



A Review of Optimization Techniques Application for Building Performance Analysis

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Received 23 January 2022; Revised 23 March 2022; Accepted 27 Marh 2022; Published 01 April 2022

Abstract

Optimization techniques (OT) are tools to find the best solution during a decision making process. Each of these techniques has its own advantages and disadvantages depending on their objectives and focus areas. Early application of OT was recorded as early as the 1930s with the introduction of the Monte Carlo Method, which is widely used in business studies. The idea was conceived due to poly-objectives, or multi-objectives, in identifying the best solution. OT theories and methods have evolved to cover various fields of study. This paper aims to provide a brief review of OT through a comparison of the pros and cons of each OT technique. The findings emphasize the suitability of each technique for different applications in various fields of study. Finally, this study aims to select the most suitable OT for building performance for energy optimization. In conclusion, the summary of findings and recommendations from Tables 2, 3, and 4 need to be combined during the process of selecting the most suitable OT. Regardless of the various categories and their multiple applications, it is the summary of characteristics of each optimization technique that determines their suitability for adoption depending on the research objectives, strength of the researcher, and availability of data. ANN is suitable for optimization for building energy performance covering energy use, energy cost and energy prediction which offer a high level of accuracy. However, it is a complex model that requires historical data input and can produce only short-term predictions. For broader optimization objectives which cover energy load, a hybrid of ANN and kNN is recommended.

Keywords: Building Application; Energy Performance; Comparative Analysis; Decision Making; Energy Efficiency; Normalisation Algorithm; Optimization Techniques.

1. Introduction

Decision-making can be regarded as a problem-solving activity, yielding a solution deemed optimal, or at least satisfactory. An optimal decision is a decision that leads to at least as good a known or expected outcome as all other available decision options. The purpose of optimization is to achieve the "best" design relative to a set of prioritized criteria or constraints. This decision-making process is known as optimization. Optimization techniques (OTs) are tools to find the best solution during a decision-making process for all possible solutions. OTs have seen some evolution over time to meet present-day demands across all sectors, with the development and refinement of different OT techniques signifying their importance and acceptability. OTs are accepted due to the shift from a subjective decision-making technique to a more quantifiable variable decision-making one whereby any decision being made has a relevant justification. OT plays an important role in all fields. For example, systematic OT in a business process can help organizations save millions by helping to reduce costs and avoid redundant activities. Thus, saving might help in investing in other areas that are more relevant and might make the organization more competitive. In built environments,

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 <http://dx.doi.org/10.28991/CEJ-2022-08-04-014>



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OT is widely used in making decisions, starting from planning, implementing, and monitoring. It involves a lot of factors, and a wrong decision will have a bad impact on the cost (economy), users (society), and sustainability (environment). The three basic components of any OT are variables (issue), cost function (objective), and constraints (equalities or inequalities). The variables for the OT can be continuous or discrete depending on the issues and functions. A continuous variable is a value obtained by measuring. However, a discrete variable is an interval of real values for which any value in the range of the variable is permitted to take on. The permitted values are either finite or countably infinite (integers 0-1).

1.1. Early Development of OT

One of the earlier known OT is the Monte Carlo method (MCM) [1]. It involves obtaining a sequence of random samples from a probability tabulation when direct sampling proves to be too challenging. MCM is applied to the computation of canonical ensemble averages for the Ising model to solve spintronic problems and intrigues by the theory of branching process. An inspiring aspect from this model is the assumption on some initial distribution of neutron in space and air speed that have been made [2]. In the early development of OT, the first two decisions occur at time, $t=Q$ (*quantity of changes*) when selected neutrons have velocity and spatial position with collision point and collision situation added later. MCM is mostly used for sampling, estimation, and optimization. Sampling is being used to gather information about a random object by their monitoring behavioural pattern. Estimation is a certain numerical quantity related to a simulation model whereby expectation on probability can be expected. Optimization in MCM is a powerful tool for complicated objectives which have more than 1 objective and need to be rationalized for all (normalization algorithm). Normalization is a scaling technique which is shifted and rescaled up ranging between 0 to 1. To simplify, it is known as Min-Max scaling with formula:

$$X^1 = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

This equation introduces artificial result to achieve more objectives efficiently. Optimization can extract the basic event and interaction from complex models. Since optimization in MCM is simple, flexible, scalable, and efficient, it is suitable for adoption in all fields. Multi Objective Optimization (MOP) is also among the earlier development of OT. It gained attention due to its capability in cooperating irregular and conflicting objectives of an analysis into a choice of decision. Common application of MOP is by Vector Optimization (VO) [3]. Currently MOP is being practised in complex estimations for problem solving in engineering, finance, statistics, mathematics, computer science, physics, and life science.

1.2. Later Development of OT

Early OT used a numerical technique to solve complex problems. However, three-dimensional problems have since become outdated as early OTs are being replaced with later development of OT using computation known as algorithm. Many researchers have discovered the development of simulation optimization in new generations of OT by computation technique. Meketon (1987) [4] provides how much information is needed for underlying models in algorithm approaches. Meanwhile, Fu et al. (2005) [5] mentions that integration simulation has a potential to address a wider scope of problems. Hong & Nelson (2009) [6] concludes that simulation optimizations have an infinity of solutions number, continuous decision variables and discrete variable with integer sequence ordered. In addition, Ammeri et al. (2011) [7] suggests that simulation of optimization application has various methods and can be applied in many fields of study.

1.3. Optimization Concept

Basic concept of optimization is derived from topological concept which is configuration of spaces. Topological spaces are defined in terms of a family of sets satisfying the properties of open set [8] (Figure 1).

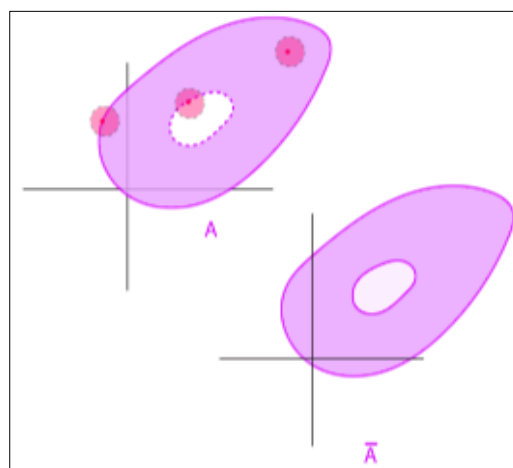


Figure 1. The topological space (E, O) is R^2 with topology induced by the Euclidean metric. The purple subset A is illustrated with three red point, each in its closure since the open ball centered at each point has nontrivial intersection with A [8]

Vector Optimization (VO) method through MOP is also known as multi-objective programming, multi-criteria optimization, multi-attribute optimization or pareto optimization. Any multi-objective optimization problems can be written as:

$$R^d - \min f(X) \quad X \in M \quad (2)$$

where $f: X \rightarrow R^d$ and R_+^d is the non-negative orthant of R^d . Thus, the minimizer of this vector optimization problem is the Pareto efficient point (Figure 2).

