Mathematical Model of Utilization Mapping for Geothermal Energy Using Machine Learning Algorithms

by

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Dedicated to my parents

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List of Abbreviations

ANN	Artificial Neural Network
CPU	Central Processing Unit
DC	Distribution Center
GB	Giga Byte
GHz	Giga Hertz
GMT	Greenwich Meridian Time
GW	Giga Watt
IDC	Intermediete Distribution Center
LDC	Local Distibution Center
LEARNGDM	Learn Gradient Descent With Momentum Weight and Bias
MATLAB	Matrix Laboratory
ML	Machine Learning
MSE	Mean Square Error
MW	Mega Watt
NFTOOL	Neural Fitting Tool
OS	Operating System
PURELIN	Purelin Transfer Function
TRAINBR	Train Bayesian-Regularization
TRAINLM	Train Levenberg-Marquardt
VLE	Vapor-Liquid Equilibrium

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Abstract

Geothermal energy has an important function and cannot be neglected in human life. Moreover, nowadays almost human activities depend on energy. Many countries are engaged in initiative that lead to alternative sources of energy. Indonesia is successfully included in the top two countries in the world that produce geothermal energy. Geothermal energy has huge potential in Indonesia. Nonetheless, the utilization capacity of geothermal energy is lesser compared to its natural potential. Our study, therefore, was motivated to explore the potential of geothermal energy utilization and laying design strategies in developing a single flash geothermal power plant. Machine learning approach in geothermal energy applications currently is not popular means of predicting performance in the geothermal industry, yet machine learning has exhibited potential in many engineering and science problems. As of recent, there is no efficient means of predicting if the potential site identified can produce the expected amount of energy without boring wells in that site. In a situation where the wells are found to be insufficient, another well is bored creating potential environmental destruction. Moreover, the cost of boring is high covering 45% of the whole geothermal project. The most important of geothermal energy sources utilization parameter is the temperature of the brine. Geothermal for power production use the thermodynamic properties of the brine to determine how much power can be produced from the geothermal site. Using the enthalpy and entropy potential, the production capacity in a single flash can be estimated. In this study, we perform a literature survey to enable understanding of the geology, reservoir characteristic of selected potential sites and collect suitable data for the supervised machine learning technique. Further, a utilization strategy to classify all the possible sites of geothermal potential resources in Indonesia was done. In addition, machine learning was used to predict power requirements on the grid, depth and lifespan of the wells. It was observed that the maximum power output can be achieved on the grid if the well temperature is between 120°C and 150°C. With respect of the organization of the thesis, Chapter 1 consist of introduction that gives the background of the study. Chapter 2 consist of review of geothermal energy in Indonesia as current status and prospects. Chapter 3 consist of the utilization mapping for geothermal energy with respect to temperature. Chapter 4 consist of machine learning model for improving single flash geothermal energy production. Chapter 5 consist of the experimental setting, results, and discussion. Chapter 6 consist of the conclusion of this thesis by summarizing all results and future observation through the researches.

Chapter 1

Introduction

Indonesia is the largest archipelago country in the world with high energy demand. The total population in Indonesia across the 17,000 islands is 265 million, of whom 70 million people don't have access to electricity [1]. Indonesia is rich in renewable energy sources such as geothermal energy, hydropower, solar energy, tidal energy, wave energy, and current energy. Moreover, bioenergy from biomass and biogas is spread over many places in the country. Nevertheless, the potential of renewable energy has not been developed to generate a great capacity of energy, hence fossil energy dominates the production of the electricity as the major energy production source [2, 3].

Indonesia is located in the ring of fire regions bearing three time zones (GMT+7, 8, 9). The geothermal energy is the real potential in Indonesia, because 127 active volcanic sites from which 342 potential geothermal wells are found, these provide a fertile ground for geothermal energy production. There are 13 power plants built as of current. Ten (10) are constructed in the west, and the rest in the central. From the total sources, 65 sites are under exploration and the rest are still as labeled potential sources of geothermal and not yet explored [4–6]

Geothermal energy is a potential energy resource in the Ring of fire regions (where the active volcanos are present), in which Indonesia is located [6]. Geothermal energy has the ability to produce a great deal of energy that has been experienced making the country the second-biggest user of geothermal energy, but as of yet, there is still an energy gap that needs to be filled [7]. Geothermal energy production can mitigate various carbon emission side effects in this region. Specifically in Indonesia, the use of geothermal energy has been practiced to a great extent despite the dominant use of fossil energy as a mean of energy production. With high energy consumption, geothermal can be a primary alternative for reducing carbon emission.

Energy is used for different purposes in industry, transportation, commercial buildings, offices, and domestic use creating potential points of carbon emission. As a country, Indonesia is one of the top greenhouse carbon emissions in the world [8]. Therefore, finding the mechanism of reducing emission further is a primary concern that is needed to achieve net or near-zero carbon emissions. This to a very significant extent is covered by energy from renewable sources, including renewable energy produced on-site, like geothermal energy, solar, biomass, hydro, etc.

Renewable geothermal energy has an important function and cannot be neglected in human life. Moreover, nowadays almost all human activities depend on energy. So, many countries start to initiate alternative energy resources or commonly called renewable energy including geothermal energy. Indonesia is in the top ten countries which produce renewable energy. Furthermore, renewable geothermal energy has huge potential in Indonesia [9]. Nevertheless, the utilization capacity of geothermal energy is small compared to fossil energy as the biggest producer of carbon. Our study, therefore, is motivated to exploring the potential of geothermal energy and laying design strategies in developing a single flash geothermal power plant.

1.1 Motivation

Advances in Machine Learning (ML) provide an opportunity to reduce cost in geothermal projects starting from resource exploration to power plant operation. Geothermal energy plays an important function in the generation of clean energy. This function cannot be neglected in this era of global warming. Moreover, almost all human activities depend on power. Many countries are looking forward to alternative energy sources to replace fossil and coal. Indonesia has successfully positioned itself second in the top ten countries in the world that produce geothermal renewable energy. Nevertheless, the utilization capacity of geothermal energy is small as compared to non-clean energy sources. Our study, therefore, is motivated to exploring the potential of geothermal energy utilization and laying design strategies to improve single flash geothermal power prediction using machine learning approach. In our study, we use machine learning to classify the utilization characteristic and improve operations in the geothermal single flash process. Specifically to predict the power production, life of well, power requirement on the grid, etc. The study, at the end, provides the utilization mapping in all the zones in Indonesia and also it provides efficient prediction mechanism of geothermal energy produced by single flash technology at a given enthalpies in the isenthalpic process where changes in kinetic and potential energy are negligible. This strategy enables efficient utilization of geothermal energy in developing green ecosystem in Indonesia.

1.2 Problem Statement

Indonesia has a high energy demand due to its rapid development, industrialization strategy, and high increase in her population. The development of geothermal energy is improving fast as part of Indonesia's energy development plan. Most of the power plants are constructed based on either single flash or dry steam power production technology. These technologies use the wells as their source of energy. The location of the geothermal well is determined by geothermal surface manifestation. As of recent, there is no efficient means of predicting if the potential site identified can produce the expected amount of energy without boring wells in that site. In a situation where the wells are found to be insufficient, another well is bored creating potential environmental destruction. Moreover, the cost of boring is high covering 45% of the whole geothermal project. The most important of geothermal energy sources utilization parameter is the temperature of the brine. Geothermal for power production use the thermodynamic properties of the brine to determine how much power can be produced from the geothermal site. Using the enthalpy and entropy potential, the production capacity in a single flash can be estimated. Therefore, in this thesis, we propose machine learning techniques for supporting geothermal energy utilization prediction, production of electricity.

1.3 Objectives

(i) To study the geology and reservoir characteristic of geothermal site.

(ii) To explore the predictive model using machine learning methodologies and the strategies in developing single flash geothermal power plant.

(iii) To create a geothermal utilization map of all potential sites of geothermal energy in the three-time zone of Indonesia.

1.4 Contribution of this thesis

(i) We modeled the utilization mapping of the geothermal potential site with respect to the temperature.

(ii) We created a model for enthalpies and entropies to generate thermodynamic properties of the brine.

(iii) We developed and implemented Simulink model for predicting the power output in a geothermal power plant.

1.5 Related Works

1.5.1 Geothermal Renewable Energy

Authors in [10] explored the aspect of geothermal energy development, geothermal power plant technology, and the common geothermal direct uses. Five power plant technologies are mentioned in this study. They include single-flash, double-flash, and dry-steam technologies for power generation in a geothermal power plant. Other technologies mentioned are binary and hybrid power plant technologies. Single flash is used for electricity conversion when geothermal production wells are producing a mixture of brine. Double flash steam power plants are an improvement on the single-flash. Dry-steam power plants are often used in the most efficient power plant with high enthalpy vapor-dominant wells at high temperatures in hydrothermal reservoirs. Binary power plant configurations are used for low-temperature geothermal resources. The hybrid may adopt more than one of a single flash, double flash or dry steam configurations for geothermal conversion. The authors mention that geothermal resources are not only used for electricity generation but can also be adopted for direct use. Direct use of geothermal energy ranges from applications that need high temperatures, and those which need moderate temperature. These applications include drying cement blocks, drying agricultural products, and house warming. In this particular study, the state-of-the-art in geothermal energy was given.

Authors in [5] investigated the Indonesian geothermal resources, based on the ability to generate power using the Specific Exergy Index (SExI). In this study, the Exergy concept was developed as a geothermal resource classification tool. Exergetic classification of geothermal resources was applied to 11 power plants under operation. The results of SExI values show that nine geothermal fields are classified as having high Exergy resources, whereas the remaining two power plants are classified as medium geothermal resources. According to them, the location of the power plants in different Islands of Indonesia determines their classes. They concluded that the power plants with medium Exergy are located in Sumatra Island, whereas the rest are found in Java, Bali, Nusa Tenggara, and Sulawesi. Geothermal resources in Java Island are ranked first with the highest Exergy resources concentration. Darajat power plant has the highest SExI value of 0.94 amongst all powered investigated in that study.

Authors in [6], investigated the geothermal potential in the ring of fire, where Indonesia is located. They mentioned that the location of Indonesia, specifically Java Island contributes, significantly to Indonesians geothermal potential. The predicted geothermal potential is almost 29 GW in 312 locations spread across most of Java, Sulawesi, Sumatra, Maluku, Bali and Nusa Tenggara. In this paper, the utilization ratio mentioned is about 5%, with power generated being 1533.5 MW of electricity from 11 geothermal power plant. Accordingly, the current power generated is close to 2000 MW making Indonesia the second geothermal biggest user in the world [7]. The characteristics of most of the geothermal reservoirs are water-dominated. They employ single flash technology for power production [6, 11, 12].

Authors in [12] investigated Exergy analysis and optimization by developing a mathematical model that is applied to the Dieng single-flash geothermal power plant in Indonesia. Calculations were conducted by using EES software using methods based on the laws of thermodynamics. The optimization of the plant is carried out by adjusting the separator pressure. The result of the optimization process shows that the Dieng geothermal power plant operates under close to optimal conditions.

Authors in [13], addressed a private sector perspective in rethinking renewable energy targets and electricity sector reform in Indonesia. It discussed Indonesia's current renewable energy policies and future outlook for achieving the targets. It serves as a literature review of Indonesia's changing energy policy landscape as part of research investigating renewable energy targets and the role of the private sector reforms in the renewable energy industry. The changes in Indonesia's policy landscape have been rapid, and the authors have tried to capture the dynamics. It also serves to understand renewable energy targets in Indonesia and to predict future trends. As the basis of policy and decision-making in renewable energy. This study enriches the existing literature on renewable energy policy which is of the importance of engaging the private sector. The lessons from Indonesia's experience may provide insights for policymakers notably in developing countries. This study calls on means of predicting the different dimensions that could result in policy improvement based on prediction mechanism. Policy issues such as how much power production is sufficient for residences in particular villages without harming the environment can easily be answered by machine learning. Other important issues that can be predicted using machine learning include the life of the well, distribution of power generated, etc. These issues may form important components of contracts between the government and the private's sector.

