0.094611	0.022873	0.00020474	-0.014309	9.461083
0.49692	0.63711	0.019652	0.14019	0.28211	0.24693	0.019652	-0.14019	28.21066
1	0.81421	0.034517	0.18579	-0.18579	1	0.034517	0.18579	-18.57877

SCATTER PLOT



F.) GHS-ANN

F.1) Model 1 GHS-ANN


input2
Actual
0.041403
0.038452
0.067372
0.092336
0.10814
0.081273
0.1539
0.29386
0.82116
0
0.019662
0.03719
0.041404
0.053773
0.060483
0.079271
0.11284
0.16607
0.30746
0.23926
0.59206
0
0.012325
0.041361
0.02797
0.097713
0.088685
0.066323
0.10071
0.13591
0.15124
0.49692
1
GHS-ANN
0.041912
0.039384
0.058272
0.090245
0.11587
0.072382
0.18901
0.30798
0.45732
0.0001962
8
0.015687
0.039637
0.042092
0.048818
0.052763
0.069974
0.1166
0.20624
0.33744
0.28745
0.86435
0.0002387
1
0.017154
0.041972
0.025122
0.09589
0.084691
0.057272
0.10359
0.16155
0.1851
0.40788
0.48281
RMSE
2.5955e-
8.6818e-
8.2811e-
4.3743e-
5.9653e-
7.9043e-
0.00123
0.000199
0.1323
3.8524e-
1.5803e-
5.9874e-
4.7242e-
2.4554e-
5.9598e-
8.6434e-
1.4158e-
0.00161
0.000898
0.0023
0.0741
5.6984e-
2.3317e-
3.734e-
8.109e-
3.324e-
1.5953e-
8.191e-
8.3107e-
0.00065
0.00114
0.00792
0.2674
MAE
0.00050946
0.00093176
0.0091001
0.0020915
0.0077235
0.0088906
0.035116
0.01412
0.36385
0.00019628
0.0039753
0.0024469
0.00068733
0.0049552
0.00772
0.009297
0.0037627
0.040165
0.029977
0.048188
0.27229
0.00023871
0.0048287
0.00061106
0.0028476
0.0018232
0.0039941
0.0090504
0.0028828
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0.033861
0.089043
0.51719
MRE
0.012305
0.024232
-0.13507
-0.022651
0.07142
-0.10939
0.22817
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-0.44309
0
-0.20218
0.065795
0.0166
-0.09215
-0.12764
-0.11728
0.033347
0.24185
0.097498
0.2014
0.4599
0
0.39179
0.014774
-0.10181