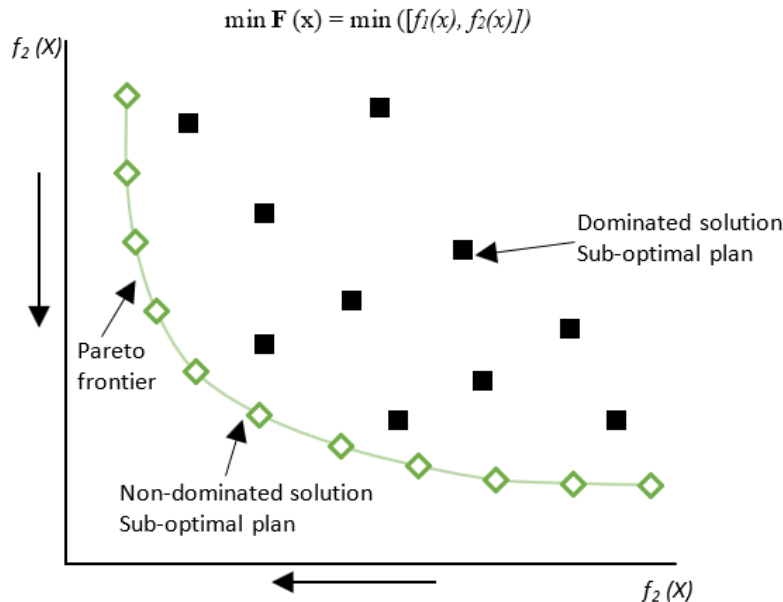


Figure 2. Pareto frontier for a multi-objective optimization problem with to objective function [9]

VO is a subarea which is derived from mathematical optimization. Optimization problems with a vector-value depends on partially ordering results which have certain constraints. A multi-objective optimization problem is an unusual case of a VO problem. The space is finite dimensional of Euclidean space by the component less than 1 or equal to 1 ordering. Figure 3 shows the area of optimization in X, Y, Z. Any values tabulated in this zone have a possibility of optimization values (minimum or maximum). Pareto optimization or pareto efficiency is considered as a minimal efficiency prediction. It can be assumed as not a holistic desirable distribution, but it is necessary even though not a sufficient condition of efficiency for minimal decision [10].

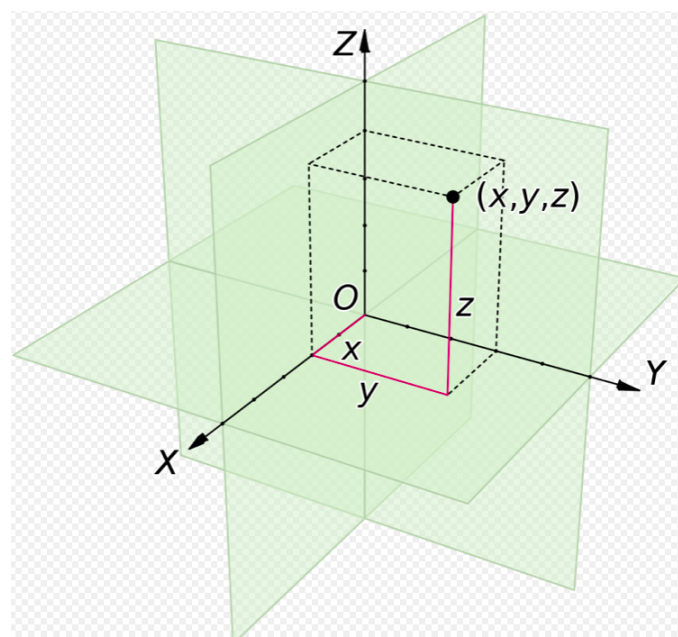


Figure 3. VO subarea. A point in three-dimensional Euclidean space located in three coordinates [10]

Basically, optimization is a mixed integer (number) setting that may contain constant variables. When integer variables are limited to the value 0 to 1, it is known as a binary decision variable. In a certain level or number accepted at an optimal solution known as discrete decision variable in which the value is 0/1. Generally, complexity of optimization can be solved by using two methods. Firstly, by applying an assumption to the problem formulation. This method is able to solve the optimization problem by traditional mathematical programming methods, i.e. Linear programming. Secondly, by heuristic optimization methods, i.e. Genetic Algorithm (GA), Evolutionary Strategies (ES) and Evolutionary Programming (EP) [9]. These algorithms are based on speculative exploration by using groups of potential solutions which is the best optimization solution. The most outstanding solution will be to keep choosing and combining with Genetic Algorithm (GA) or alteration of Evolution Strategy (ES) and Evolutionary Programme (EP) to get the better solution until all objectives are gathered. Multi-objective optimization does not have a single solution, it must comprise of several optimal solutions. Therefore, the dominance concept will be used to determine the solution whereby dominate solution is better than other solutions.

2. Objectives

This paper aims to review existing literatures on concept, classification and characteristics of OT that are commonly featured in building and energy related journals. Features, benefits, characteristics, and application of each OT are being highlighted to assist in the decision-making process on which technique is suitable for specific application on building performance. Eight (8) techniques of optimization are being reviewed in this paper namely; Artificial Neural Network (ANN), Support Vector Machine (SVM), Grey Prediction (GM), Auto Regressive Integrated Moving average (ARIMA), Ant Colony, Case-Based Reasoning (CBD), k-Nearest Neighbor Prediction (k-NN) and Genetic Algorithm (GA). All these reviews provide crucial information on OTs and their application in various fields of study. Each OT shall be categorized based on its application in specific fields. Based on the principle concept of OT about forecasting, most of the OT are related to a time series either univariate or multivariate. This study emphasizes on the criteria for each OT in forecasting techniques and examples of OT that have been conducted. This review paper shall also provide a basis of qualitative comparison for all the 8 techniques mentioned here. It is to be noted that the hybrid technique is a combination from any other technique with others and normally, the combination is more than 2 techniques. This technique is commonly used nowadays due to its ability to produce multi-objectives outcomes for both types of time series (univariate and multivariate). Therefore, the objectives of this review paper can be simplified to:

- Provide a concept principle of OT that is widely used in all fields of study.
- To establish the categories of OT for each technique in providing information of complexity level for each technique.
- To perform a comparative analysis on eight OT generally adopted based on qualitative aspects of these techniques.
- To summarize the suitability of each OT for building performance analysis specifically on energy efficiency.

3. Methodology

An explanation on the principles of the OT concept should be provided to facilitate understanding of all these optimization techniques. Simply put, OT uses a number integer array, and the optimization technique depends on the value (min, average, and max) depending on the objectives and respective data of study. The determination of this value also depends on the field study performed. Reviews of this OT classification are also identified based on the categories that previous research have created to facilitate the decision-making as appropriate. Comparative analysis for each OT will describe the characteristics of each of these techniques and will determine the best techniques for each field of study. This paper reviews related literature on optimization concept, literature on OT that is related to highlighted concept and most widely-used OT.

A total of 78 articles published in the established journal scholar database Web of Science, Scopus and IEEE were reviewed to cover all OT backgrounds, concepts and which were evaluated covering the eight OTs with no limited year but with limits to the scoping area related to performance analysis specifically on built environment effects. Selection on scoping method due to effectiveness of scoping review in organizing them into groups (charting), and highlighted gaps as to achieve the objectives. This OT selection is based on time series forecasting. Based on the reviews made, OT can be divided into 2, namely time series forecasting and non-time series forecasting. This research focuses on time series forecasting since OT is closely related to time [11-22]. OT time series is widely used for comparison. Therefore, in the OT it is used to find the best results. For example, in a building energy study, comparisons of data on past and present energy consumption need to be taken into consideration to find the optimum and optimal energy consumption. In the field of economic economics, time series forecasting is important to make comparisons of economic developments. Other fields also come down to having close relationships with time series such as engineering, statistics, mathematic, computer science, physics, and life science.