1.5.2 Machine Learning in Geothermal Renewable Energy

Advances in Machine Learning (ML) provide an opportunity to reduce cost in geothermal projects starting from resource exploration to power plant operation. The application of machine learning in geothermal exploration is still in its infant stages. Specifically, there are still existing gaps in the use of machine learning strategies in geological, geochemical, borehole, etc.

Artificial Neural Networks (ANN) are computational system models that are obtainable as of interconnected neurons. It computes values from inputs by feeding information through the network. An Artificial Neural Network is used for a particular application through a training and learning process. Similar to other machine learning methodologies, neural networks are used to answer a widespread in many hard to solve tasks. ANN is an efficient machine learning mechanism used to predict the state of events from data with acceptable error results. It provides high accuracy and reliability prediction experiments. ANN is used to predict the performance of a specific system [14].

Authors in [14], describes the prediction of geothermal power plant system performance using an artificial neural network(ANN) under a broad range of operating conditions. The applicability and capability of artificial neural network approaches were used for predicting geothermal power plant-specific steam consumption. They used the data collected from the Kamojang geothermal power plant to predict the performance in the first quarter of 2015. From this study, a combination of good sufficient training data, and independent measurement of steam flow for validation using the neural network approaches can be utilized to develop a good performance prediction. It is able to identify the degradation of the plant or instruments. Nonetheless, an independent measurement of steam flow is required to validate the measurement of ANN prediction. The data shift from ANN predicted value can be a good sign to perform a comprehensive analysis of the plant to prevent losses, especially in the steam sales contract scheme. Plant operator also gets a better perspective on the plant real-time performance by comparing plant real-time data and data prediction from ANN. This study is one of the kinds that make the use of machine learning methodologies useful in geothermal power generation problems.

Authors in [15] surveyed different machine learning techniques used to address the issues related to the generation of renewable energy. More importantly a discussion on the integration of machine learning in the power grid utilization. In this study, they assert that machine learning techniques have been successfully used in the planning of renewable energy plants based on available data with reasonable accuracy. They published literature on location, sizing, and configuration of wind and PV systems based on machine learning techniques. They continued to underline their popularity, particularly in isolated areas. They also indicate that to generalize the machine learning models for each and every aspect of renewable energy generation and integration into the grid is quite difficult. But strong coordination is necessary among the different prediction and decision-making models to better enhance the grid's overall efficiency and effectiveness. This shows the potential of machine learning as a design tool in strategic planning and policy-making in renewable energy environment.

In this thesis, we use MATLAB/Simulink for our single flash geothermal model operations. Simulink is one of the common tools for soft computing. Soft computing provides a natural way to argue a complex phenomenon in which computational mechanism is based on mathematical modeling. It is a basis of many applications in medical engineering, computer vision, and pattern recognition. Soft computing includes Artificial Neural Network, a method imitated the brain mechanism in solving problems. Secondly, fuzzy logic attempts to solve problems with an open and precise spectrum of data that make it possible to find a list of the precise solution without involving complex math. Lastly, in genetic algorithms have been inspired as a soft computing method that is used to find problems that include natural selection. It is one of the common software to develop machine learning.

1.5.3 Utilization in Geothermal Renewable Energy

Authors in [16] investigated the special collection for advances of exploration and utilization technology of geothermal resources in China. As a renewable energy source, geothermal energy is becoming important in energy conservation, emission reduction, and climate change. Medium- and low-temperature geothermal resources are widely distributed in the continental of China, and high-temperature geothermal resources also exist. In recent years, the direct utilization of geothermal energy in heating, industry, and agriculture has been developing rapidly. There is a need to strengthen the study of geothermal basic theory to discover more efficient geothermal resources. At the same time, there is also a need to develop geothermal utilization technologies to efficiently utilize geothermal resources. In this Special Collection, the study focus on the basic geothermal fields in China. They mainly discuss deep geothermal processes, heat flow, thermal lithosphere, and geothermal resource assessment. The authors mentioned that geothermal reservoir evaluation is one of the most important topics in geothermal exploration and utilization.

Authors in [17] reviewed the worldwide direct utilization of geothermal energy. The information is based on country update papers published in the World Geothermal Congress 2010. The growth rate of installed capacity and annual energy use over the past 15 years is increasing. The lower capacity factor and growth rate for annual energy use is due to the increase in geothermal heat pump installations which have a low capacity factor of 0.19 worldwide. The growing awareness of heat pumps has had the most significant impact on the direct use of geothermal energy. From this study concluded several countries stand out as major consumers of geothermal fluids for direct uses; however, in most countries development has been slow. Thus, geothermal energy becoming increasingly more competitive with fossil fuels and the development of this natural “heat from the earth” should accelerate in the future.

Authors in [18] studied the geothermal energy utilization it is used commercially for both generating electricity and direct use. Geothermal plants have the capacity to generate about 10 GW of electricity and supply 0.3% of global electricity demand.

Geothermal energy is considered a renewable resource due to the limitless ability of the earth to produce magma, and the continuous transfer of heat. It is cost-effective, reliable, sustainable, and environmentally friendly, but limited to areas near tectonic plate boundaries. Recently, technological advances have expanded the range and size of viable resources, especially for applications such as home heating, opening a potential for widespread exploitation. Geothermal power is able to help mitigate global warming if deployed in place of fossil fuels. Geothermal energy has been used for direct applications in many parts of the world such as Iceland, the USA, Turkey, China, and many European countries. This has proven to be economical and reliable source of energy because of more than 90%availability.

Authors in [19] investigated the geothermal energy in utilization and technology. Geothermal systems are in regions with above normal geothermal gradient. The regions around plate margins where the geothermal gradients may be higher than the average value. In the first case, the systems will be characterized by low temperatures, usually no higher than 100°C at economic depths; in the second case, the temperatures could cover a wide range from low to very high, and even above 400°C. The resources are divided into low, medium and high enthalpy (or temperature) resources. The criteria generally based on the energy content of the fluids and their potential utilization. The distinction is made between liquid-dominated and vapor-dominated geothermal systems. These geothermal systems have temperatures range from 125 to 225 °C. Depending on temperature and pressure conditions, they can produce steam mixtures, wet steam, and dry steam. Electricity generation is the most important form of utilization of high-temperature geothermal resource > 150 °C. The medium-to-low temperature resources < 150°C are suited to many different types of applications. The Lindal model [20] shows the possible utilization of geothermal fluids from sources at different temperatures.

1.6 Outline of Thesis

This thesis consist of six(6) chapters, **Chapter 1** provides the introduction that includes motivation for the studies, the aim of the research, contribution of the thesis, background, and related works. In **Chapter 2** a review of geothermal energy in Indonesia as current status and prospects has been given. **Chapter 3** focuses on the utilization mapping for geothermal energy with respect to temperature, while **Chapter 4** addresses machine learning model for improving single flash geothermal energy production. Results of the experiment have been presented in **Chapter 5**. Conclusion and future work is presented in **Chapter 6**.

Chapter 2

A Review of Geothermal Energy Resources in Indonesia, Current status and Prospect

There is plenty of untapped geothermal resources in Indonesia. Indonesia is part of the Pacific Ring of Fire and is dominated by volcanoes. Its geology makes it perfect for geothermal energy generation. However, despite the fact that Indonesia is currently the second largest geothermal electricity producer in the world, plenty of the country's geothermal resources remain untapped. In this chapter therefore, we review the geothermal energy resources in Indonesia, the current status and prospect.

2.1 Introduction

Geothermal energy is a constant base-load power of natural renewable energy resources stored in the earth crust with potentially no green-house gas emissions compared to fossil energy. The thermal is generated basically in between tectonic plates which trigger the heat to come up beneath of earth's surface which almost occurs in the volcanic area. In the recent era, much progress has been made in research on geothermal energy. Geothermal energy utilization fills the gap of electricity production in power generation and geothermal direct use[1] [21–24]

The development of geothermal energy resources in Indonesia began in 1983 for utility-scale production in the Kamojang geothermal power plant. The production of zero-carbon emission is the most compelling feature of geothermal energy, identifiably proven as one of the cleanest sources of energy at our disposal as compared to other renewable energies [4]. Unlike most renewable energy sources, such as solar or wind, geothermal energy sources are able to create a constant 24-hour base-load power. This makes geothermal energy more beneficial and independent of daylight, cloud coverage, and wind speed [25].

[1] Geothermal use other than power production such as in space heating with heat pumps. The application involves air conditioning, animal husbandry, soil warming, swimming pool and fish farming as per Lindal's diagram

The geothermal industry in Indonesia has grown significantly in recent years. The vision is to achieve 23% of renewable energy production by 2025 [13]. All projects to this end-utilize ground-source heat located in various places in the country to exploit their geothermal potential. The primary focus of exploiting geothermal is to reduce carbon emission as well as maintaining consistency with the Paris Agreement [26]. So far, Indonesia achieved 1.9 GW of electricity from geothermal sources, making it the second-biggest user of geothermal energy in the world [7]

Geothermal energy has a major prospective in electricity generation and direct-use applications. Presently proportion of power plant technology such as dry-steam, flash, binary and advanced technology exist. Indonesian bases its power generation on use single-flash and dry-steam technology. Of the 13 geothermal power plants, 11 use single flash while the rest use dry steam. Till now, geothermal energy has not been explored for direct use. Power generation use is driven by the fact that most geothermal resources in Indonesia are accessible at very high-temperature. Geothermal electricity in Indonesia is rapidly increasing as opposed to direct-use application. [5, 6, 10]

It is critical for Indonesia to utilize rich geothermal energy resources for the country's development. Obviously constant utilization of geothermal energy makes the best use of large energy demand consumption. Potentially there are more than 342 potential geothermal wells of which 70 sites are under exploration and the rest are still as labeled potential sources of geothermal energy and not yet explored [27]. At present, the progressive utilization of geothermal energy resources is the main approach in order to gain sustainable development in Indonesia.

2.2 Worldwide Geothermal Energy

The proportion of utilization from different energy sources and renewables are slightly unequal. Geothermal energy currently accounts for only a small share of the world's energy resources. Particularly on electricity generation, as well as direct-use applications, lower temperature geothermal resources are used. The significant potential is in areas with the hydrothermal system located in countries with active volcanoes. United States, Indonesia, the Philippines, Turkey, New Zealand, Mexico, Italy, Iceland, Kenya, and Japan are top ten geothermal installed capacity producers [7]. Specifically, Indonesia, standing as the biggest geothermal potential resources contains 28.9 GW as 40% of 70 GW total world [9].