-0.018659
-0.045038
-0.13646
0.028626
0.18869
0.22389
-0.17919
-0.51719
NSE
0.0017142
0.0014786
0.004539
0.008526
0.011695
0.0066053
0.023685
0.086351
0.67431
0
0.0003866
0.0013831
0.0017143
0.0028915
0.0036582
0.0062838
0.012732
0.02758
0.094534
0.057247
0.35054
0
0.0001519
0.0017107
0.00078232
0.0095479
0.007865
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0.010142
0.018471
0.022873
0.24693
1
SI
2.5955e-07
8.6818e-07
8.2811e-05
4.3743e-06
5.9653e-05
7.9043e-05
0.0012331
0.0001993
9
0.13238
3.8524e-08
1.5803e-05
5.9874e-06
4.7242e-07
2.4554e-05
5.9598e-05
8.6434e-05
1.4158e-05
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0.0008986
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0.002322
0.07414
5.6984e-08
2.3317e-05
3.734e-07
8.109e-06
3.324e-06
1.5953e-05
8.191e-05
8.3107e-06
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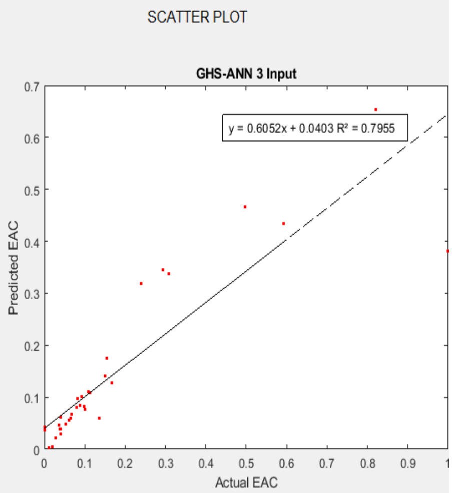
0.0011466
0.0079287
0.26749
BIAS
-0.0005094
6
-0.0009317
6
0.0091001
0.0020915
-0.0077235
0.0088906
-0.035116
-0.01412
0.36385
-0.0001962
8
0.0039753
-0.0024469
-0.0006873
3
0.0049552
0.00772
0.009297
-0.0037627
-0.040165
-0.029977
-0.048188
-0.27229
-0.0002387
1
-0.0048287
-0.0006110
6
0.0028476
0.0018232
0.0039941
0.0090504
-0.0028828
-0.025644
-0.033861
0.089043
0.51719
RE
1.2305
2.42316
-13.5072
-2.26508
7.14199
-10.9392
22.8173
4.80522
-44.3086
0
-20.2182
6.5795
1.66003
-9.21496
-12.7639
-11.7281
3.33467
24.1851
9.74978
20.14
45.9895
0
39.1787
1.47741
-10.1811
-1.86586
-4.50375
-13.646
2.86256
18.8685
22.3893
-17.9189
-51.7194
SCATTER PLOT
GHS-ANN 2 Input
y = 0.6732x + 0.0403 R² = 0.7267
Predicted EAC
Actual EAC
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0
0.2
0.4
0.6
0.8
1