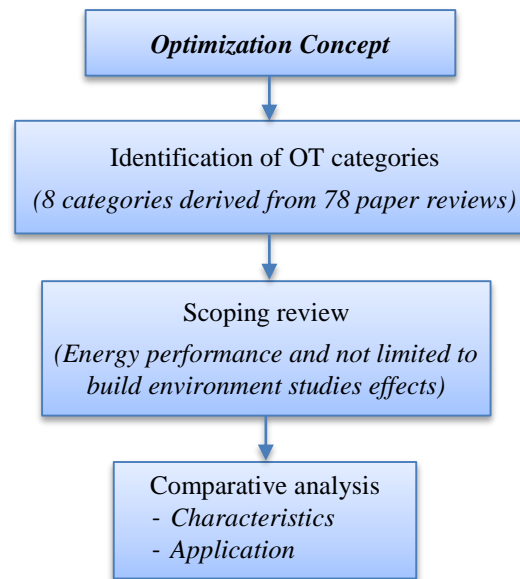


Figure 4. Reviewing process flowchart

4. Optimization in Building Performance

Optimization of energy consumption and thermal comfort in buildings is influenced by many factors. However, it can be divided into 2 main factors which are technical & physically influenced factors, as well as human influenced factors. Climate, building envelope and building equipment are technical & physical influenced factors, whereas operation & maintenance, occupant behaviour and indoor environmental conditions are human influenced factors. Design is a physical factor giving significant impact to the building performance by optimizing building design [23]. Research conducted by Rabani et al. (2021) [24], zero-energy building performance can be achieved by enhancement of fenestration, envelope, shading device and electrical system. Integration of physical factor and system application requires tool system for monitoring. Another study which was conducted by Liu et al. (2020) [25], with additional photovoltaic (PV) novel system and integrated to the building design will reduce energy use and improve the building performance. In Addition, climate conditions are vital factors in contributing towards energy consumption. Many elements such as temperature, air velocity, humidity, heat radiation directly contribute to energy consumption. Meanwhile, metabolic rate, clothing insulation, behaviour and psychology are varying and subjective to measure form each person and indirectly contribute to energy consumption. Some studies focus on simplifying weather conditions in building for energy consumption. By multi objectives optimization concept, it is possible to measure all variables related to building performance and weather condition for getting optimization in terms of energy consumption and thermal comfort. William & Gomez (2016) [26] used average monthly temperature to forecast monthly household energy consumption and showed that accuracy prediction rate was 74%. The same study conducted White & Reichmuth (1996) [27] to complex buildings shows the similar result which is prediction is more accurate than standard procedure which normally uses of heating and cooling by days.

In another study conducted by Westphal & Lamberts (2004) [28], findings showed that good accuracy on low mass envelope building can be achieved by using annual prediction of heating and cooling load for non-residential buildings incorporated with maximum and minimum of monthly average temperature, sky cover, relative humidity and barometric pressure. As a conclusion, weather condition plays a vital role in determining energy use. White & Reichmuth (1996) [27] and Williams & Gomez (2016) [26] conducted a study at the same weather type (temperate ocean) with suitable use of monthly average prediction. Meanwhile Westphal & Lamberts (2004) [28] and Albatayneh (2021) [29], conducted a study in semi-arid climate with extreme weather shows that energy use throughout the year is high for cooling and heating process. Therefore, it is suitable to use annual prediction. For this reason, in tropical climate, annual data can be used for accuracy prediction. Increasing building envelope airtightness has a potential to save energy up to 12%, improve IAQ for air-conditioning buildings and reduce indoor concentrations of contamination with outdoor sources [30]. Research done by Raji et al. (2016) [31] in temperate climates on integration of building design with high performance building materials found that energy saving around 42% for heating, 64% for electric and 34% for lighting. Cao et al. (2015) [32] has the same opinion as Raji which is high performance building materials used contribute to energy saving. In his research insulation thickness increased from 10 to 40 mm thick for external wall can save energy by approximately 20%.

Occupant behavior also has a valid factor in contributing towards building energy consumption. Naylor et al. (2018) [33] affirms that occupants significantly affect the energy consumption through varying energy pattern and energy-

related behaviours. Besides, current building control systems are not suited to the task of occupant-responsive control. Zahiri & Elsharkawy (2018) [34] study on energy pattern found that diversity was due to occupancy use heating pattern (activities). Energy saving potentially can be done through a better understanding of human-building interaction [35]. Thus, many researchers prefer to conduct studies on office building rather than residential due to diverse occupant behavior related to hour and activities significantly affect to uneven energy pattern. The challenges in monitoring occupant behavior are reflected in the period of monitoring and number. Wang & Shao (2017) [36] and Balvedi et al. (2018) [35] share the same views whereby occupancy profiles will dramatically change the occupancy pattern of energy use over time, for example while seated for a long time in one place occupants tend to make a movement in the circulation area. According to Yang et al. (2016) [37], proper management and appropriate operational supervision in energy system may result in optimum level of energy performance. Even with a good system but without proper management, it is still vulnerable to performance failure. Monitoring and management can be divided into two, namely, time series and non-time series [38].

Continuous management based on time series has a significant role to energy consumption in building. Time series management is also able to provide data to be used for future research in forecasting model whereby prediction on future energy pattern and consumption can be determined by previous data. In addition, non-time series management can also be used in building optimization by integration with computer simulation models like EnergyPlus, EnergyIQ, IES, COMBAT [37, 39, 40] to derive occupancy activity related to energy consumption and operational activities. Industry revolution 4.0 (IR 4.0) plays important roles in OT through combination of building performance optimization and computer simulation models and this mixed method is highly in demand due to its ability to accurately predict the anticipated outcomes for various fields of study, such as environment, occupant thermal comfort and energy consumption. Zhou et al. (2020) [41], integration of design, systems, weather and occupancy by optimization technique through computer simulation can optimize building performance. Petri et al. (2014) [42] used Artificial Neural Network (ANN) combined with EnergyPlus in getting building energy optimization in a sports complex building in Europe and Yang et al. (2014) [43] used the same optimization for the KUBIK sports complex in Spain. Meanwhile Beccali et al. (2017) [44] used ANN for optimization method at non-residential building: school. All showed significant energy saving in kWh with application of building automatic system (BAS) for monitoring in large-scale public buildings. The challenges in applying hi-tech building systems are financial constraints, building materials used, local policy, awareness in green technology, not user-friendly tools and initiatives given [45]. Therefore, computational optimization techniques are utilized to address the challenge by giving the best solution [46].

5. Optimization Techniques

OT is a prediction method with several techniques already available for adoption to suit various applications. A few studies analysed OT approaches and grouped them in certain classes. Zhao & Magoulès (2012) [17] class OT into three groups namely, Engineering method (EM), Statistical method (SM) and Artificial Intelligence (AI). Meanwhile, Deb et al. (2017) [38] and Wang et al. (2018) [22] identified OT into two groups which are Non-time Series (NS) forecasting and Time Series (TS) forecasting. Di Somma et al. (2016) [9] clarifies that OT has two main methods, namely traditional methods and evolution methods. Evolution methods is further classified into three categories namely, Genetic Algorithm (GA), Evolution Strategy (ES), and Evolutionary Program (EP). Meanwhile, Masouleh (2018) [47] identifies OT into 2 main classes which are Gradient-Based (GB) algorithm and Derivative-Free (DF) algorithm. All these grouping and categories of OT share the same objectives which are to achieve the best solution for multi-objectives in getting optimal solutions. Zhao & Magoulès (2012) [17] describe that Engineering methods use physical principle to analyze. By using tools in analyzing data gathered, the accuracy of prediction can be determined. Meanwhile, statistical methods use regression or classification. Artificial method needs simulation agent in generating prediction. AM is classified as intelligent method due to its capability at solving non-linear problems and is an effective approach to the complex application. Yang et al. (2016) [37] time series is an ordered sequence of value in interval of time and vice-versa to the non-time series. Meanwhile, Di Somma et al. (2016) [9] classified traditional and evolution method as based on tools use in OT and Masouleh (2018) [47] it classify as gradient-based algorithm using the gradient function to find the optimal solution and derivative-free algorithm do not use derivative information to find optimal solution. From all these classes, OT in forecasting can be categorized into two major techniques, which are data driven technique and deterministic technique. Both techniques have merits and demerits. OT is a procedure that is being implemented repeatedly by comparing various solutions until an optimization or satisfactory solution is found. With the development of the latest technologies, the use of Artificial Intelligent (AI) through computer applications has become an option in the OT where AI is one of the OT categories [17]. There are two types of optimization algorithms that are widely used today through AI such as Deterministic Algorithm (DA) and Stochastic Algorithm (SA). The DA uses specific rules to move one solution to another. This algorithm is also used frequently and successfully solves many optimization problems. SA is also a perception of probability and this method is popular nowadays because of its specific properties that the DA does not have. In other words, SA is more of an "instinct" based on the information or knowledge available.