Figure 1 provides information on the worldwide geothermal capacity as per October 2018. The Figure shows that the United States has the biggest geothermal installed capacity of 3591 MW. Followed by Indonesia and the Philippines with installed capacity of almost 2000 MW. Turkey and New Zealand follow with installed capacity

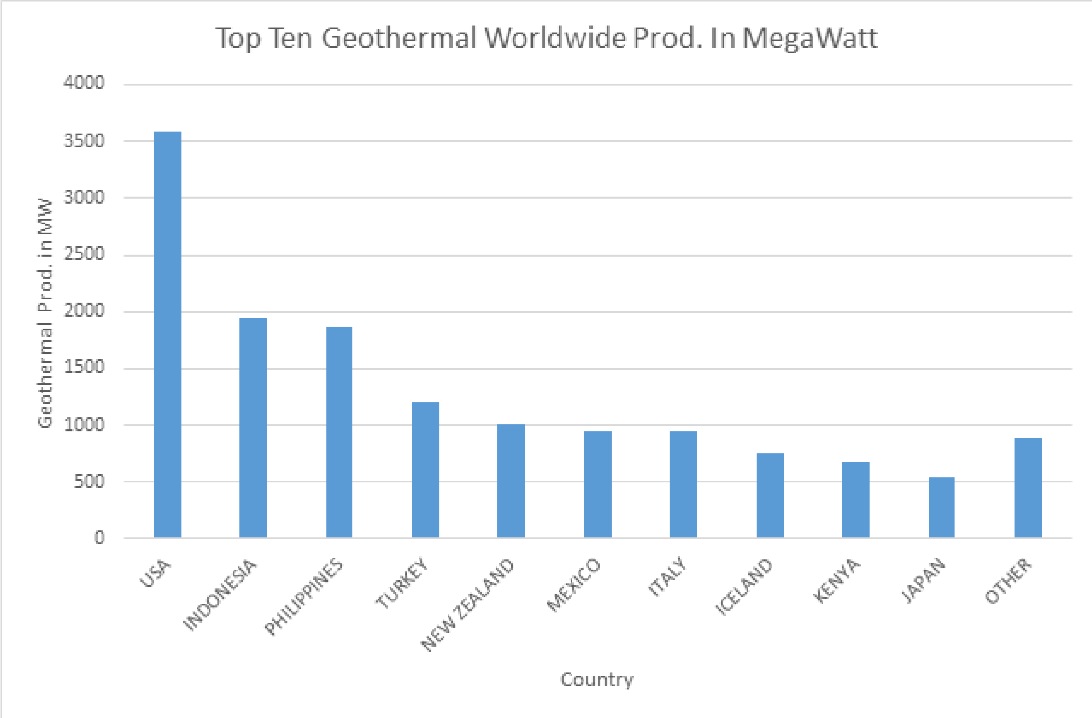

Figure 2.1: Shows top ten geothermal world wide capacity

of slightly above 1000 MW. At that moment other countries' individual installation is below 1000MW. The above five mentioned countries are currently labeled as 1 GW club in the geothermal energy industry [7]. Countries such as Mexico and Italy have their geothermal installations, approximately approaching 1000 MW. The other countries with less than 800 MW are Iceland, Kenya, and Japan. The total capacity of these non-1GW countries combined does not exceed the total 889 MW, excluding the top ten geothermal producers above, the overall installed capacity will reach 11000 MW by 2025 of which 40% is predicted to be installed in Indonesia. The total world potential of geothermal is about 70,000 megawatts of which most of the potential is located in the ring fire in which Indonesia is located.

2.3 Indonesia's Geothermal Resources

Indonesia has 265 million people as its population. It is the world's fourth most populous country besides having substantial carbon emission per capita [8]. As there are many active volcanoes on the Indonesian islands, Indonesia surpasses hydrothermal resources in the world [28]. Moreover, Indonesia has the substantial average potential for a high temperature of geothermal above 150°C based on a database of temperature geothermal potential recorded at the bottom of wells [29]. Indonesia possesses an enormous opportunity for energy production, having an abundance of such high-temperature hydrothermal systems [30]. Furthermore, many geothermal resources in

Indonesia are situated in ideal locations, both near major population centers where electricity demand is high and still increasing, and near impoverished eastern parts of the country where electrification rates are low [31].

The Indonesian government has repeatedly stated its intention to develop the country's abundant geothermal resources. As of April 2018, the Geological Agency of the Ministry of Energy and Mineral Resources has announced 342 geothermal working areas in Indonesia. However, the updated installed capacity was 1.9 GW. In addition, the government's stated goal is to increase geothermal capacity and become the biggest geothermal installed capacity by 2021. The geological and thermal environment of Indonesia possesses an abundance of geothermal energy estimated at 40% of the world's global geothermal energy potential.

The challenge of geothermal development in Indonesia provides an exemplary case study—Indonesia being a highly populous island and rapidly industrializing nation for which the problems of sustainable electrification, the mitigation of climate change and sea-level rise, severe health risks owing from air pollution, and poverty alleviation and marginalization loom large.

As of March 2018, several companies have utilized geothermal resources in Indonesia. The existing geothermal power generation in Indonesia is spread in all the 17000 islands [32]. The power plant so far constructed, utilizes high-temperature hydrothermal-type geothermal resource accessing reservoir from wells that tap a confined aquifer in the underlying place. Exploration has been largely focused on the high temperature with the depth of exploration cover varying from about 500 meters from the surface to 2000 kilometer. This potential has stimulated significant interest in the exploration of geothermal resources for electric power generation. Other potential sources, whose temperatures are small attract potential for direct-use applications which has not been explored enough. At present geothermal energy resources are mostly utilized on a local-scale in Indonesia. High and moderate temperature geothermal energy resources may be utilized to produce base-load electricity for distribution through the transmission grid [33]. In addition, geothermal energy resources could be employed as geothermal direct use. The Indonesian geothermal industry development framework and roadmap were released in August 2017. [34] There are three time zones in Indonesia. The time zones separate the country into three regions; the GMT+7 region of 18 provinces are located in the west of Indonesia, GMT+8 region of 12 provinces are in central Indonesia, and GMT+9 region of four provinces is in the east of Indonesia.

The figure above shows the Distribution of Geothermal Resources in Indonesia in terms of utilization in their zones. They have been categorized into installed resources, resources under exploration and potential resources. Most of the installed resources

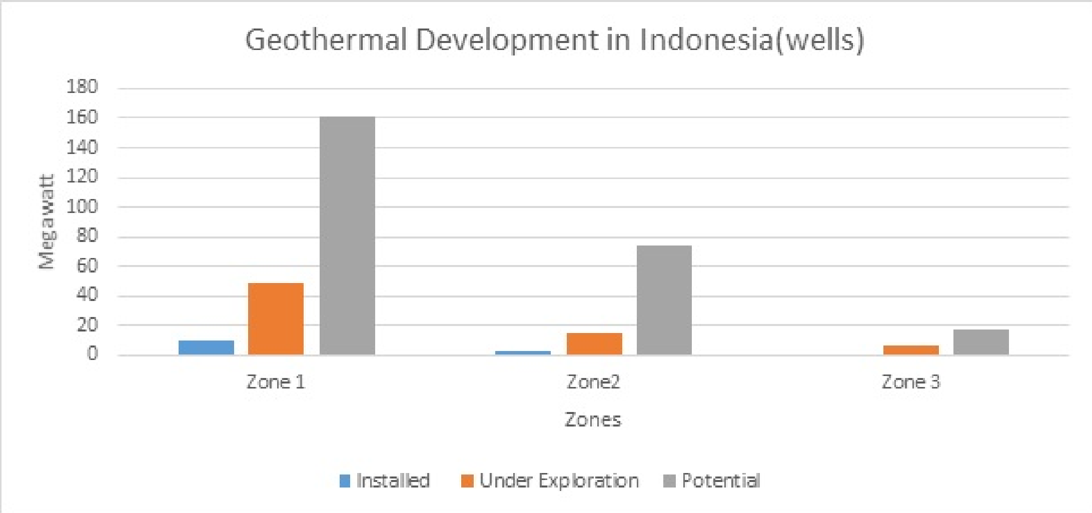

Figure 2.2: Shows the distribution of geothermal resources in Indonesia

have been built in the western region (Zone 1), and the rest in the central region (Zone 2) and none are built in the eastern region (Zone 3) of Indonesia. The total resources under exploration in Zone 1 are slightly above 40 sites, in zone 2 slightly less than 20 and in zone 3 less than 10 sites are under exploration. The rest of the sites are labeled potential resources of geothermal. There are 160 sites in zone 1, about 75 in zone 2 and less than 20 in zone 3. Overall most of the potential and installed capacity is located in zone 1, followed by zone 2 and Zone 3 registers less potential mainly because of a smaller number of sites that could produce geothermal energy.

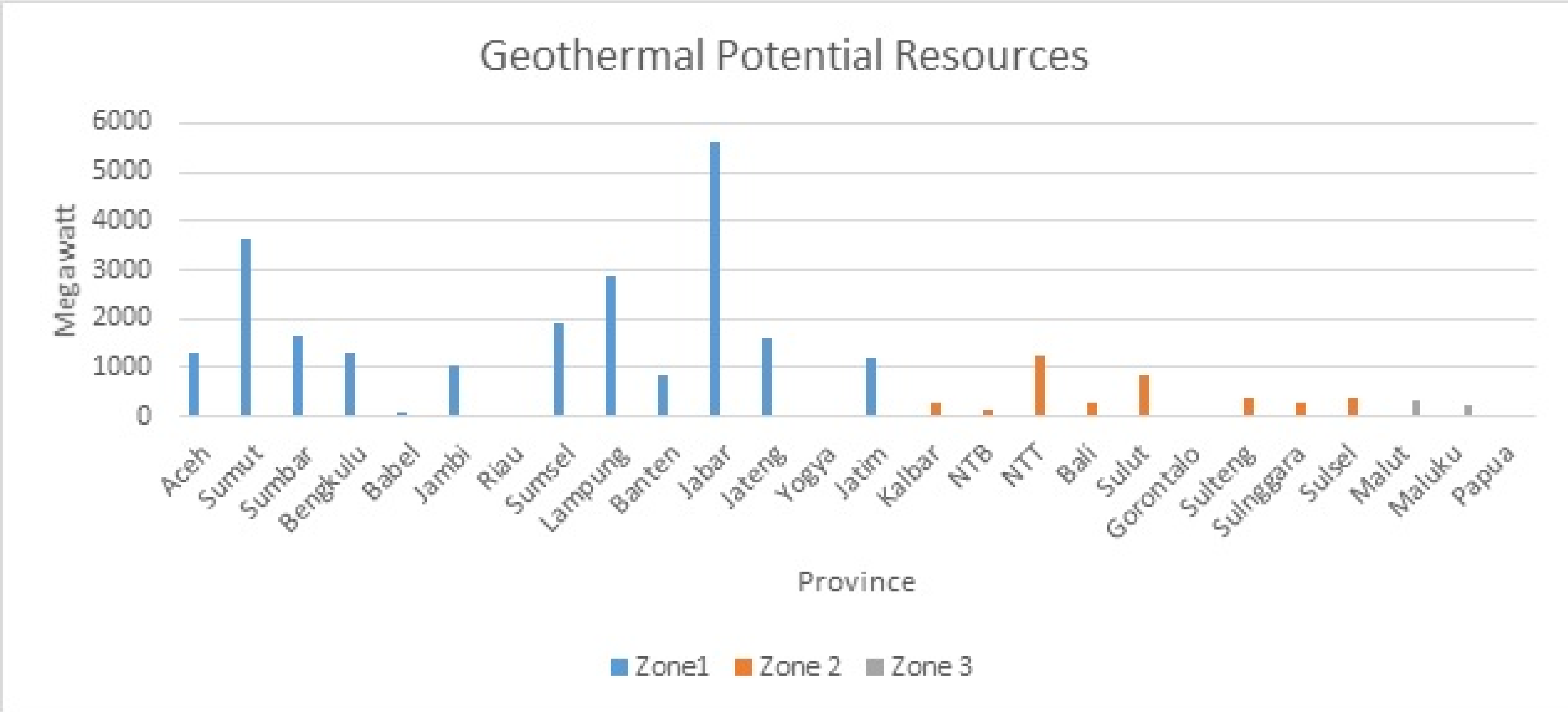

Figure 2.3: Shows geothermal potential resources

From the total geothermal potential resources per province has given above. Most of the geothermal potential resources spread in all the islands in Indonesia. Zone 1 has an average huge geothermal potential resources. Three provinces are above 2000 MW with one province Jabar surpassing potential generation of 5000 megawatts followed by Sumut and Lampung having the capacity of 3600 and 2800 megawatts respectively. Most of the provinces in zone 1 have a high potential for geothermal energy production. In Zone 2 most of the potential site is below 1000 MW with exception of NTT whose potential is slightly above 1200 MW. The geothermal potential resources from the eastern part are less compare to the other zones, all of them are less than 1000.