F.2) Model 2 GHS-ANN

input3

Actual	GHS-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.061356	0.00039812	0.019953	0.48193	0.0017142	0.00039812	-0.019953	48.1926
0.038452	0.039175	5.2283e-07	0.00072307	0.018804	0.0014786	5.2283e-07	-0.00072307	1.88043
0.067372	0.067212	2.5573e-08	0.00015992	-0.0023736	0.004539	2.5573e-08	0.00015992	-0.237364
0.092336	0.10198	9.301e-05	0.0096442	0.10445	0.008526	9.301e-05	-0.0096442	10.4446
0.10814	0.11133	1.0134e-05	0.0031834	0.029437	0.011695	1.0134e-05	-0.0031834	2.9437
0.081273	0.097164	0.00025254	0.015892	0.19553	0.0066053	0.00025254	-0.015892	19.5533
0.1539	0.1745	0.00042419	0.020596	0.13383	0.023685	0.00042419	-0.020596	13.3827
0.29386	0.34457	0.0025715	0.05071	0.17257	0.086351	0.0025715	-0.05071	17.2568
0.82116	0.65427	0.027852	0.16689	-0.20324	0.67431	0.027852	0.16689	-20.3237
0	0.043273	0.0018726	0.043273	0	0	0.0018726	-0.043273	0
0.019662	0.0050083	0.00021473	0.014654	-0.74528	0.0003866	0.00021473	0.014654	-74.5282
0.03719	0.047214	0.00010048	0.010024	0.26954	0.0013831	0.00010048	-0.010024	26.9537
0.041404	0.03891	6.2215e-06	0.0024943	-0.060242	0.0017143	6.2215e-06	0.0024943	-6.02422
0.053773	0.047547	3.8765e-05	0.0062262	-0.11579	0.0028915	3.8765e-05	0.0062262	-11.5787
0.060483	0.055688	2.2992e-05	0.004795	-0.079279	0.0036582	2.2992e-05	0.004795	-7.92787
0.079271	0.079691	1.7708e-07	0.00042081	0.0053085	0.0062838	1.7708e-07	-0.00042081	0.530854
0.11284	0.10813	2.2164e-05	0.0047079	-0.041723	0.012732	2.2164e-05	0.0047079	-4.17229
0.16607	0.12677	0.0015446	0.039301	-0.23665	0.02758	0.0015446	0.039301	-23.6654
0.30746	0.33802	0.00093373	0.030557	0.099384	0.094534	0.00093373	-0.030557	9.93843
0.23926	0.31917	0.0063851	0.079907	0.33397	0.057247	0.0063851	-0.079907	33.3972
0.59206	0.43428	0.024896	0.15779	-0.2665	0.35054	0.024896	0.15779	-26.65
0	0.037162	0.001381	0.037162	0	0	0.001381	-0.037162	0
0.012325	0.0019105	0.00010846	0.010414	-0.84499	0.0001519	0.00010846	0.010414	-84.4986
0.041361	0.028944	0.00015416	0.012416	-0.30019	0.0017107	0.00015416	0.012416	-30.0193
0.02797	0.021726	3.8982e-05	0.0062436	-0.22322	0.00078232	3.8982e-05	0.0062436	-22.3225
0.097713	0.081895	0.00025021	0.015818	-0.16188	0.0095479	0.00025021	0.015818	-16.1882
0.088685	0.083951	2.2404e-05	0.0047333	-0.053372	0.007865	2.2404e-05	0.0047333	-5.33724
0.066323	0.060505	3.3849e-05	0.005818	-0.087722	0.0043987	3.3849e-05	0.005818	-8.77224
0.10071	0.077307	0.00054763	0.023401	-0.23237	0.010142	0.00054763	0.023401	-23.2369
0.13591	0.058726	0.005957	0.077182	-0.5679	0.018471	0.005957	0.077182	-56.7899
0.15124	0.14064	0.00011235	0.0106	-0.070085	0.022873	0.00011235	0.0106	-7.00854
0.49692	0.46597	0.00095783	0.030949	-0.062281	0.24693	0.00095783	0.030949	-6.22811
1	0.38171	0.38228	0.61829	-0.61829	1	0.38228	0.61829	-61.829