Table 1. Merits and Demerits

Technique	Data -Driven	Deterministic
Merits	Fast computation	Based on building physics
	For non-linear modelling	Transparent
	More accurate to deterministic	Easy to establish
Demerits	Need previous record	Difficult to model
	Non-transparent	Data unavailable
	Difficult to establish	Not accurate

There are a few methods available in determining optimization. With advance development of information technology, hybrid methods have gained popularity due to their ability to combine best features from different methods while processing data during the problem-solving process. In order to come up with the most suitable combination between different techniques, it is crucial to understand how the original methods of OT are derived. For example, ANN uses the concept of AI based on "function of human brain" and CBR is based on "instinct". While AC uses the concept of ant movement similar to the concept of Swarm Particle Optimization (SPO), which leads to the concept of movement in a "swarm" and SVM uses the concept of significant "diversion". Therefore, understanding the original concept of each optimization technique is important to determine how these techniques can be adopted in solving a problem. Search strings on scholarly research published in Energy & Building, Renewable & Sustainable Energy review, Energy Policy and Building Environment journals related to building energy performances, indicate that there are eight (8) most frequently reviewed original non hybrid OTs as summarized below:

5.1. Artificial Neural Network (ANN)

The concept of ANN was introduced by McCulloch & Pitts (1943) [48]. ANN is an OT similar to the function of the human brain. The processing units that occur in the brain are called neurons acting in parallel with existing data. These neurons are connected to the synapse nerve. A synapse nerve is a structure that allows neurons (or nerve cells) to transmit electrical or chemical signals to neurons. An important advantage of ANNs is its ability to connect data based on instances, which makes it an attractive model ANN for a smart system [49, 50]. This connection saves information (data) that has been entered and can be reused when needed. In the ANN model, this relationship is organized into input and output sets in a non-linear relationship and the pattern is found within the data generated. Schenker (1996) [51] identify and quantify ANNs in 3 aspects: 1) the number of neurons in hidden layers, 2) the optimum size of the data set and 3) the training algorithm to be used. ANN is a flexible and widely applied model, often used to find the relation between the input and the output variables [52]. ANNs do not need a lot of neurons to get the best results in making predictions. This algorithm revolutionizes the use of ANNs for predictions as it reduces computation time and improves prediction accuracy. In a sense, for the simplest neural networks, the back propagation algorithm works similarly to the least square estimation method for simple linear regression. For forecasting of energy consumption, ANN has been widely implemented for short, medium, and long term forecasting of energy. Often, energy consumption time series are combined with other series data such as weather and occupancy. For the three-layer perceptron, the network function takes the following form; i.e. three-layer perceptron network [52].

$$\hat{Y}(k) = f(x, w) = \sum w_j \Psi_j \left[\sum w_{ji} x_i + j_o \right] + w_o \quad (3)$$

where the network outputs are the predicted values of the variable y , expressed by the function $f(x, w)$ of the inputs x and the free parameters to be fitted are the synaptic weights w_{ji} and w_j grouped into the "weight vector" w . ANN has gained more attention lately as the effectiveness of ANN has been recognized. Among these ANNs have been used by Nasr et al. (2002) [53] in making assumptions about the use of electricity. This method is also used by Nizami & Al-Garni (1995) [54]. Nasr conducted a study in Lebanon while Nizami used ANN for the purpose of assuming this energy use in Saudi Arabia. Kaytez et al. (2015) [55] also studied the use of ANN in making assumptions about energy use in Turkey. The variables they used by them are in the determination of energy usage: weather data, water temperature, humidity, solar radiation, and population. Apart from the assumption of energy consumption, ANN also applies to the assumption of electricity tariff costs [50, 56, 57]. For their research, the variables involved are the amount of energy use (hourly, weekly, monthly, yearly) and the cost of the resource. Another research conducted by Platon et al. (2015) [58] with six variables of prediction mean vote (PMV) used in assessing human comfort, it took a longer time because all these variables were non-linear relationships. However, by sensitivity analysis modelling of ANN, it shows effective, fast and accuracy result with R2 value of 0.99 and low RMSE value. Figure 5 illustrates the ANN on Multi-layer Perceptron.

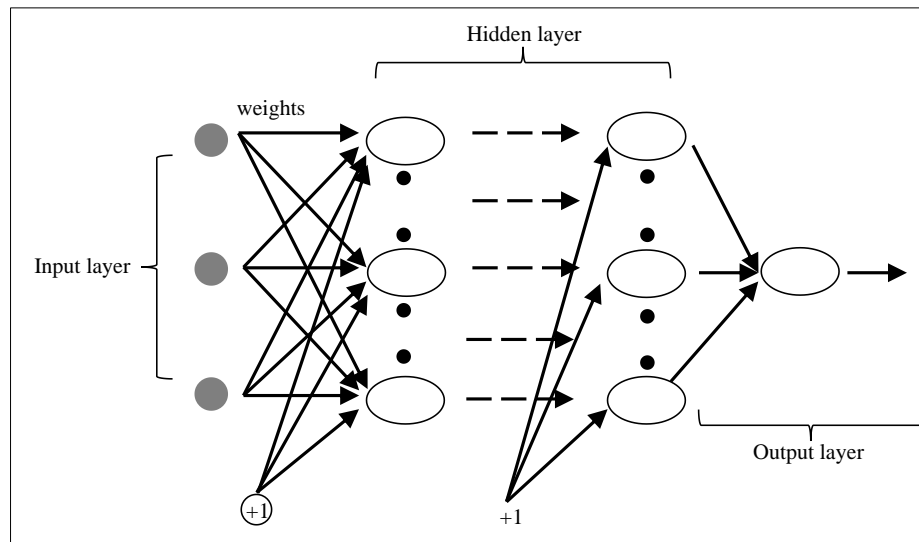


Figure 5. Illustration the ANN on Multi-Layer Perception [55]

In addition, longitudinal studies were also conducted using ANN by Çunkaş & Altun (2010) [59], Azadeh et al. (2008) [60], Ekonomou (2010) [61]. They use ANNs to make assumptions of moderate and long-term electricity consumption used in factories. Çunkaş conducted a 6-year assumption study from 2008-2014. Meanwhile, Azadeh uses a feed forward neural network with back propagation model taken from 1979 to 1999 (20 years). In addition, a long-term assumption study was also carried out by Ekonomou from 1992 to 2004. All assumptions and data testing found that the decision was similar. This shows the accuracy of the ANN model's ability to make assumptions. Meanwhile, Rahman et al. (2021) [62] conducted a study on prediction of renewable energy sources on solar, wind, hydro power generation in forecasting volume required and influences of its value in future prediction.

In a study on confirmation of 2 data sets, feed-forward neural network and back propagation are required. A feed-forward neural network is a biologically inspired classification algorithm. It consists of a (possibly large) number of simple neuron-like processing units, organized in layers. Every unit in a layer is connected with all the units in the previous layer. Therefore, they are called feed forward neural networks. Back propagation, short for "backward propagation of errors," is an algorithm for supervised learning of artificial neural networks using a descent gradient. Given an artificial neural network and an error function, the method calculates the gradient of the error function with respect to the neural network's weights. This confirmation will be made by comparing the previous data with the data obtained by computer simulation. Among the simulations used together with ANN are EnergyPlus by Neto & Fiorelli (2008) [63] and MATLAB by Çunkaş & Altun (2010) [59]. In internet of things (IoT) era, machine learning such as ANN has gained increasing popularity in making a decision due to its powerful capability and flexibility in model development. Not only for longitudinal studies, short term period of study by ANN conducted [64] for 24 hours showed a significant result in developing optimum model of operational control strategies and improving demand and supply of electrical load. As such, this provides the opportunity to conduct studies on the Sefaira simulation tested for the same assumptions. The performance criteria used in this study is the Absolute Percentage Error (APE) which consists of the difference (error) between the forecasts load and the actual load. The APE can be defined as:

$$APE = \frac{Actual(i) - Forecast(i)}{Actual(i)} \quad (4)$$

5.2. Support Vector Machine (SVM)

Support-vector machines (SVMs) also known as support-vector networks (SVNs) are studies related to data analysis using "classification and regression analysis". SVM is used to build a new model into a new category created through a "non-probabilistic binary linear classifier". The SVM model is presented using a dot within the mapped space to reveal significant divisions (separation categories). This SVM concept is based on a "decision hyperplane" which distributes data into two sets [65]. Figure 6 shows classification of data by SVM, non-linear kernel method.