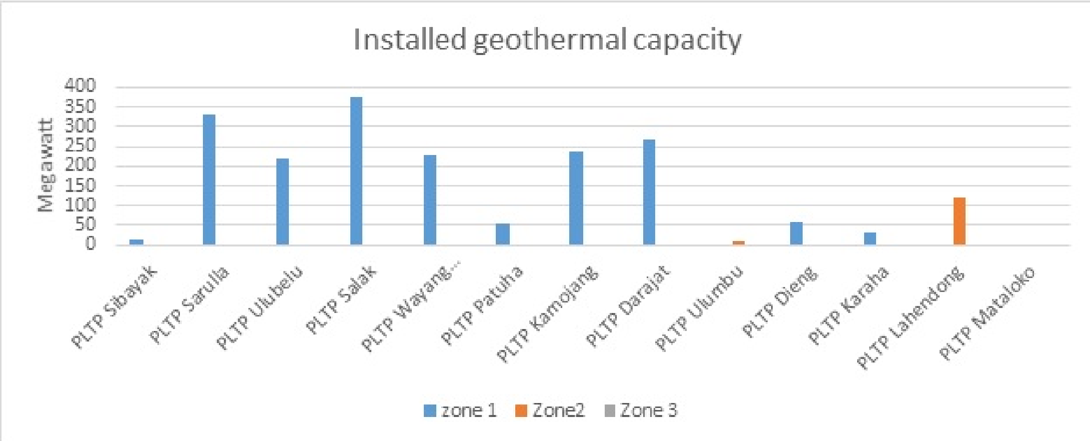

Figure 2.4: Shows installed geothermal capacity

The figures above show the total installed capacity in all the zones in Indonesia. Only 13 power plants have been built from the total geothermal potential resources. The higher capacity of power plants built in the western part of Indonesia. The biggest installed capacity is in PLTP Salak with above 370 MW installed capacity followed by PLTP Sarulla with capacity330 MW and PLTP Darajat with capacity 270 MW. PLTP Kamojang, PLTP Wayang Windu and PLTP Ulubelu have install capacity of 235 MW, 227 MW, and 220 MW respectively. The installation PLTP Sibayak, PLTP Patuha, PLTP Ulumbu, PLTP Dieng, PLTP Karaha, PLTP Lahendong, PLTP Mataloko are below 125 MW. Of the 13, Ten (10) are built-in zone 1 and the rest are in zone 2 and non are built-in zone 3 yet.

2.4 Use case of geothermal energy

2.4.1 Electricity generation

Up to the present time, 13 geothermal power plant has been undertaken in Indonesia. Moreover, several geothermal energy projects increasingly will be utilized for upcoming years [6]. In 1983, the Kamojang power plant in West Java in Indonesia was the first power plant. However, another project on the power plant was subsequently ceased operation. Electricity generation from geothermal energy in Indonesia is currently producing 1980 MW at all the power plants in Indonesia. Most of the plant uses a single flash cycle power system.

2.4.2 Direct-use applications

Direct-use applications generally require access to low to moderate geothermal resources. Lack of geothermal energy resources develops for direct-use applications in Indonesia. However, several sectors for example agriculture and Geopark include swimming pool heating. Particularly are used in the existing hot spring. Therefore, integration in direct use application improves energy performance and energy saving as well as overall energy efficiency and reduce greenhouse emission [35].

2.5 Promising Factors

2.5.1 Cost of access efficiency

A potential impediment to the development of some of Indonesia's geothermal resources for geothermal electricity generation is the distance. Most geothermal plants are built at the site of the reservoir since it is not practical to transport geothermal resources over long distances. High-voltage direct current transmission lines are used to reduce line loss carrying power capacity. Additional power lines must be built if transmission infrastructure does not exist where a geothermal resource is located.

In order to increase economically worthwhile geothermal industry. Hybrid power plants are known to more cost-effective than separate power plants. This combined system increase the overall energy conversion efficiency and reduced cost for electricity. [36]

2.5.2 Environmental considerations

Geothermal energy is generally regarded as one of the most environmentally benign sources of electricity generation. Compared to the environmental footprint associated with the natural gas and nuclear energy, renewable energy technology such as wind, water, ocean, and geothermal energy use contribute to diminishing the pollution because of their limitless reserves and zero-carbon content [37]

2.5.3 Air emissions

Geothermal fields in Indonesia will generally utilize ground-water systems and will have very few air emissions. Some concerns have been raised over radon release;

however, these are projected to be well within Indonesian occupation health and safety guidelines. The only emissions created are in building infrastructure (well completion, plant, power lines) which is necessary for all generation technologies.

2.5.4 Noise pollution

Geothermal plants produce noise during the exploration drilling and construction phases. With direct-heat applications, noise is usually negligible during operation. Noise from normal operation of power plants generally comes from the cooling tower fans, steam ejector and turbine.

2.5.5 Low environmental impacts

There is no acid rain, mine spoils, open pits, oil spills, radioactive wastes, or damming of rivers due to geothermal energy utilization. All phases of a geothermal project can potentially produce environmental impacts, including exploration e.g., active seismic exploration methods. Another reason for the development of new geothermal projects is the issue of social acceptability for some local communities who are concerned by environmental issues. [38].

2.6 Challenges of Geothermal Energy Usage

2.6.1 Environmental Challenge

Most of the geothermal potential sites located in the protected forest or national parks. During the drilling the number of environmental been destroyed. To produce enough steam for 30 MW it needs 5 to 6 wells and 3 to 4 injection wells [11]. With a large area of drilling nearly 28 Km for 11 wells [39]. This must be a serious consideration in environmental ethic. Within area covering for geothermal power plants for electricity production, environment effect is the biggest issue for the sustainable life cycle.

2.6.2 Lack of technical geothermal experts

The number of geothermal experts in electricity production must be increased due to huge potential which can be self-maintenance by the Indonesian expert as the key role person. Most of the geothermal engineers have been taken from oil and gas engineers [40]. It is quite different between geothermal experts and oil and gas experts. Another issue oil and gas engineers seem to have more prospects in the future compared to the geothermal engineers. Increasing geothermal experts is substantial as the country owned 40% total geothermal potential.

2.6.3 Cost Challenge

Due to the high investment of building geothermal power plants, the cost is one of the big issues. For typical 50 MW geothermal power plant, \$3000 to \$4000 per installed kW [41]. With 46.75% of the total cost for plant and construction, 42% of the total cost for production and exploratory drilling and the rest of the total cost for steam gathering, transmission and permitting.

2.7 Indonesia's geothermal energy market

Government policies relating to geothermal energy research, development are critical to the outlook for electricity generation from geothermal energy. The Indonesian government's renewable energy utilization program is the key contributor. A major uncertainty is the cost of electricity production as the technology has yet to be proven commercially viable. Present estimates show a wide range in the cost of geothermal electricity generation, reflecting the current of the industry, as the cost of electricity generation is highly dependent on future technology development and grid connection issues. The geothermal industry in Indonesia is progressing, with under exploration been attained in projects and expected to be achieved in at least five to seven years. Several pilot projects are expected to be completed within the next few years. Progress is being assisted by government grants with private companies to developing geothermal projects. In the Indonesian project latest long-term energy projections include the biggest installed geothermal capacity and renewable energy target to reach energy mixed 23% to fill the gap of emissions reduction target. The extraction and use of geothermal energy both for electricity generation and direct use are critical to attracting the capital investment required. Utilized the Improved information on geothermal energy potential in many parts of Indonesia data to regions with geothermal resources and reduce exploration costs. [42]

2.8 Conclusion

Geothermal energy is one of the major resources of renewable energy suitable for baseload electricity generation and direct-use applications. In general, Indonesia has significant potential geothermal resources associated with high heat-producing temperature geothermal resources. The most current geothermal potential well site has not explored yet as projects at advance commercial stage. The development of some remote geothermal resources will require additional transmission infrastructure. Geothermal energy is projected to produce around 7200 MW in 2025. The major geothermal energy developments occurring in Indonesia are focused on electricity generation.

Chapter 3

Utilization Mapping for Geothermal Energy

Geothermal brine can be utilized either for electricity generation or direct applications. Electricity generation is the most important form of utilization of high-temperature geothermal resources while low to medium resources are better suited for non-electric (direct) application. In this chapter we explore the utilization of geothermal brine.

3.1 Utilization mapping for geothermal energy with respect to temperature

The brine contains varying temperatures from low to high temperatures that can be utilized for different purposes ranging from recreation, farming, and drying and electricity production. From the brine temperature, we can predict the utilization. In our utilization mapping model, the temperature is the main source of the utilization. We use Lindal's diagram to refer to the class of utilization [20]. We apply machine learning approach to predict utilization using an input temperature and utilization as the outputs. In our model, the utilization mapping has classifications in terms of classes, sub-classes and utilization category. Class 1 uses the temperature higher than 10°C and but less than 60°C, the utilization categories in this range include fish farming, swimming pool, distillation, health facilities, and mushroom growing. Class 2 uses the temperature above 60°C and below 100°C and sub-classes $1, 2, 3$ refer to agriculture, heating and drying utilization respectively. Sub-class 1 having refrigeration and warm water as their utilization. Sub-class 2 having utilization washing and drying heavy material, and textile industry where sub-classes 3 includes drying agriculture product and drying building material as their utilization. Class 3 uses temperature range between 100°C to 180°C which contains sub-classes of freshwater distillation and flash electricity generation. Class 4 is above 180°C used for dry steam electricity production.