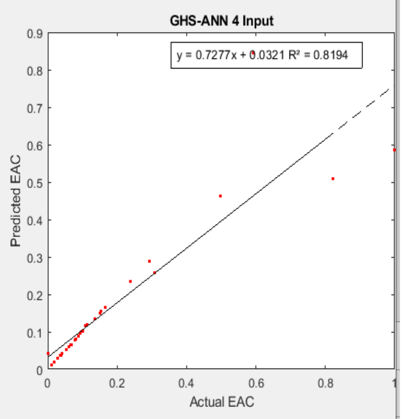


F.3) Model 3 GHS-ANN

input4

Actual	GHS-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.041098	9.2648e-08	0.00030438	-0.0073518	0.0017142	9.2648e-08	0.00030438	-0.735177
0.038452	0.037772	4.6341e-07	0.00068074	-0.017703	0.0014786	4.6341e-07	0.00068074	-1.77035
0.067372	0.065958	2.0012e-06	0.0014146	-0.020997	0.004539	2.0012e-06	0.0014146	-2.09971
0.092336	0.096385	1.639e-05	0.0040485	0.043845	0.008526	1.639e-05	-0.0040485	4.38451
0.10814	0.11578	5.8379e-05	0.0076406	0.070653	0.011695	5.8379e-05	-0.0076406	7.06531
0.081273	0.07984	2.0523e-06	0.0014326	-0.017627	0.0066053	2.0523e-06	0.0014326	-1.76268
0.1539	0.15395	2.7736e-09	5.2665e-05	0.0003422	0.023685	2.7736e-09	-5.2665e-05	0.0342205
0.29386	0.28929	2.0856e-05	0.0045668	-0.015541	0.086351	2.0856e-05	0.0045668	-1.55411
0.82116	0.509	0.097445	0.31216	-0.38015	0.67431	0.097445	0.31216	-38.0145
0	0.041243	0.001701	0.041243	0	0	0.001701	-0.041243	0
0.019662	0.020116	2.0642e-07	0.00045433	0.023107	0.0003866	2.0642e-07	-0.00045433	2.3107
0.03719	0.037709	2.6913e-07	0.00051878	0.013949	0.0013831	2.6913e-07	-0.00051878	1.39494
0.041404	0.041652	6.1371e-08	0.00024773	0.0059832	0.0017143	6.1371e-08	-0.00024773	0.598322
0.053773	0.053522	6.2702e-08	0.0002504	-0.0046567	0.0028915	6.2702e-08	0.0002504	-0.46567
0.060483	0.059769	5.1008e-07	0.0007142	-0.011808	0.0036582	5.1008e-07	0.0007142	-1.18083
0.079271	0.077679	2.5347e-06	0.0015921	-0.020084	0.0062838	2.5347e-06	0.0015921	-2.0084
0.11284	0.11795	2.6164e-05	0.0051151	0.045332	0.012732	2.6164e-05	-0.0051151	4.53317
0.16607	0.16543	4.1506e-07	0.00064425	-0.0038794	0.02758	4.1506e-07	0.00064425	-0.387935
0.30746	0.25863	0.0023848	0.048834	-0.15883	0.094534	0.0023848	0.048834	-15.883
0.23926	0.23441	2.3571e-05	0.004855	-0.020292	0.057247	2.3571e-05	0.004855	-2.02917
0.59206	0.84368	0.063313	0.25162	0.42499	0.35054	0.063313	-0.25162	42.499
0	0.041047	0.0016849	0.041047	0	0	0.0016849	-0.041047	0
0.012325	0.012277	2.3037e-09	4.7997e-05	-0.0038943	0.0001519	2.3037e-09	4.7997e-05	-0.389427
0.041361	0.041575	4.6108e-08	0.00021473	0.0051916	0.0017107	4.6108e-08	-0.00021473	0.519163
0.02797	0.028619	4.2175e-07	0.00064942	0.023219	0.00078232	4.2175e-07	-0.00064942	2.32185
0.097713	0.101	1.0786e-05	0.0032842	0.03361	0.0095479	1.0786e-05	-0.0032842	3.36104
0.088685	0.089022	1.1365e-07	0.00033712	0.0038014	0.007865	1.1365e-07	-0.00033712	0.380136
0.066323	0.065306	1.0332e-06	0.0010165	-0.015326	0.0043987	1.0332e-06	0.0010165	-1.53263
0.10071	0.10011	3.5853e-07	0.00059878	-0.0059457	0.010142	3.5853e-07	0.00059878	-0.594567
0.13591	0.13481	1.2061e-06	0.0010982	-0.0080808	0.018471	1.2061e-06	0.0010982	-0.80808
0.15124	0.15097	7.2644e-08	0.00026952	-0.0017821	0.022873	7.2644e-08	0.00026952	-0.178213
0.49692	0.4621	0.0012129	0.034827	-0.070085	0.24693	0.0012129	0.034827	-7.00854
1	0.58615	0.17127	0.41385	-0.41385	1	0.17127	0.41385	-41.3853