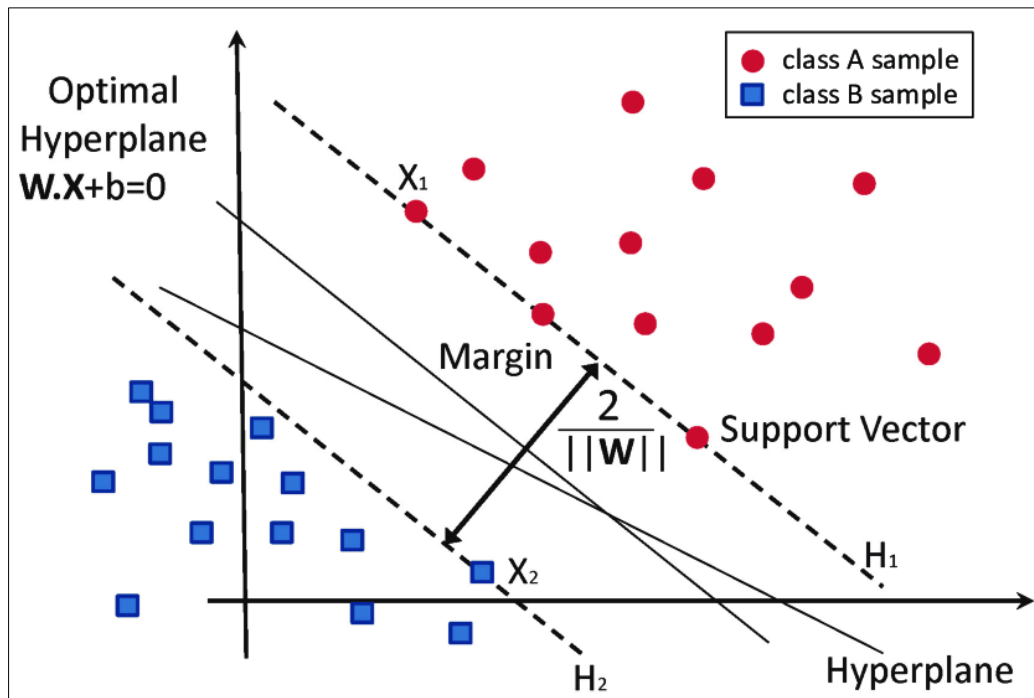


Figure 6. Classification of data by Support Vector Machine (SVM), non-linear kernel method [65]

The method of determining this hyperplane is based on the largest margin between the two sets. This concept of hyperplane was introduced by Vapnik (2000) [66]. Hyperplane is a set point data that forms a distribution in a space that can form significant isolation. The distribution chamber is known as a set of vectors (hyperplane). Therefore, SVM is suitable for use in the study to build a regression model. The regression formula can be expressed as:

$$F(x) = \sum_{i=1}^n w_i \phi_i(x) + b \quad (5)$$

Usually, the problem arises in the optimization process using this method, “Differential Evolution” (DE) should be used for optimum isolation as DE uses a “nonlinear kernel” function that can make data distribution more prominent (high). The Kernel represents the inner product in the dimensional space:

$$K(x, y) = \sum_{i=1}^D \phi_i(x) \phi_i(y) = \langle \phi(x) \phi(y) \rangle \quad (6)$$

A study by Zhang et al. (2016) [67] used SVM DE in predicting energy use for office and laboratory in a campus of university in Singapore. The assumption of energy use over a period of one year and 10 days was made to test the accuracy of the forecast using SVM DE. The results of both datasets for this model found that energy consumption estimates were very accurate. SVM is therefore not affected by time, but its accuracy is influenced by the probability distribution in the vector. A study was conducted by Li et al. (2018) [68] in Beijing, China to make the assumptions of energy sources needed to meet China's energy needs by 2030 as well as the assumption of carbon emission from energy used. This assumption was made using data from 2000-2016 using SVM applied to the Extreme Learning Machine model (SVM-ELM). The results suggest that the SVM-ELM accuracy value is high. Therefore, by understanding the concept of SVM using nonlinear kernels, a significant distribution of data will generate high accuracy assumptions. Like Li et al. (2018) [68], Zhou et al. (2019) [69] also applied SVM combinations to five models. The data used to build and test these models are from 1986 to 2000. The results of this study found that the combination of these models with SVM showed a low percentage of Mean Absolute Percentage Error (MAPE) of 2.139%. This shows that the accuracy of the assumptions made using SVM is high. A study conducted by Kaytez et al. (2015) [55] found that MAPE results between SVM and ANN were 1.004% and 1.19% respectively.

5.3. Grey Prediction (GP)

Grey system was initiated by Ju-Long (1982) [70]. The theory of this system is based on lack of information, such as structure message, operation mechanism and behaviour document, are referred to as Grey system. “Grey” means poor, incomplete, uncertain, etc. The goal of Grey System is to bridge the gap existing between social science and natural science. In other words, grey system is interdisciplinary across a variety of specialized fields and it proved its stands since 1982. This system has gained popularity in solving uncertainty problems with discrete data where information is not adequate. Grey matrix is a property of numbers in rows and columns known but some elements unknown. The unknown elements are called grey matrix. Therefore, this is the main benefit of Grey Model (GM) whereby any prior

information is not necessary, such as probability distribution when the data is limited. It only needs a set of equations differential to be adopted for parameter variance. GM (1,1) is denoted in equations as [69, 73]:

$$x^{(0)} = [x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)] \quad (7)$$

Since introduced, GM concept has been successfully applied in agricultural, ecology, economy, meteorology, medicine, history, geography, industry, earthquake, geology, hydrology, irrigation strategy, military affairs, sports, traffic management, material science, environment, biological protection and judicial system [71].

According to Zhou et al. (2019) [69] due to uncertainty and complexity of operating conditions or cyclic fluctuation on the renewable energy, GM prediction is suitable to be used for prediction on adopting portable power system such as lithium-ion battery or fuel cell aging test for hybrid automotive application or small-scale renewable energy integration. In Zhou's proposal using an Error Correction GM (ECGM) factor ψ to eliminate the inherent error of the original GM and at the same time retain the original simplicity and fast prototyping. As a result, ECGM prediction accuracy compared to traditional GM is higher at least 11.7% against original (GM) 9.2%. Another improvement method that can be used to enhance the result of prediction is hybrid on Genetic-Algorithm-Based remnant GM (1,1) (GARGM (1,1)). It is proven by Hu (2017) [72] and Jin et al. (2012) [11] in a study on energy demand in China. It shows that it simultaneously optimizes the parameter specifications of the original and its residual models by modification of GM with GA. The result pertaining to the Mean Absolute Percentage Error (MAPE) compared to original (GM (1,1)) and GARGM is greater which is 27.7 lessened to 17.51. Meanwhile, Tsai et al. (2017) [73] study in renewable energy consumption by modification of GM (1,1) also confirms that when making prediction using small samples of data, the modified GM to Nonlinear Grey Bernoulli Model NGBM(1,1) gives a great result with higher forecast accuracy than the GM model. In another study done by Pao et al. (2012) [74] by using same model as Tsai et al. (2017) [73], it shows that NGBM forecasting ability with optimal parameter model gives a better result which is 1.10 MAPE compared to GM(1,1) and ARIMA. Therefore, hybrid optimized GM for improving the forecasting accuracy has been verified in previous studies. It shows that GP model with inadequate information makes it easier to be combined with other model for better forecasting accuracy result.