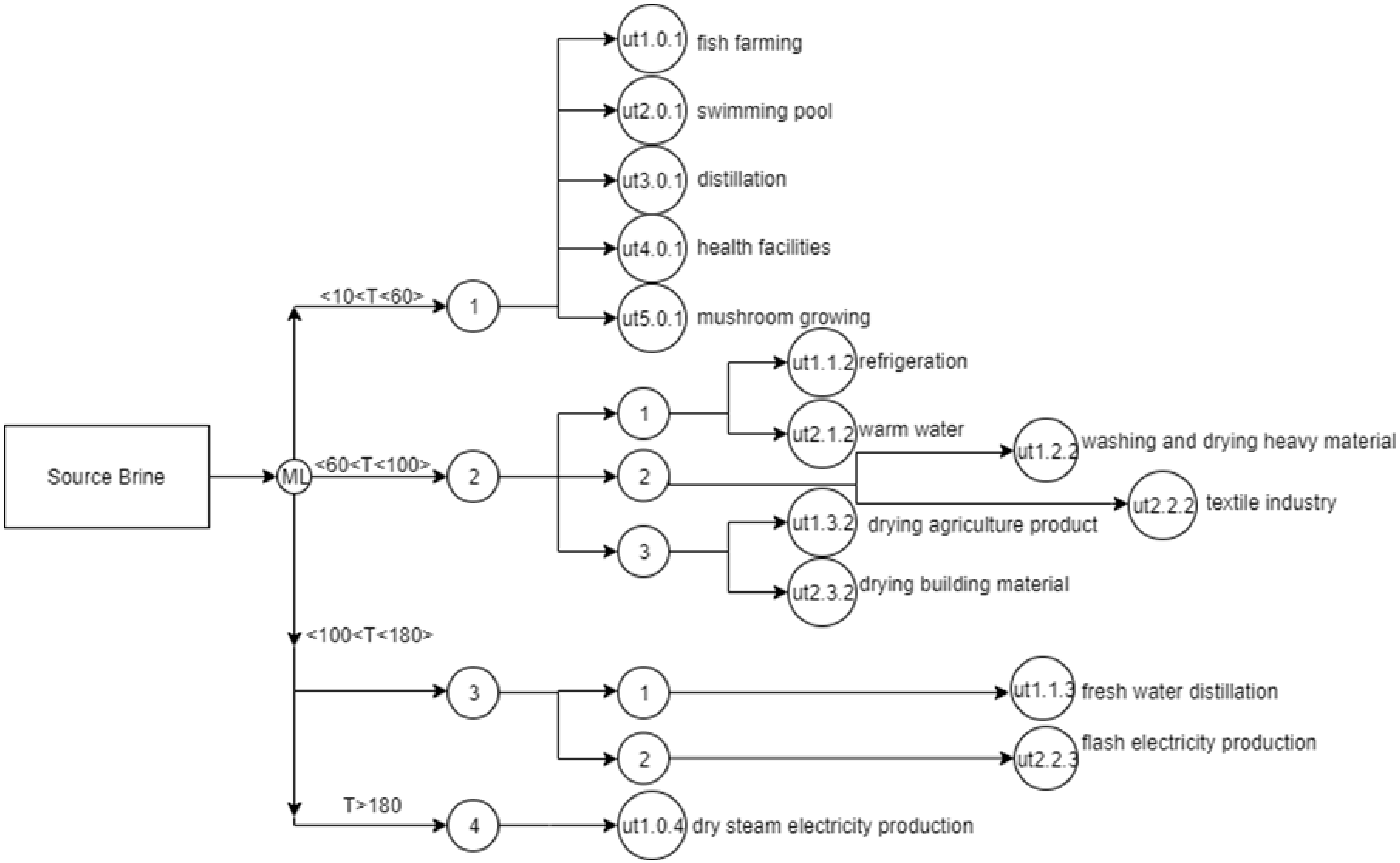

Figure 3.1: Shows Geothermal Energy Utilization Mapping

From fig. 3.1 show the brine temperature with respect to the classification of its utilization. In our model, we trained the data set based on the Lindal's diagram utilization categories [20]. The output result shows the utilization classification mapping of the brine. Our results show that there are four classes of utilization with respect to the temperature. The utilization class 1 is for brine temperature between 0°C and below 60°C. The brine in this category is used for fish farming, swimming pool, distillation, health facilities, and mushroom growing. The utilization class 2 consists of temperatures between 60°C and below 100°C, which is further categorized in three sub-classes. The brine in sub-class 1 in this category is used for refrigeration and warm water, whereas sub-class 2 is used for washing and drying heavy material and textile industry. In sub-class 3 the brine is used for drying agriculture product and drying building material. The temperature ranges of the three sub-classes are 60°C to 75°C, 76°C to 85°C, and 86°C to 99°C respectively. Utilization class 3 comprise of brine whose temperature range between 100°C to 180°C. The brine in this category is further categorized into two i.e. for clean water production and electricity production. The brine with temperatures between 100°C to 120°C is used for water distillation whereas the brine with temperatures above 120°C is used for single flash. Beyond 180°C the brine is super-hot and is used for dry steam electricity power production. This form its own class 4.

$Temp(T)$	$Class$	$SubClass)$	$Utilization$
10	1	0	1
30	1	0	3
60	1	0	5
70	2	1	2
80	2	2	2
100	2	3	2
150	3	2	2
180	3	2	2
200	4	0	1

Table 3.1: Showing snapshot of the training data in geothermal utilization

Based on the brine temperature with its utilization of Lindal's diagram from fig3.1, we can make the dataset of geothermal utilization in table3.1. the dataset consist of temperature, class, subclass, and utilization. We trained the machine learning module so that when we impute the temperature into the system the output in the form of classification(class, sub-class, and utilization) is presented. For example, if the input temperature is 70° C, the result produced is [70, 2, 1, 2] which means the brine at 70°C belongs to the second class, first sub-class, and second utilization, which is direct use for warm water.

Algorithms Representing Figure 3.1

Method `utilizationMapping` (*temp*)**:**
  while *error>acceptableError* **do**
    weight=random(-0.5,0.5)
    bias=random(-0.5,0.5)
    Classify into class , subclass, utilization
    Compute error=ua-up
    Propagate the error to adjust the weight
  end
  return class , subclass, utilization
End utilizationMapping

Algorithm 1: Machine learning algorithm for the utilization mapping

.

The backpropagation artificial neural network for geothermal utilization is represented in algorithm 1. In this algorithm, we enter the temperature as inputs and the output is class, subclass, and utilization. From the presented dataset, random and bias are set between -0.5 to 0.5. The ANN classify the predicted class, subclass, and utilization within the acceptable error. The algorithm computes the error from the subtraction of actual utilization to the predicted utilization using training data. If the error is greater than acceptable error, the algorithm continues training the ANN until the error threshold is reached. When the error is less, the algorithm produces the output of class, subclass, and utilization. Target outputs and the sample used to verify our trained Neural Network are set accordingly. Using training data with one input, three outputs, and ten layers , training functions TRAINBR, the fitting function chosen is NFTOOL, and the performance function (MSE). The input to ANN is temperature and the output are classes, subclass and utilization.

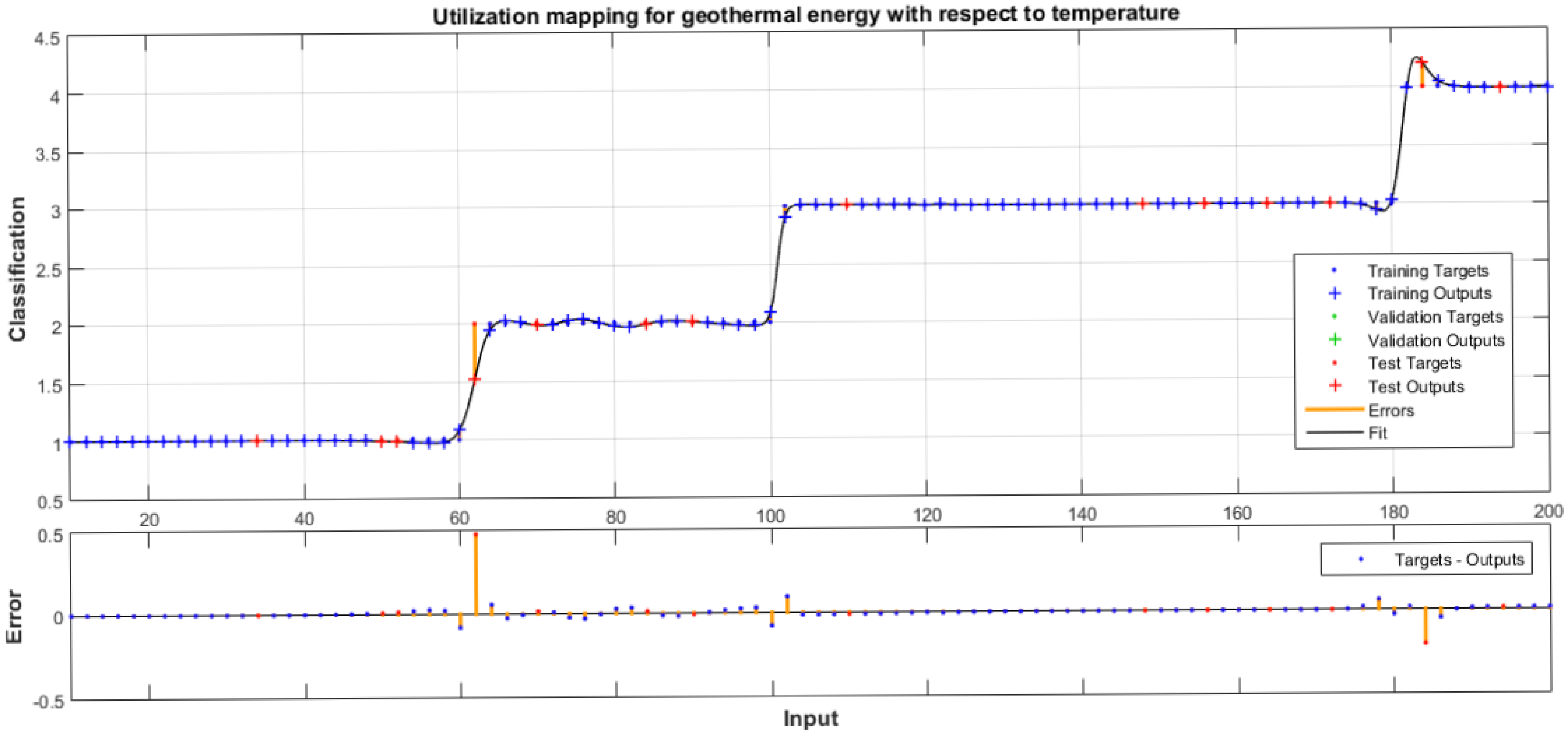

Figure 3.2: Shows Mathematical model for utilization mapping of the brine

From the machine learning model, the brine is divided into four classes shown in fig. 3.2. For each of the categories, data is fitted based on mathematical model $y = 0.9 * T + 0.24$ where T is the temperature of the well and y is the category (class of utilization).

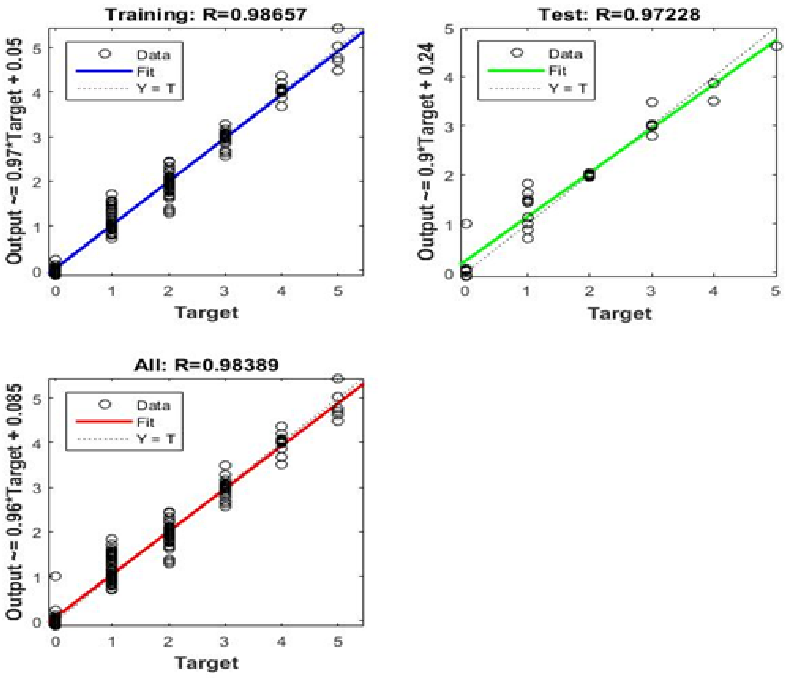

Figure 3.3: Shows class of utilization

The graph in fig 3.3 represents the result of training, testing, and all data. When we train the data into the neural network, the data automatically classify themselves into their classes. It validates the classes according to the data we have trained.

According to the report from the Ministry of Energy and Mineral Resources of Indonesia, there are 271 geothermal potentials sites in three time zones in Indonesia. They consist of different measurements that include geophysical characteristics and temperature. In our study, we use temperature as a matrix of modeling geothermal utilizations. According to Lindal's diagram, the utilization of geothermal energy vary depending upon the temperature. When the temperature is low the site is appropriate for direct uses, otherwise, the site is appropriate for power generation. From our model of utilization mapping; 87 potential site is for dry steam power generation, 75 potential site is for flash power generation, 28 potential site is for water distillation, 17 potential site is for health facility, 11 potential site is for textile industry, 11 potential site is for agricultural products, 6 potential site is for mushroom growing, 5 potential site is for warm water, 3 potential site is for distillation, 2 potential site is for drying material, and 1 potential site is for refrigeration.

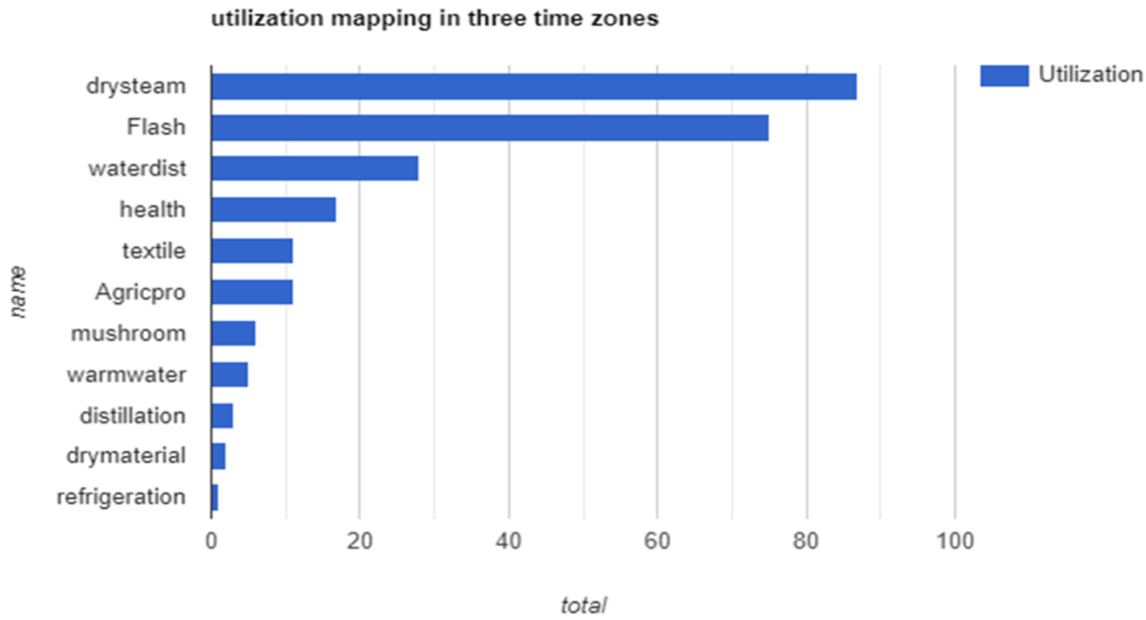

Figure 3.4: Shows utilization mapping in three time zones

3.2 Conclusion

In this chapter, utilization mapping has considered based on the mathematical model. For example model to classified the temperature best-fit utilization. The utilization mapping spread across electricity generation to the applications of direct use with respect to the temperature. Conclusively, the higher brine temperature is best for electricity generation whereas the lower temperature is best fit for direct uses.