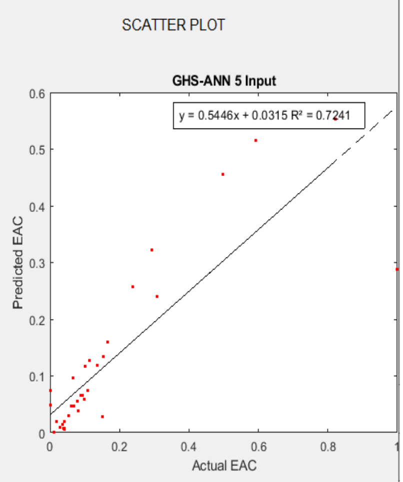
SCATTER PLOT



F.4) Model 4 GHS-ANN

input5

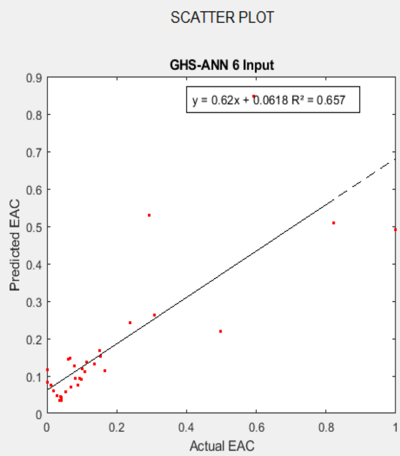
Actual	GHS-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.0063244	0.0012305	0.035078	-0.84725	0.0017142	0.0012305	0.035078	-84.7245
0.038452	0.0082406	0.00091275	0.030212	-0.78569	0.0014786	0.00091275	0.030212	-78.5693
0.067372	0.047817	0.00038239	0.019555	-0.29025	0.004539	0.00038239	0.019555	-29.0249
0.092336	0.065759	0.00070638	0.026578	-0.28784	0.008526	0.00070638	0.026578	-28.7837
0.10814	0.073966	0.001168	0.034176	-0.31603	0.011695	0.001168	0.034176	-31.603
0.081273	0.038146	0.0018599	0.043127	-0.53064	0.0066053	0.0018599	0.043127	-53.0645
0.1539	0.13368	0.00040894	0.020222	-0.1314	0.023685	0.00040894	0.020222	-13.1399
0.29386	0.32275	0.00083511	0.028898	0.098342	0.086351	0.00083511	-0.028898	9.83416
0.82116	0.55348	0.071654	0.26768	-0.32598	0.67431	0.071654	0.26768	-32.5979
0	0.07353	0.0054067	0.07353	0	0	0.0054067	-0.07353	0
0.019662	0.019676	1.8134e-10	1.3466e-05	0.00068488	0.0003866	1.8134e-10	-1.3466e-05	0.0684881
0.03719	0.013939	0.00054061	0.023251	-0.6252	0.0013831	0.00054061	0.023251	-62.5195
0.041404	0.019224	0.00049197	0.02218	-0.5357	0.0017143	0.00049197	0.02218	-53.5703
0.053773	0.030175	0.00055688	0.023598	-0.43885	0.0028915	0.00055688	0.023598	-43.8853
0.060483	0.046302	0.0002011	0.014181	-0.23446	0.0036582	0.0002011	0.014181	-23.4461
0.079271	0.055946	0.00054404	0.023325	-0.29424	0.0062838	0.00054404	0.023325	-29.4242
0.11284	0.12658	0.00018889	0.013744	0.1218	0.012732	0.00018889	-0.013744	12.1803
0.16607	0.15979	3.9394e-05	0.0062764	-0.037794	0.02758	3.9394e-05	0.0062764	-3.77937
0.30746	0.24023	0.0045209	0.067238	-0.21869	0.094534	0.0045209	0.067238	-21.8686
0.23926	0.25679	0.0003072	0.017527	0.073255	0.057247	0.0003072	-0.017527	7.32552
0.59206	0.51504	0.0059324	0.077022	-0.13009	0.35054	0.0059324	0.077022	-13.009
0	0.049029	0.0024038	0.049029	0	0	0.0024038	-0.049029	0
0.012325	0.00023431	0.00014618	0.012091	-0.98099	0.0001519	0.00014618	0.012091	-98.0989
0.041361	0.0079606	0.0011156	0.0334	-0.80753	0.0017107	0.0011156	0.0334	-80.7532
0.02797	0.009656	0.0003354	0.018314	-0.65477	0.00078232	0.0003354	0.018314	-65.4771
0.097713	0.058173	0.0015635	0.039541	-0.40466	0.0095479	0.0015635	0.039541	-40.4661
0.088685	0.066559	0.00048956	0.022126	-0.24949	0.007865	0.00048956	0.022126	-24.949
0.066323	0.095978	0.00087947	0.029656	0.44715	0.0043987	0.00087947	-0.029656	44.7145
0.10071	0.11733	0.0002762	0.016619	0.16503	0.010142	0.0002762	-0.016619	16.5025
0.13591	0.11852	0.00030221	0.017384	-0.12791	0.018471	0.00030221	0.017384	-12.7912
0.15124	0.028045	0.015176	0.12319	-0.81457	0.022873	0.015176	0.12319	-81.4565
0.49692	0.45479	0.0017754	0.042136	-0.084793	0.24693	0.0017754	0.042136	-8.47931
1	0.28869	0.50597	0.71131	-0.71131	1	0.50597	0.71131	-71.1315