5.4. Autoregressive Integrated Moving Average (ARIMA)

ARIMA is an analysis statistical model by time series data used to better understand the data set to predict the future trend. Originally ARIMA model came from Autoregressive Moving Average (ARMA) model (p,q) by Peter Whittle 1951 and was popularized by George E.P. Box and Gwilym Jenkin in 1970 and has been extended by integration to ARIMA. ARIMA model applies in cases where data shows evidence of non-stationarity. Therefore, integration part of the model can be applied (more than one) to eliminate the non-stationarity. In other words, ARIMA is a time series in a linear equation which consists of a lag dependent variable. It cannot be taken as an independent variable as they are not linear functions of the coefficients. Therefore, the lag of ARIMA model must be computed by stationary time series and it referred to as an autoregressive. An autoregressive ARIMA is a form of regression analysis that gauges the strength of one dependent variable relative to other changing variables. To simplify the concept of ARIMA for better understanding, ARIMA components are outlined as follows:

- *Autoregression (AR)* is a model that shows a changing variable that regresses on its own lag.
- *Integrated (I)* represents the difference of raw observation to become stationary.
- *Moving average (MA)* integrates the dependency on observation and residual error from moving average model applied to lagged observation.

The ARIMA model can be defined as [75]:

$$\begin{aligned} (B)(1 - B) d_{xt} &= \theta(B)at, \\ \varphi(B) &= 1 - \varphi_1 B - \dots - \varphi_p B^p \\ \theta(B) &= 1 - \theta_1 B - \theta_2 B^2 \dots \theta_q B^q \end{aligned} \quad (8)$$

$\varphi(B)$ is the AR (autoregressive) model of order p and $\theta(B)$ is the moving average function of order q. The parameters p; d; q are integers. The parameters d, p and q denote the lag order of the non- seasonal differences, autoregressive terms and moving average terms, respectively.

In Turkey, energy consumption prediction has been made using the ARIMA model [76]. In the study, coal, oil, natural gas, renewable and total energy consumption data for 1970-2015 is used to forecast energy consumption of Turkey for the next 25 years, The ARIMA models are determined to be ARIMA (1, 1, 1) for coal consumption, ARIMA (0, 1, 0) for oil consumption, ARIMA (0, 0, 0) for natural gas consumption, ARIMA (1, 1, 0) for renewable energy consumption and ARIMA (0, 1, 2) for total energy consumption. The results indicate that Turkey's energy consumption

will continue to increase by the end of 2040 with an annual average rate of 4.87 %, 3.92 %, 4.39 %, 1.64 % and 4.20 %, respectively in the next 25 years. In another research done by Zhuang et al. (2015) [77], ARIMA model was used to predict on optimal control of heating and air-conditioning (HVAC) system that is used in ice energy storage. It shows an effective cost saving and energy reduction by integrating ARIMA and neural network (NN) compared with the use of the time series data only. The result shows that combined methods (ARIMA + NN) can be used effectively for long term prediction. Other than resources variables, Yasmeen & Sharif (2014) [78] and Wang et al. (2012) [79] used ARIMA model in prediction of electricity consumption trend due to socioeconomic factors (variables) and reveal that electricity consumption is increasing with the passage of time.

5.5. Ant Colony (AC)

The Ant Colony Optimization (ACO) algorithm is a probabilistic technique for solving computational problems which is to find the good paths by graphs. ACO is an algorithm modelled inspired by ant moving action and this model has led to the concept of swarm intelligence. Artificial ants (simulation agents) locate optimal solutions by travelling through spaces represent all possible solutions. Initiated by Marco Dorigo in 1992 aiming to search on optimal path based on ant behaviour seeking a path between colony and source of food. Since its introduction, ACO has been applied in many optimization problems such as medicals, transportation and businesses. The first adaptation of ACO was in solving salesman's travelling problem which is the goal to find the shortest best trip. In general, ACO is:

$$p_{xy}^k = \frac{(T_{xy}^\alpha)(\eta_{xy}^\beta)}{\sum_{z \in \text{allowed}_x} (T_{xz}^\alpha)(\eta_{zy}^\beta)} \quad (9)$$

In 2000 multi-objective algorithm was tested by ACO and the result showed that multi objectives or bi-criteria are also suitable to be applied in this model [80, 81]. Within a decade, ACO has been applied in various fields. In Bamdad et al.'s (2017) [82] study, low-energy commercial building design in Australia proves that ACO is a powerful tool for minimizing energy consumption. The result shows that energy saving more than 14% referred to the three benchmarks optimization algorithms; Nelder-Mead (NM) algorithm, Particle Swarm Optimization with Inertia Weight (PSOIW) and the hybrid Particle Swarm Optimization and Hooke-Jeeves (PSO-HJ). A study done by Yuan et al. (2012) [83] in the same field showed that Building Life-Cycle (BLC) in energy consumption prediction improved by multi-objective ant colony optimization (MACO) using mechanism of Pareto Optimal solution concept. Besides energy studies, research conducted by Sun et al. (2017) [84] and Blas et al. (2011) [85] in communication technology revealed that wireless sensor networks (WSNs) can find the optimum new path of data transmission by ACO method. It improved heuristics function and considered the node communication transmission distance, transmission direction and residual energy. Thus, network energy consumption is reduced, and network lifetime is prolonged (See Figure 7).

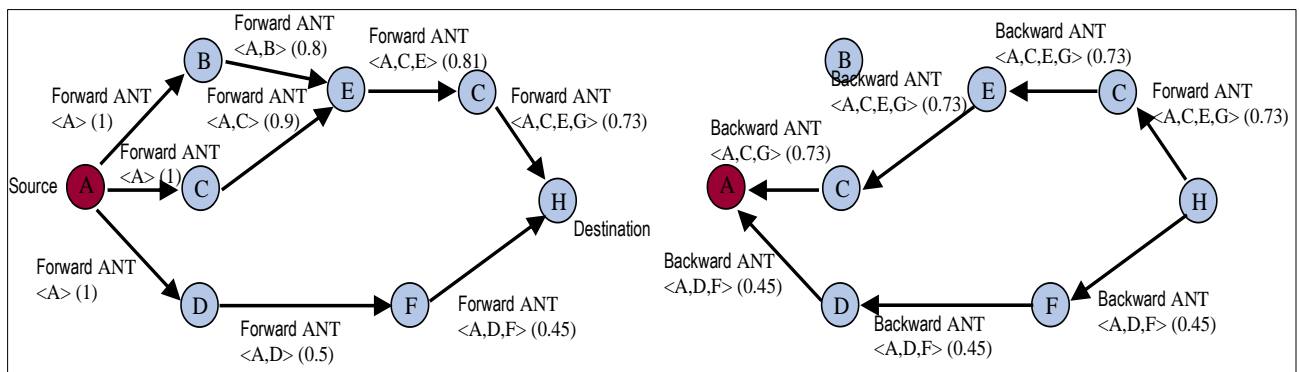


Figure 7. Ant Colony Routing in Wireless Sensor Network (WSN) protocol

5.6. Case-Based Reasoning (CBR)

Case-Based Reasoning was initiated by Schank Roger in 1882. CBR is a solving process based on similar past problems solution. The main information needed in CBR solving is recorded memories on solved cases [86]. Research in cognitive science on human memory was the main driver for the development of CBR, as it tried to portray how the human brain reacts when situations that require reasoning emerge [20].