Chapter 4

Machine Learning Model for Improving Single Flash Geothermal Energy Production

A geothermal system can be described schematically as convecting water in the upper crust of the Earth, which, in a confined space, transfers heat from a heat source to a heat sink, usually the free surface. Normally to discover geothermal site, experts must drill into the earth crust after observing some signs of existing near surface hot reservoir. The chances of finding sustainable reservoir depend on the temperature of the brine in the reservoir. Generally apart from drilling there are no feasible mechanism to predict how much power can be generated from such reservoir. Secondly, it is difficult to guest how long the reservoir will continue producing power and how deep the reservoir is. In this chapter, we devised a machine learning mechanism to assess the depth of the well, its lifespan, and how much power can be produced.

4.1 Introduction

Indonesia has a high energy demand. This is because of its rapid development, industrialization strategy, and high increase in her population [43]. Comparing to other countries, increasing population, and rapid industrialization demands high energy consumption. Thus, high energy demand results in using energy sources that may increase the effect of global warming. To decrease the effect of global warming, finding green energy alternatives become a key role in such countries. Moreover, the use of fossil as a source of power dominates [13]. The development of greener sources of energy is likely to bridge the energy gap and preserve the environment. Increasing the trend of renewable energy utilization, for example, geothermal energy, solar, wind, etc. has the capacity to fill the gap of energy consumption in Indonesia.

The development of geothermal energy is improving fast as part of Indonesia's energy development plan [44]. One part of the improvement is the development of a geothermal power plant in high enthalpy reservoirs in the country. Being in the ring of fire, Indonesia is surrounded by high enthalpy reservoirs that provide excellent geothermal potential [6]. In fact, Indonesia is estimated to possess 40% of the world's geothermal potential [45]. As of current, it is rated as the second biggest user of geothermal energy in the world [7].

Most of the power plants are constructed based on either single flash or dry steam power production technology. The nature of the power plant technology used is determined by the type of the well. In cases where the well is water dominated at high temperatures, single flash technology is adopted. Otherwise, dry steam technology is used. Other geothermal power plants that may be used include binary and hybrid. In a binary system, the well is water dominated at a lower temperature compared to the geothermal single flash system. The binary system is not used in Indonesia, because most of the wells have high temperatures. Moreover, the hybrid technology of power production may be used. The hybrid may consist of a pipeline of the geothermal system to create a multiple flash system. They may consist of a combination of other green sources of energy e.g. hydro, solar, and wind. Hybrid technologies are used to maximize the production of power. Currently, hybrid technologies are not common in Indonesia.

Using enthalpy potential, the production capacity in a single flash can be estimated. Modeling a single flash environment enables the prediction of power output from the well as a source of energy. Further, the utilization of the power output of the plant can be effectively predicted.

Machine learning techniques for supporting green energy production and prediction have been proposed in [14, 15, 46–48]. Recently, machine learning has been adopted in science and engineering. Machine learning has a dominant power to solve complex problems [49]. For example in computing, it has been used in image processing and speech recognition, in business it has been used to predict business trends, in government, it has been used for policy improvement, etc. [50–55]

In this thesis, we use machine learning to improve the single flash geothermal energy prediction of power output using the thermodynamic properties of the brine harvested from the well.

4.2 Geothermal Basic

Geothermal energy is categorized as renewable energy because it is naturally produced. The utilization of geothermal energy is commonly harvested from the underground reservoir which contains hot water or steam. Typically, the hot underground reservoir is located in the active volcanic region. A typical reservoir is either water or steam dominated with hydrothermal characteristics. Unlike other sources of green energy e.g., wind and solar that are dependent on factors such as wind speed or intensity of the sun, geothermal energy are independent and available always. For example, solar power generation depends on the sun strength, when the sun strength is low, energy harvested is low. Ideally when investing in solar, investing in batteries is a requirement. This investment makes solar power plant more expensive than geothermal in the long run.

In general, the location of the geothermal well is determined by geothermal surface manifestation. These include the availability of hot springs, hot rocks, scarce vegetation, etc. The indication through the surface might assume the development of geothermal energy for power production. Finding wells is done by drilling process in strategic positions around manifestations. This process is used to discover the initial parameter such as temperature, depth, pressure, etc. that form the basis of the decision to develop a viable geothermal plant.

The most important of geothermal energy sources utilization parameter is the temperature. The availability of temperature varies depending upon the depth of geothermal wells. Generally, the geothermal gradient in the ring of fire is about 0.025°C m-1 to 0.03°C m-1 [56]. Therefore, knowing the temperatures allows the feasible design of the geothermal power plant system. Moreover, the temperature is an important factor in classifying the use of geothermal energy source. For higher temperatures above 130°C and below 180°C the source can be used for power production using the single flash system, otherwise, at low temperatures below 100°C, the source may be used in drying organic material, space heating, animal husbandry, etc. [20].

Geothermal for power production basically use the thermodynamic properties of brine. These properties include temperature, enthalpy, concentration, entropy, flow rate, pressure, etc. They are used in combination with the laws of thermodynamics to calculate the ability to do work of the geothermal power plant. The power production potentially predicted along with thermodynamic and chemical properties of the brine in the reservoir allows us to estimate the amount of power that will be produced.

4.3 Geothermal Single Flash System

4.3.1 Single Flash Model

In this technology, the geothermal fluid is harvested from liquid dominant wells heated earth crust as a result of movement in the tectonic plates. This technology is dominantly applied in geothermal plants in Indonesia [12].

The components in designing geothermal electricity plant include the geothermal well, flash tank, turbine attached to a generator, condenser, and the pump. The geothermal well is the major source of energy that drives the production of geothermal power.

There are two types of wells constructed at the site. That is production well and injection well. The production well is responsible for the production of brine at high temperatures that is fed into the flash tank. The flash is to stabilize the pressure and temperature through vapor-liquid equilibrium. In this case, the flash tank acts as a separator between vapor and liquid. The liquid is injected back to the well, whereas the vapor is scrubbed before being directed through a jet nozzle, then to the impeller which in turn drives the generator. During operation, the brine from production well enters the flash tank. The pressure causes the liquid to turn into steam (flashing). At vapor-liquid equilibrium (VLE), the inflow brine is separated into two, the steam and the liquid. The steam is harvested at steady temperature and velocity to drive the turbine. At the same time, the liquid residue is pumped back into the well. At the turbine end, the vapor temperature reduces and is converted into steam which is not useful. This steam can be condensed and pumped back into the well or used for other purposes. The liquid in the flash is drained out and pumped to the well if the temperature has dropped below a certain threshold, otherwise, the liquid can be fed in another flash to achieve double flash technology. The power generated from the turbine end is placed on the grid for transmission.

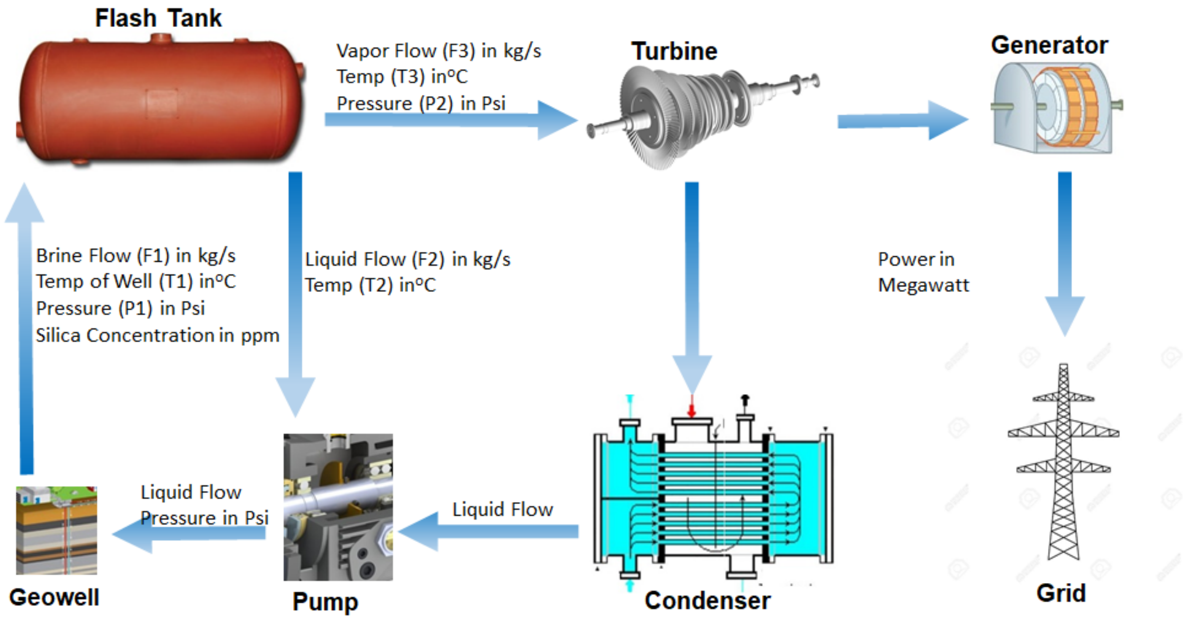

Figure 4.1: Shows Geothermal Single Flash Design Model

4.3.2 Overview of the components of the geothermal single flash system

The Well

The heat source of geothermal energy is well located deep below the earth's surface. The center of the earth is very hot. The tectonic activity causes fractures in the earth's crust. Because of the high temperature, there is a difference in pressure from the heat source and the surface of the earth. This causes the magma to flow through the cracks, which in turn causes water along the path of the cracks to heat up. The underground contains hot fluid or brine that is collected in a specific pool creating a form of the reservoir. The brine contains hot water and another component of silica in a certain concentration. Normally, the well close to the earth's surface is exhibited by existing of hot spring, mud bubbling, and fumarole. The well is characterized into either vapor-dominated or water dominated. The well is a major component of geothermal power production plant [57].

Determining Depth of the well

In the exploration phase of the well, open wells are drilled. From these wells samples of the brine are collected and their concentration measured along with the temperature and pressure. In this process depth of the well is determined. Temperature is one of the major variable used to determine the viability of power generated. As you dig deeper into the well, the temperature continuous increasing that allows for determining the temperature gradient. The temperature gradient is used for predicting the depth of the well [58].

The depth of the geothermal well is given by the following equation .4.1

$$d_m = g_t \times T + K \tag{4.1}$$

where K is a scalar constant reflecting the minimum depth before hitting the surface of the well, g_t is the temperature gradient, T is the temperature at a specific depth, and d_m is the depth of the well.