F.5) Model 5 GHS-ANN

input6

Actual	GHS-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.042213	6.5707e-07	0.0008106	0.019579	0.0017142	6.5707e-07	-0.0008106	1.957853
0.038452	0.044711	3.9173e-05	0.0062588	0.16277	0.0014786	3.9173e-05	-0.0062588	16.27688
0.067372	0.07099	1.309e-05	0.003618	0.053701	0.004539	1.309e-05	-0.003618	5.370113
0.092336	0.094641	5.3104e-06	0.0023044	0.024957	0.008526	5.3104e-06	-0.0023044	2.495697
0.10814	0.11228	1.7121e-05	0.0041378	0.038262	0.011695	1.7121e-05	-0.0041378	3.826232
0.081273	0.093546	0.00015063	0.012273	0.15101	0.0066053	0.00015063	-0.012273	15.10106
0.1539	0.15171	4.8071e-06	0.0021925	-0.014246	0.023685	4.8071e-06	0.0021925	-1.42464
0.29386	0.52911	0.055344	0.23525	0.80058	0.086351	0.055344	-0.23525	80.05772
0.82116	0.51015	0.096728	0.31101	-0.37874	0.67431	0.096728	0.31101	-37.87438
0	0.1171	0.013713	0.1171	0	0	0.013713	-0.1171	0
0.019662	0.059316	0.0015724	0.039654	2.0168	0.0003866	0.0015724	-0.039654	201.6755
0.03719	0.03551	2.8217e-06	0.0016798	-0.045168	0.0013831	2.8217e-06	0.0016798	-4.516808
0.041404	0.042044	4.085e-07	0.00063914	0.015437	0.0017143	4.085e-07	-0.00063914	1.543661
0.053773	0.057943	1.7388e-05	0.0041699	0.077547	0.0028915	1.7388e-05	-0.0041699	7.754699
0.060483	0.14473	0.007098	0.084249	1.3929	0.0036582	0.007098	-0.084249	139.2944
0.079271	0.12688	0.0022667	0.047609	0.60059	0.0062838	0.0022667	-0.047609	60.05941
0.11284	0.1379	0.0006281	0.025062	0.22211	0.012732	0.0006281	-0.025062	22.21087
0.16607	0.11387	0.002725	0.052201	-0.31433	0.02758	0.002725	0.052201	-31.43289
0.30746	0.26404	0.0018857	0.043425	-0.14124	0.094534	0.0018857	0.043425	-14.12357
0.23926	0.24281	1.2615e-05	0.0035517	0.014844	0.057247	1.2615e-05	-0.0035517	1.484442
0.59206	0.84784	0.06542	0.25577	0.432	0.35054	0.06542	-0.25577	43.20035
0	0.083361	0.006949	0.083361	0	0	0.006949	-0.083361	0
0.012325	0.074896	0.0039151	0.062571	5.0768	0.0001519	0.0039151	-0.062571	507.6774
0.041361	0.035752	3.1459e-05	0.0056088	-0.13561	0.0017107	3.1459e-05	0.0056088	-13.56075
0.02797	0.048268	0.000412	0.020298	0.7257	0.00078232	0.000412	-0.020298	72.56996
0.097713	0.090831	4.7368e-05	0.0068824	-0.070435	0.0095479	4.7368e-05	0.0068824	-7.043507
0.088685	0.076834	0.00014044	0.011851	-0.13363	0.007865	0.00014044	0.011851	-13.36282
0.066323	0.14745	0.0065813	0.081125	1.2232	0.0043987	0.0065813	-0.081125	122.3188
0.10071	0.11862	0.00032093	0.017914	0.17789	0.010142	0.00032093	-0.017914	17.78855
0.13591	0.13331	6.7673e-06	0.0026014	-0.019141	0.018471	6.7673e-06	0.0026014	-1.9141
0.15124	0.16767	0.00026993	0.01643	0.10863	0.022873	0.00026993	-0.01643	10.86344
0.49692	0.22016	0.076597	0.27676	-0.55695	0.24693	0.076597	0.27676	-55.69513
1	0.49178	0.25828	0.50822	-0.50822	1	0.25828	0.50822	-50.82157