CBR was used in analyzing energy reduction in house buildings [20]. In this study, innovation of CBR model with Particle Swarm Optimization (PSO) had been used to optimize the solution in which the result showed that energy was significantly reduced without compromising the comfort of users. González-Briones et al. (2018) [19] with a combination of CBR and Artificial Neural Network (ANN) used these in solving problem of optimization energy consumption associated with HVAC in office buildings and achieving 41% energy saving. Besides, house buildings and office, research on energy use in commercial buildings has also been done by Monfet et al. (2014) [87]. González-

Briones et al. (2018) [19], and Monfet et al. (2014) [87] used ANN and a significant reduction of energy in commercial buildings has been found [75]. The root-mean-square-error (RMSE) is 13.2% below reference which is 14% (Figure 8).

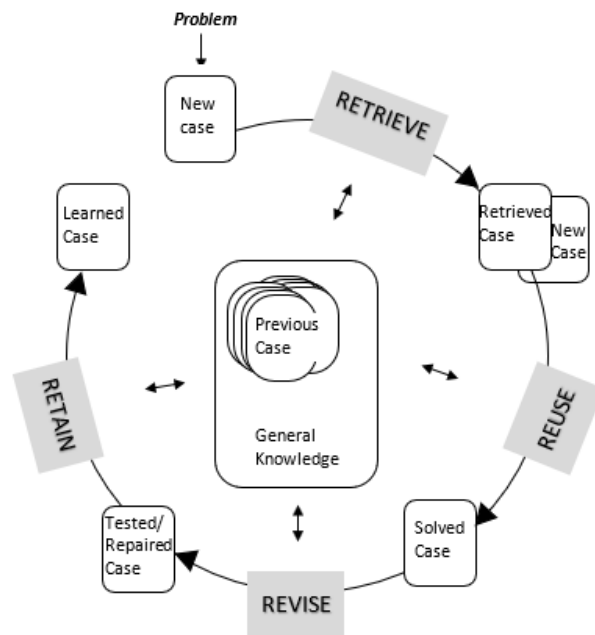


Figure 8. CBR Cycle [86]

5.7. K-Nearest Neighbour Prediction (k-NN)

K-Nearest Neighbour Prediction (k-NN) is a non-parametric method proposed by Thomas Cover [88] used for classification and regression matters [21, 89]. Classification and regression are useful techniques that can be assigned weights to the contributions of neighbours, so that the nearer neighbours contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbour a weight of $1/d$, where d is the distance to the neighbor (Figure 9).

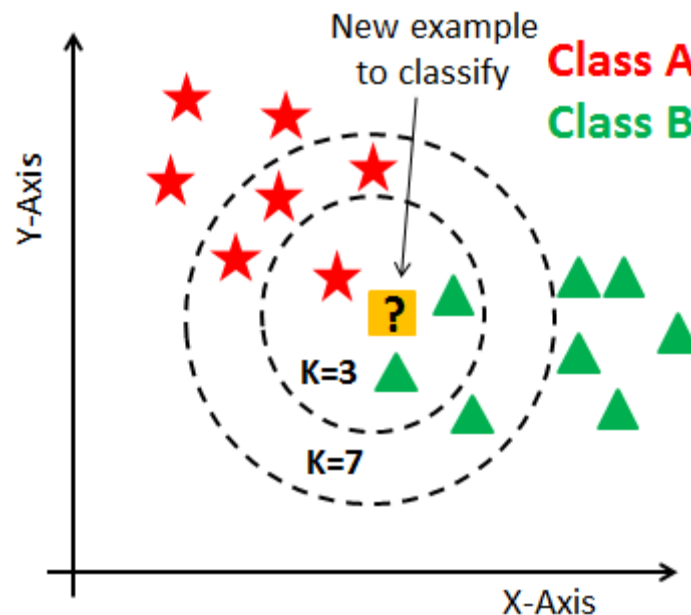


Figure 9. Classification using kNN algorithm

K-NN is not prominently used in energy as it is more focused in finance and transportation based on a few researches published using this OT. In electric transmission, Kristianto et al.'s (2018) [90] study on fault location with high accuracy results. This is proven by a high value of the coefficient of determination (R^2) and small error whereby the smallest is 0.9998. In another study conducted by Haerani et al. (2016) [91], k-NN was used in financial economy to predict the

currency value rupiah to dollar and the result of prediction was high in accuracy by MAPE 1.544%. Chantakamo & Ketcham (2015) [92] in transportation field used k-NN to classify the vehicle colours by using blob analysis and Diez et al. (2009) [93] studied on queries on road network. The classification of vehicles into three types are car, pickup, and truck. The result showed that the accuracy of k-NN was 80% to actual and 92% accuracy based on vehicle colours. In Diez et al.'s (2009) [93] studies it showed that query time requires only 0.55 seconds in managing traffic flow. Meanwhile, in energy usage, a study conducted by Lachut et al. (2015) [94] on seven types of appliances (computer, cooking, entertainment, lights, fridge, wash/dry and miscellaneous) by total energy usage showed that classification on them can be made based on time which are hour, quarter-day, day and week.

5.8. Genetic Algorithm (GA)

Genetic Algorithm (GA) is a metaheuristic procedure by process of nature selection that belongs to the larger class of evolutionary algorithm. It is used to generate high-quality solution to optimization. GA was introduced by John Holland in 1960 based on Darwin's theory of evolution. Extension and modification of GA happened in 1989 by David E. Goldberg. Due to its capability in generating high-quality solution in optimization, GA is shown to be not suitable for scheduling problems in finding a near-optimal solution in reasonable time such AC and CBR [18]. In this modern era, computing techniques are in demand for solving forecasting problems [12] and integration of these techniques has several unique features which are flexible and able to identify the best model by ANOVA method [60]. Her study revealed that significant MAPE relative error results and discovered that conventional time series forecasting is the best method to be used for future prediction in energy consumption due to GA's dynamic structure. Besides, Reynold et al. (2018) [95] used GA in aiming to minimize energy consumption for small office buildings in Cardiff, United Kingdom (UK) and shows that reduction of energy is about 25% compared to baseline heating strategy. Thus, when an electric tariff is introduced, the energy efficiency strategy has altered the cost to minimize it and not to the volume of energy consumption. Finally, optimization strategy in UK successfully opted for the cheaper cost of electric and reduces energy cost by 27% respectively. In the same field studied by Jung et al. (2015) [96], MATLAB2010 was adopted in analyzing energy consumption by GA technique. Integration of MATLAB2010 and GA improved computation time. Other than that, a study by Carlucci et al. (2015) [97] used GA in optimization of detached net zero-energy house in Southern Italy by EnergyPlus simulation. The study revealed that GA was able to find the best solution for four (4) objectives in this study namely, thermal discomfort during winter, thermal discomfort during summer, visual discomfort due to glare and daylighting. The findings revealed that it is only through good design that the best solutions can be achieved for the four (4) objectives. In a recent, study conducted by Eniola et al. (2021) [98] on renewable energy by photovoltaic (PV) power short-term prediction shown by associating hidden Markov model (HMM) and GA are suitable techniques for forecasting PV demand on hour basis is accurate.

6. Discussion

Availability of hybrid model of optimization by integration of two or more OTs became a common practice in findings due to their unique features or broader outcomes [53]. More than a hundred models can be found in articles published by different scholars. A few hybrids have been highlighted in this paper which have been used related to energy field. SVM-ELM hybrid model by Wang, GABGM by Zhou, NGBM by Tsai, ARIMA-NN by Zhuang and CBR-ANN by Gonzalez-Briones. However, only original OT and non-hybrid OT are being analysed for this paper as summarized in Tables 2 to 4.