Determining life of the well

The most promising case for successful geothermal power plant is the availability of geothermal wells. Every 1000 meter of the depth the temperature increases by $25 - 30^oC$ [11][14]. The activity of drilling a well costs 45% of the total project of building a geothermal power plant [23]. Therefore, having a well which will live for a short time is infeasible. In our study, we lay a method to estimate the life of a well-using machine learning. This follows a supervised model in equation 4.2.

$$t_a = f(T_o, \frac{\delta T}{\delta H}, V_o, \dot{W}_e) \tag{4.2}$$

where t_a, is the lifespan of the well, T_o the original temperature of the well, $\delta T/\delta H$ is the geothermal gradient, V_o is the volume flow rate, and $\dot{W}_e$ is the system power output [59].

We assume there exist $n = 1, 2, 3...$ wells that power geothermal power plant. From each well, temperature, pressure, flow rate and concentration of the brine can be measured from time to time. Keeping other conditions such as the wear and tire of the pipes in the well, the life of the well mainly depends on temperature. From the time of first utilization, the temperature of the well reduces gradually. The reduction may be so small but after a long period of time the well may cool down, thus the well becomes unusable for power production.

We may find the high pressure, temperature and high flow rate during exploration as well as power generation for some considerable amount of time. Nonetheless, continuous use may result in a decrease in the efficiency of the well. When the efficiency reduces below the threshold the well is closed. Authors in [11] assert that well may live between $20-30$ years. Along with the decreasing temperature, pressure and flow rate, tire and wear of the infrastructure, and environmental factors may cause well to be shut down. As a result of decreasing the efficiency of a well, it is important to determine the life of the well before the well is brought to complete shutdown.

At the same vicinity, there are often many wells (production wells and injection wells). Each of these wells may have their own parameter that varies. Every single well has its temperature, pressure, flow rate, etc. therefore, the lifespan of well differ.

The Flash tank

The device used in geothermal electricity power production to separate a mixture of vapor and liquid is the flash tank. This is achieved by the separation mechanism. The flash tank is one of the unit operations of brine. The brine contains many components which include water, pentane, butane ammonia, etc., [11] on entry into the flash tank the saturated liquid is immediately flashed due to pressure drop as a result of passing through a throttling device at some pressure and temperature. Evaporation occurs within the vessel causing the brine to separate into vapor and liquid. The brine may be partially or totally flashed into a vapor.

Flash process

The brine at temperature (T) enters the inlet of the separator. Flashing occurs at state 1 (as shown in fig.2 and 3), near to the critical point on the saturation curve. Two phases of brine occur i.e. vapor and liquid form. This process occurs steadily, spontaneously and adiabatically. No work is involved. This allows us to neglect any changes in kinetic and potential energy, hence the process is isenthalpic. That means enthalpies at point 1 and 2 are the same, see fig.3. Generally, enthalpy is labeled as h_i, where $i = (1, 2, 3, \cdot)$ is points along the enthalpy curve that describes the condition of the brine. During the flashing process $h_1 = h_2$ at constant pressure. The above process allows us to compute the dryness fraction.

The dryness fraction is a ratio of liquid to vapor in the brine. The dryness fraction is given by the following equation (4.3).

$$x_2 = \frac{h_2 - h_3}{h_4 - h_3} \tag{4.3}$$

The dryness fraction determines the quality of the mixture after flashing. It is an important factor in predicting the amount of power generated at the turbine. By definition, it is the ratio of evaporating enthalpies $(h_2 - h_3)$ to steam enthalpies $(h_4 - h_3)$. This gives a steam mass fraction of the mixture which flows to the turbine.

The analysis for generating electricity for a single flash geothermal power plant is based on the principle of thermodynamics of the conversion process. The Temperature-entropy diagram fig. 4.2 and Temperature-enthalpy diagram fig. 4.3 explains the ideal process of flashing. Authors in [60] provide a comprehensive discussion about the flashing process.

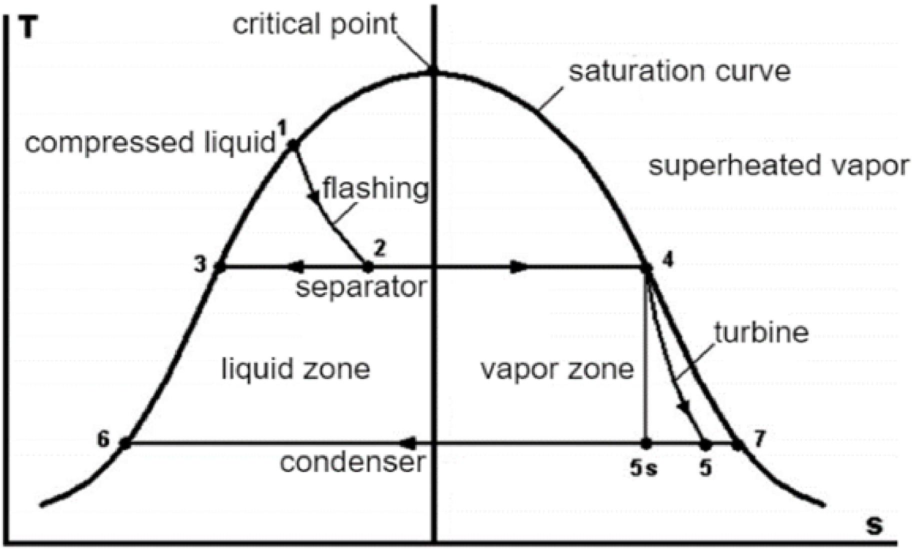

Figure 4.2: Shows Temperature-entropy diagram

From the diagrams, the left portion from the critical point is a saturated liquid which forms enthalpies and entropies in the liquid condition, whereas the right-side forms enthalpies and entropies in the vapor condition. The intersection of the conditions forms a critical point that occurs at the maximum temperature where liquid starts to turn into vapor. For further explanation refer to the works in [11].

Turbine

This component of the geothermal system consists of impellers which are rotated by a vapor that comes from the flash tank through jet nozzles directly pointed to them. The turbine is attached to the generator which is responsible for producing power. The power produced by the turbine is critical for determining the capacity of a power plant

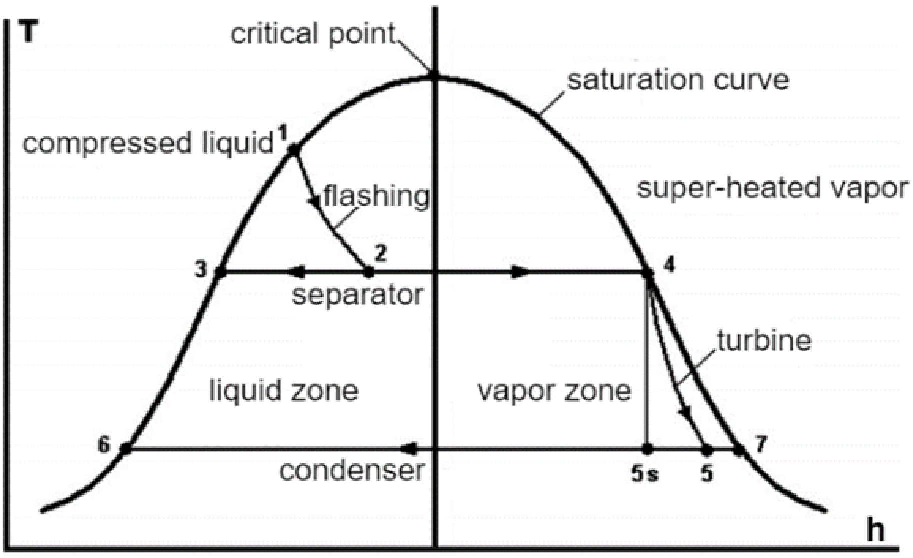

Figure 4.3: Shows Temperature-enthalpy diagram

[11]. In our study, we modeled this process based on turbine expansion computation.

Turbine expansion process

The turbine expansion process is based on the work done by the turbine $(w_t).w_t$ is the enthalpy difference at the inlet of the turbine (h_4) and the enthalpy at the outlet of the turbine (h_5).

Work produced by the turbine is given by the following equation (4.4)

$$w_t = h_4 - h_5 \tag{4.4}$$

The ideal process occurs between point 5 and 5_s. To compute the efficiency of the turbine we find the ratio of actual turbine work to ideal turbine work is represented by the following equation (5).

$$n_t = \frac{h_4 - h_5}{h_4 - h_{5s}} \tag{4.5}$$

The turbine power is expressed by equation (4.6), which is computed as a product of dryness fraction, total mass flow, and work produced by the turbine. To this end, we can compute the gross electric power as in equation (4.7), which is the product of generator efficiency and turbine power. In another way, the generator efficiency can be considered as a constant specification of the generator. Otherwise, isentropic efficiency is considered as computed in equation (4.8)

$$\dot{W}_t = m_s - w_t = w_t = x_2 \times m_{total} \times w_t \tag{4.6}$$

The gross electrical power equal to generator efficiency and turbine power is expressed as

$$\dot{W}_e = n_g \times \dot{W}_t \tag{4.7}$$

Isentropic efficiency is written by

$$n_{tw} = n_{td} \times \frac{(x_4 + x_5)}{2} \tag{4.8}$$

Generally speaking, $n_td = 0.850$ assume by 85% of dry turbine efficiency, this assumes a threshold of 85% is sufficient.

Enthalpy (h_{5s}) can be computed by following equation 4.9.

Enthalpy (h_5) can be computed by the following equation (4.10). Where factor $A = 0.425(h_4 - h_{5s})$.

$$h_{5s} = h_6 + [h_7 - h_6] \times \frac{(s_4 + s_6)}{(s_7 - s_6)} \tag{4.9}$$

As well as the enthalpy of 5 is found by the following equation

$$h_5 = \frac{h_4 - A[1 - \frac{h_6}{h_7 - h_6}]}{1 + \frac{A}{h_7 - h_6}} \tag{4.10}$$

When the dryness fraction is 1 double flash technology is appropriate and h5 is computed by the following equation (4.11).

$$h_5 = \frac{h_4 - A[x_4 - \frac{h_6}{h_7 - h_6}]}{1 + \frac{A}{h_7 - h_6}} \tag{4.11}$$

$(forx_4 < 1)$

The comprehensive discussion about the turbine expansion process is given in. [11]

Condenser

The condenser is a kind of heat exchanger where vapors are converted into liquid. It is the art of removing the heat using a coolant such as water. The cooling is attained from a cooling tower. A condenser is normally used in all geothermal plants. The aim of the condenser is to maximize turbine efficiency. It maintains removing dissolved noncondensable gases from the condensate. Further, the cooling content is re-injected into the well. The processes in the condenser can be modeled using equation (4.12) and (4.13). [61]

$$\dot{m}_{cw} = x_2 \times \dot{m}_{total} \times [\frac{h_5 - h_6}{c\Delta T}] \tag{4.12}$$

$$\dot{m}_{cw} = x_2 \times \dot{m}_{total} \times [\frac{h_5 - h_6}{c(T_6 - T_{cw})\Delta T}] \tag{4.13}$$

4.4 Machine Learning Models for Single Flash System

4.4.1 The Well Machine Learning Model

The use of the neural network as part of machine learning to predict the desired depth of the well. We measure temperature and depth at different point of well that composes the dataset. The sample of the data used for training to the neural network. The trained neural network is used to predict the depth of the well by capturing the temperature as an input. The dataset is attained from [27]

The fig. 4.4 represent the geothermal machine learning well model. In this model, there are two machine learning modules. The first module imputes temperature and output depth, while the second neural network module imputes temperature, gradient, flow rate and power output generated from the turbine. From the presented dataset, we enter the temperature, temperature gradient, volumetric flow rate and power output as inputs. Neural Network module one accepts temperature and outputs depth. The second module accepts all the inputs and outputs the lifespan of the well. Target outputs and the sample used to verify our trained Neural Network are set accordingly. The training function used in here is TRAINLM, the adaption learning function chosen is LEARNGDM, the performance function is MSE. We use 10 layers and the transfer function is PURELIN. The machine that we develop learns through many times of

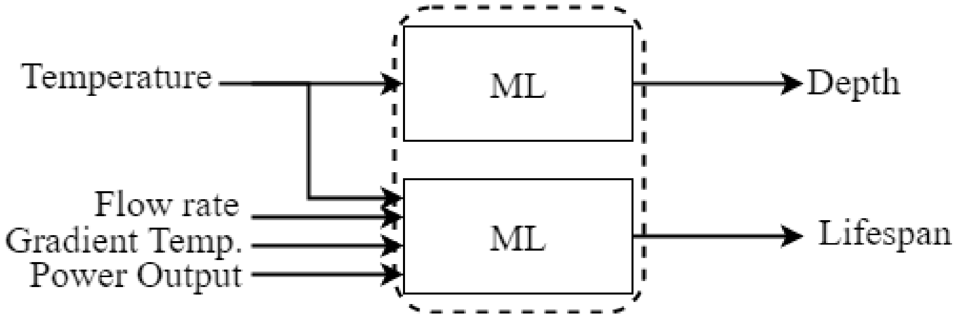

Figure 4.4: Shows the well machine learning model

training. We observed, our results through adjusting temperature different values. For instance, at the temperature 180°C, the depth attained to 570 meters from the surface of the well according to the trained data.