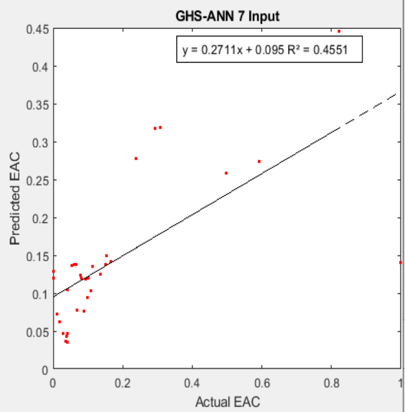


F.6) Model 6 GHS-ANN

input7

Actual	GHS-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.046915	3.0391e-05	0.0055128	0.13315	0.0017142	3.0391e-05	-0.0055128	13.31516
0.038452	0.043528	2.5757e-05	0.0050751	0.13199	0.0014786	2.5757e-05	-0.0050751	13.19852
0.067372	0.077382	0.0001002	0.01001	0.14858	0.004539	0.0001002	-0.01001	14.85791
0.092336	0.11798	0.00065749	0.025642	0.2777	0.008526	0.00065749	-0.025642	27.7697
0.10814	0.10376	1.9235e-05	0.0043857	-0.040555	0.011695	1.9235e-05	0.0043857	-4.055505
0.081273	0.11934	0.0014494	0.038071	0.46843	0.0066053	0.0014494	-0.038071	46.84332
0.1539	0.14908	2.3247e-05	0.0048215	-0.031329	0.023685	2.3247e-05	0.0048215	-3.132887
0.29386	0.31721	0.00054537	0.023353	0.079472	0.086351	0.00054537	-0.023353	7.94716
0.82116	0.44511	0.14142	0.37605	-0.45795	0.67431	0.14142	0.37605	-45.795
0	0.12844	0.016497	0.12844	0	0	0.016497	-0.12844	0
0.019662	0.061557	0.0017552	0.041895	2.1308	0.0003866	0.0017552	-0.041895	213.0768
0.03719	0.036314	7.6823e-07	0.00087649	-0.023568	0.0013831	7.6823e-07	0.00087649	-2.356789
0.041404	0.10475	0.0040132	0.063349	1.53	0.0017143	0.0040132	-0.063349	153.002
0.053773	0.13701	0.0069285	0.083238	1.548	0.0028915	0.0069285	-0.083238	154.7951
0.060483	0.13741	0.0059177	0.076927	1.2719	0.0036582	0.0059177	-0.076927	127.1873
0.079271	0.12371	0.0019748	0.044439	0.5606	0.0062838	0.0019748	-0.044439	56.06012
0.11284	0.13551	0.00051431	0.022678	0.20098	0.012732	0.00051431	-0.022678	20.09849
0.16607	0.1419	0.00058445	0.024175	-0.14557	0.02758	0.00058445	0.024175	-14.55727
0.30746	0.31832	0.00011792	0.010859	0.035319	0.094534	0.00011792	-0.010859	3.531864
0.23926	0.27804	0.0015036	0.038776	0.16206	0.057247	0.0015036	-0.038776	16.20643
0.59206	0.27381	0.10129	0.31826	-0.53754	0.35054	0.10129	0.31826	-53.75409
0	0.11946	0.014271	0.11946	0	0	0.014271	-0.11946	0
0.012325	0.072868	0.0036654	0.060543	4.9122	0.0001519	0.0036654	-0.060543	491.222
0.041361	0.035001	4.0442e-05	0.0063594	-0.15376	0.0017107	4.0442e-05	0.0063594	-15.37561
0.02797	0.046727	0.00035182	0.018757	0.67061	0.00078232	0.00035182	-0.018757	67.06104
0.097713	0.093595	1.6964e-05	0.0041187	-0.042151	0.0095479	1.6964e-05	0.0041187	-4.21507
0.088685	0.076868	0.00013965	0.011817	-0.13325	0.007865	0.00013965	0.011817	-13.32502
0.066323	0.13773	0.0050987	0.071405	1.0766	0.0043987	0.0050987	-0.071405	107.6632
0.10071	0.12045	0.00038994	0.019747	0.19608	0.010142	0.00038994	-0.019747	19.60801
0.13591	0.12522	0.00011422	0.010687	-0.078636	0.018471	0.00011422	0.010687	-7.863638
0.15124	0.13798	0.00017581	0.013259	-0.087672	0.022873	0.00017581	0.013259	-8.767231
0.49692	0.25795	0.057109	0.23898	-0.48091	0.24693	0.057109	0.23898	-48.09098
1	0.13983	0.73989	0.86017	-0.86017	1	0.73989	0.86017	-86.01678