Table 2. Category of Optimization Technique as summarized by previous researchers

	Author	Masouleh (2018) [47]		Deb et al. (2017) [38]		Di Somma et al. (2016) [9]		Zhao & Magoulès (2012) [17]		
	Cat.	GB	DF	TS	NS	GA	ES	EM	SM	AI
Optimization techniques	ANN		/	/			/			/
	SVM		/	/			/		/	
	GP		/	/			/		/	
	ARIMA		/	/			/		/	
	AC	/		/			/		/	
	CBR	/		/			/		/	
	k-NN		/	/			/			/
	GA		/	/		/			/	

List of abbreviations: **Cat**: Category, **GB**: Gradient base, **DF**: Derivative-free, **TS**: Time series, **NS**: Non time series, **GA**: Genetic algorithm, **ES**: Evolution Strategy, **EM**: Engineering method, **SM**: Statistical method, **AI**: Artificial Intelligence

Table 3. Summary of optimization techniques by different researchers and their applications to specific fields of study

OT	Energy usage			Energy load		Infrastructure	Comfort	Economic	Others
	Energy use	Energy cost	Energy prediction	Household Appliance Load	Electricity supply	Physical cabling	Human comfort	currency comparison	Automotive Industry
ANN (1940)	Nasr et al. (2001) [53], Nizami & Al-Garni (1995) [54], Kaytez et al. (2015) [55]	Panapakidis & Dagoumas (2016) [56], Karatasou et al. (2006) [52], Platon et al. (2015) [58]	Çunkaş & Altun (2010) [59], Azadeh et al. (2008) [60], Ekonomou (2010) [61], Rahman et al. (2021) [62]		Li (2021) [64]		Dyvia & Arif (2021) [57]		
SVM (2000)	Zhang, et al. (2016) [67], Kaytez et al. (2015) [55]		Li et al. (2018) [68]		Zhao & Magoulès (2012) [17]				
GP (1982)			Zhou et al. (2019) [69], Hu (2017) [72], Tsai et al. (2017) [73], Jin et al. (2012) [11], Pao et al. (2012) [74]						
ARIMA (1951)	Ozturk & Ozturk (2018) [76], Zhuang et al., (2015) [77],	Zhuang et al. (2015) [77]	Yasmeen & Sharif (2014) [78], Wang, et al. (2012) [79]						
AC (1992)	Bamdad et al. (2017) [82], Yuan et al. (2012) [83]					Sun et al. (2017) [84], Blas et al. (2011) [85]			
CBR (1982)	Faia et al. (2017) [20], González-Briones et al. (2018) [19], Monfet et al. (2014) [87]								
kNN (1967)				Lachut et al. (2015) [94]	Kristianto et al. (2018) [90]			Haerani et al. (2016) [91]	Chantakamo & Ketcham (2015) [92], Diez et al. (2009) [93]
GA (1960)		Reynold at al. (2018) [95]	Azadeh et al. (2008) [60], Jung et al. (2015) [96] Eniola et al. (2021) [98]				Carlucci et al. (2015) [97]		

Table 4. Summary on characteristics for OT in term of user-friendliness and suitability of application

Criteria	ANN	SVMs	GP	ARIMA	Ant Colony	CBR	k-NN	GA
Technique	Deterministic	Data driven	Deterministic	Data driven	Deterministic	Deterministic	Data driven	Deterministic
Model Complexity	High	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	High
Easy to use	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Running speed	High	Low	Low	Low	Low	High	Low	High
Input needed	Historical data	Historical data	Simplified (able to use incomplete data)	Simplified	Historical data	Historical data	Simplified	Simplified
Accuracy	high	Moderate	high	Moderate	Moderate	Moderate	Moderate	High
Time series	multivariate	multivariate	multivariate	univariate	univariate	multivariate	univariate	multivariate
Forecasting	Short-term	Long-term	Long-term	Long-term	short-term	Short-term	Short-term	Long-term
Application	Various type of buildings: IAQ, Energy (heating & cooling) Economy GDP, import & export energy demand, population	Various type of buildings: Climate variation, energy (cooling & heating)	Various type of buildings: IAQ, energy (heating & cooling), solar radiation.	Engineering: cost reduction in water technology	Economy: GDP, import & export, population	Various type of building: energy reduction and energy saving	Economy: Financial, marketing	Various type of buildings: IAQ, Building envelope, energy (heating & cooling), solar radiation.

Table 2 shows that, according to Masouleh (2018) [47], AC and CBR grouped under "Gradient Based" are suitable for prediction on conforming data (upward or downward), while all remaining OTs which are "Derivative Free" are suitable for prediction on fluctuating data. Deb et al. (2017) [38] suggested that all reviewed OTs are based on "Time Series" since the predictions are based on records for a specific period. Di Somma et al. (2016) [8] categorized GA as "Genetic Algorithm" and is suitable for prediction under flexible circumstances, while the remaining OTs grouped under "Evolutionary Strategy" are suitable for prediction of continuous scenarios. Zhao & Magoulès (2012) [17] labelled ANN and k-NN as "Artificial Intelligence" as the prediction requires simulation input. The remaining OTs, which are "Statistical-Based", can provide a prediction based on specific statistical data. None of the reviewed OTs falls under the category of "Engineering Method", as such methods require complex engineering input.

Table 3 shows that ANN and ARIMA are suitable for broader aspects of energy that involve energy usage, energy cost, and energy prediction. kNN is suitable for OT that involves energy load prediction for households and supply, whereas AC is suitable to predict the length of cable required for electrical infrastructure. GA is capable of predicting comfort levels. A hybrid model of optimization by integration of two or more OTs may be necessary to predict a wider scope of optimization. For example, a hybrid of ANN and kNN is able to predict basic energy requirements and energy load.

Table 4 shows the background, characteristics, and suitability of applications for different OTs. SVM, ARIMA, and kNN are "data-driven," while the remaining are "deterministic-driven". ANN and GA are complex OT models. With the exception of SVM and GP, all the remaining OTs are easy to operate. GP, ARIMA kNN, and GA can simulate prediction with simplified data input. ANN, CBR, and GA are capable of producing predictions at high running speeds as compared to other OTs. ANN, GP, and GA offer high levels of accuracy for prediction. Most importantly, it is the suitability of the type of applications that determines which OTs are to be shortlisted for the optimization process, while the remaining factors depend on the strength, capabilities, and limitations of the researcher.

7. Conclusion

This paper, which aims to review existing literature on concepts, classification, and characteristics among different categories of OT that are commonly featured in building and energy-related journals, has been successfully presented. In conclusion, this paper has also met the research objectives in demonstrating the qualitative aspects and principles concepts for different categories of eight (8) common OTs that are widely used in various fields of study, in particular their level of complexity. The suitability of each OT for building performance analysis, specifically on energy efficiency, is tabulated in Tables 2, 3 and 4. The summary of findings and recommendations from the three tables need to be combined during the process of selecting the most suitable OT. Regardless of the various categories and their multiple applications, it is the summary of characteristics of each optimization technique that determines their suitability for adoption, depending on the research objectives, strength of the researcher, and availability of data. ANN is suitable for optimization for building energy performance covering energy use, energy cost and energy prediction which offer high levels of accuracy. However, it is a complex model that requires historical data input and can produce only short-term predictions. A hybrid of ANN and kNN is recommended for broader optimization objectives that cover energy load. This research supports an earlier hypothesis which states that a hybrid technique combining more than 2 techniques may be required for complex outcomes. It is recommended for future research to explore the application of different models commonly attached to specific OT among the eight OTs to determine the level of effectiveness.

8. Declarations

8.1. Author Contributions

Conceptualization, N.A.A.R.; methodology, N.A.A.R., S.N.K. and F.W.A.; validation, S.N.K. and F.W.A.; formal analysis, N.A.A.R.; investigation, N.A.A.R.; resources, N.A.A.R.; data curation, N.A.A.R.; writing—original draft preparation, N.A.A.R.; writing—review and editing, N.A.A.R. and S.N.K.; visualization, N.A.A.R.; supervision, S.N.K. and F.W.A.; project administration, S.N.K.; funding acquisition, S.N.K. All authors have read and agreed to the published version of the manuscript.

8.2. Data Availability Statement

The data presented in this study are openly available on request from the corresponding author.

8.3. Funding

The author received financial support for the research, authorship, and/or publication of this article by RU Grant, ST013-2020, University of Malaya.

8.4. Conflicts of Interest

The authors declare no conflict of interest.

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