SCATTER PLOT



F.7) Model 7 GHS -ANN

input8

Actual	GHS-ANN	RMSE	MAE	MRE	NSE	SI	BIAS	RE
0.041403	0.094156	0.0027829	0.052754	1.2742	0.0017142	0.0027829	-0.052754	127.4162
0.038452	0.087394	0.0023953	0.048941	1.2728	0.0014786	0.0023953	-0.048941	127.2778
0.067372	0.073051	3.2245e-05	0.0056785	0.084286	0.004539	3.2245e-05	-0.0056785	8.428561
0.092336	0.11673	0.00059489	0.02439	0.26415	0.008526	0.00059489	-0.02439	26.41471
0.10814	0.09991	6.7769e-05	0.0082322	-0.076124	0.011695	6.7769e-05	0.0082322	-7.612358
0.081273	0.12053	0.0015411	0.039256	0.48302	0.0066053	0.0015411	-0.039256	48.30181
0.1539	0.17951	0.00065586	0.02561	0.16641	0.023685	0.00065586	-0.02561	16.64058
0.29386	0.63245	0.11464	0.33859	1.1522	0.086351	0.11464	-0.33859	115.2237
0.82116	0.27318	0.30029	0.54798	-0.66732	0.67431	0.30029	0.54798	-66.73244
0	0.12411	0.015403	0.12411	0	0	0.015403	-0.12411	0
0.019662	0.07708	0.0032968	0.057418	2.9202	0.0003866	0.0032968	-0.057418	292.0238
0.03719	0.10178	0.0041716	0.064588	1.7367	0.0013831	0.0041716	-0.064588	173.6698
0.041404	0.10451	0.0039827	0.063109	1.5242	0.0017143	0.0039827	-0.063109	152.4203
0.053773	0.12951	0.0057361	0.075737	1.4085	0.0028915	0.0057361	-0.075737	140.8459
0.060483	0.11114	0.0025663	0.050659	0.83758	0.0036582	0.0025663	-0.050659	83.75762
0.079271	0.088591	8.6868e-05	0.0093203	0.11758	0.0062838	8.6868e-05	-0.0093203	11.75759
0.11284	0.12267	9.6638e-05	0.0098305	0.087121	0.012732	9.6638e-05	-0.0098305	8.712145
0.16607	0.13309	0.001088	0.032986	-0.19862	0.02758	0.001088	0.032986	-19.86224
0.30746	0.62719	0.10223	0.31973	1.0399	0.094534	0.10223	-0.31973	103.9888
0.23926	0.47523	0.05568	0.23597	0.98622	0.057247	0.05568	-0.23597	98.62216
0.59206	0.13404	0.20978	0.45802	-0.7736	0.35054	0.20978	0.45802	-77.35999
0	0.11153	0.012438	0.11153	0	0	0.012438	-0.11153	0
0.012325	0.067462	0.0030401	0.055137	4.4737	0.0001519	0.0030401	-0.055137	447.3652
0.041361	0.086749	0.0020601	0.045388	1.0974	0.0017107	0.0020601	-0.045388	109.7375
0.02797	0.05091	0.00052625	0.02294	0.82017	0.00078232	0.00052625	-0.02294	82.01718
0.097713	0.09304	2.1843e-05	0.0046736	-0.04783	0.0095479	2.1843e-05	0.0046736	-4.782986
0.088685	0.079872	7.7658e-05	0.0088124	-0.099367	0.007865	7.7658e-05	0.0088124	-9.93673
0.066323	0.13314	0.0044647	0.066818	1.0075	0.0043987	0.0044647	-0.066818	100.7476
0.10071	0.13042	0.0008831	0.029717	0.29508	0.010142	0.0008831	-0.029717	29.50803
0.13591	0.13318	7.4477e-06	0.002729	-0.02008	0.018471	7.4477e-06	0.002729	-2.008015
0.15124	0.16555	0.00020474	0.014309	0.094611	0.022873	0.00020474	-0.014309	9.461083
0.49692	0.63711	0.019652	0.14019	0.28211	0.24693	0.019652	-0.14019	28.21066
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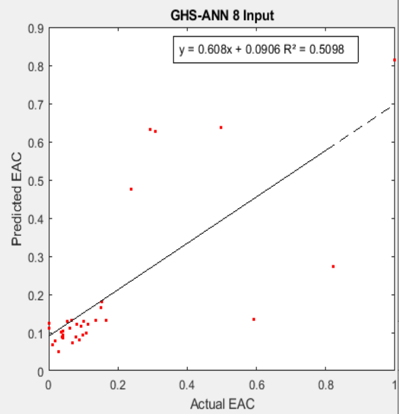
SCATTER PLOT



PUBLICATIONS FROM THE THESIS

Contact Information: enasmurad2020@gmail.com

Papers

[1] Estimation at Completion Simulation Using the Potential of Soft Computing Models: Case Study of Construction Engineering Projects 2019.

[2] Schedule Delay in Construction Project Using Time Impact Analysis 2013.

[3] Study of Delay in Project Planning and Design Stage of Civil Engineering Projects 2013.