Algorithms Representing Figure 4.4

Method `wellProcess(` *wellData*`)`**:**
  depth=depth(wellData)
  lifeSpan=lifespan(wellData)
End wellProcess

Algorithm 2: Machine learning algorithm for the well depth and life span

.

The well process is represented in algorithm 2. In this algorithm, two ML methods have been presented. Well data that includes temperature, volumetric flowrate, gradient temperature and power out is used to determine the depth and lifespan. the details of depth and lifespan methods are presented in algorithm 3 and 4 respectively.

```
Method depth( temp):
    while error>acceptableError do
        weight=random(-0.5,0.5)
        bias=random(-0.5,0.5)
        Compute depthOfWell=d
        Compute error=da-dp
        Propagate the error to adjust the weight
    end
    return depth=d
End depth
```

Algorithm 3: Machine learning algorithm for the well depth

.

The backpropagation artificial neural network depth of the well is represented in algorithm 3. In this algorithm, we enter the temperature as inputs and the output is depth. Random and bias are set between -0.5 to 0.5 within the acceptable error. The algorithm computes the error from the subtraction of actual depth to the predicted depth. If the error is greater than acceptable error, the algorithm train again until the error is less than acceptable error. When the error is less, the algorithm produces the output of depth. Target outputs and the sample used to verify our trained Neural Network are set accordingly. The training function used here is TRAINLM, The adaption learning function chosen is LEARNGDM, the performance function is MSE, and the transfer function is PURELIN. The number of inputs, layers and output are one, ten, and one respectively.

```
Method lifeSpan( temp,flowRate,grad,powerOut):
    while error>acceptableError do
        weight=random(-0.5,0.5)
        bias=random(-0.5,0.5)
        Compute lifespan=lp
        Compute error=la-lp
        Propagate the error to adjust the weight
    end
    return lifespan
End lifeSpan
```

Algorithm 4: Machine learning algorithm for the well lifespan

.

The backpropagation artificial neural network lifespan of the well is represented in algorithm 4. In this algorithm, we enter the temperature, flow rate, gradient and power output as inputs and the output is lifespan. Random and bias are set between -0.5 to 0.5 with the acceptable error. The algorithm computes the error from the subtraction of the actual lifespan to the predicted lifespan. If the error is greater than acceptable error, the algorithm train again until the error is less. When the error is less, the algorithm produces the output of lifespan. Target outputs and the sample used to verify our trained Neural Network are set accordingly. The training function used here is TRAINLM, The adaption learning function chosen is LEARNGDM, the performance function is MSE and the transfer function is PURELIN. The number of inputs, layers and output are four, ten, and one respectively

4.4.2 The Flash Machine Learning Model

In this model, machine learning is used to predict the enthalpies in fig. 4.5 and entropies in fig. 4.6. We choose to use machine learning to generate the values of enthalpies and entropies at a given temperature. We are inspired to use machine learning to predict the correct value to replace the huge saturated water temperature table [60]. The use of machine learning lifts the burden of lookup for values of enthalpy and entropy of a given temperature in the flash. Using similar neural network setting in section 4.4.1 and the saturated water temperature table data we train the neural network to predict the entropies and enthalpies with at most accuracy. For enthalpies, we assume temperature at the Vapor-Liquid Equilibrium, where for entropies we assume temperature at condensation point i.e. the point at which vapor ceases to produce efficient work at the turbine. Literature suggests that if the temperature drop by 15% then the vapor is not sufficient for power production [11]. In this case, we adopt this temperature to compute entropies at condensation. Therefore, a drop of 15% is the threshold against dryness of the steam is acceptable at the turbine [11]. Based on these conditions, the

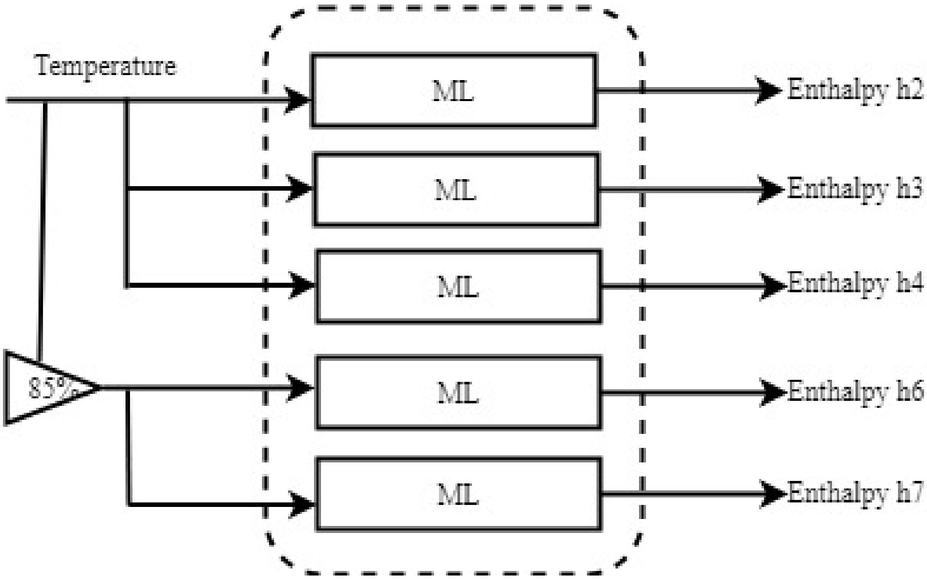

Figure 4.5: Shows Flash machine learning model

machine learning strategy can be applied to simulate enthalpy and entropy.

Using enthalpy and entropy generated through a machine learning process, the dryness fraction can be computed using equation (4.3). The dryness fraction is used to determine the quality of steam that goes to the turbine at the isobaric condition. To produce the enthalpy and entropy, the machine learning modules have been trained using data obtained from the property table and charts for saturated water in [60]. We observed during simulation, the enthalpies and entropies produced by our system are the same with a very small margin of error. We conclude that the predicted steam quality maintains the turbine efficiency. Therefore, the predictions are used to compute turbine efficiency using equation (4.5), turbine power using equation (4.6), power on the grid using equation (4.7). The characteristics of ANN in determining entropies and enthalpies remain the same as those in section 4.4.1

Algorithms Representing Figure 4.5

```
Method flashEnthalpy( temp,satLiq,satEvap,satVap):
    while error>acceptableError do
        weight=random(-0.5,0.5)
        bias=random(-0.5,0.5)
        Compute h1
        Compute error=h1a-h1p
        Compute h2
        Compute error=h2a-h2p
        Compute h3
        Compute error=h3a-h3p
        Compute h4
        Compute error=h4a-h4p
        Propagate the error to adjust the weight
    end
    return h1,h2,h3,h4
End flashEnthalpy
```

Algorithm 5: Machine learning algorithm for the enthalpy

.

The backpropagation artificial neural network of the enthalpy is represented in algorithm 5. In this algorithm, we enter the temperature, saturated liquid, saturated evaporation, and saturated vapor as inputs and the output is enthalpies. Random and bias are set between -0.5 to 0.5 with the acceptable error. The algorithm computes the error from the subtraction of actual enthalpy to the predicted enthalpy. If the error is greater than acceptable error, the algorithm train again until the error is less. When the error is less, the algorithm produces the output of enthalpies. Target outputs and the sample used to verify our trained Neural Network are set accordingly. The training function used here is TRAINLM, The adaption learning function chosen is LEARNGDM, the performance function is MSE and the transfer function is PURELIN. The number of inputs, layers and output are one, ten, and four respectively

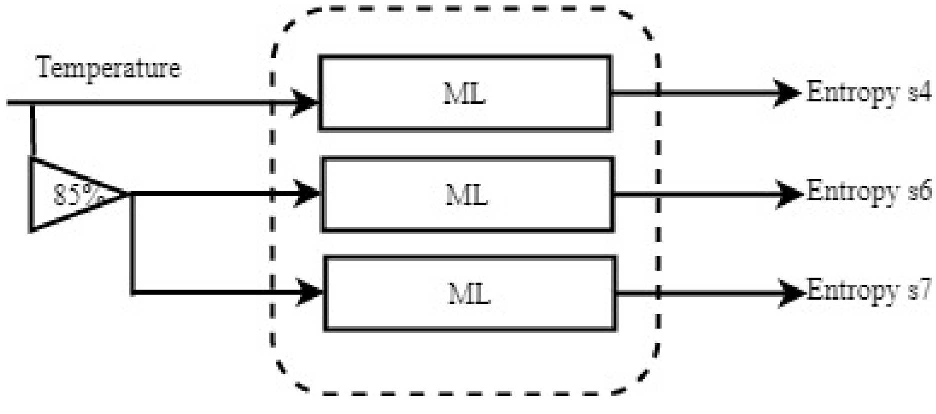

Figure 4.6: Shows Entropy machine learning model

Algorithms Representing Figure 4.6

```
Method flashEntropy(temp,satLiq,satEvap,satVap):
    while error>acceptableError do
        weight=random(-0.5,0.5)
        bias=random(-0.5,0.5)
        Compute s4
        Compute error=s4a-s4p
        Compute s6
        Compute error=s6a-s6p
        Compute s7
        Compute error=s7a-s7p
        Propagate the error to adjust the weight
    end
    return s4,s6,s7
End flashEntropy
```

Algorithm 6: Machine learning algorithm for the entropy

.

The backpropagation artificial neural network of the entropy is represented in algorithm 6. In this algorithm, we enter the temperature, saturated liquid, saturated evaporation, and saturated vapor as inputs and the output is enthalpies. Random and bias are set between -0.5 to 0.5 with the acceptable error. The algorithm computes the error from the subtraction of actual entropy to the predicted entropy. If the error is greater than acceptable error, the algorithm train again until the error is less. When the error is less, the algorithm produces the output of entropies. Target outputs and the sample used to verify our trained Neural Network are set accordingly. The training function used here is TRAINLM, The adaption learning function chosen is LEARNGDM, the performance function is MSE and the transfer function is PURELIN. The number of inputs, layers and output are one, ten, and three respectively.

4.4.3 Mass Flow Rate Model

The flow rate is an important component of determining the power produced by the turbine. According to authors in [11], the mass flow rate at a given absolute pressure can be determined by equation (4.14) for chocked well, moreover, for the non-chocked well equation (4.15) is used to compute the mass flow rate. We use this equation (4.14) to generate data that is used to train a NN for determining the mass flow rate. Fig. 4.7 represents the mass flow rate machine learning model.

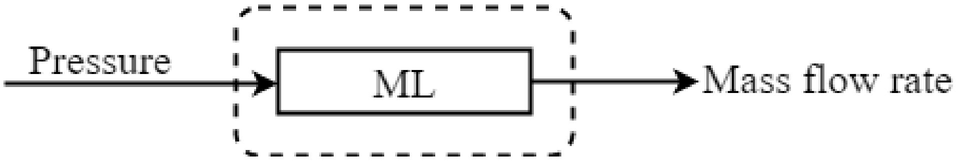

Figure 4.7: Shows mass flow rate machine learning model

$$\dot{m}_{total} = 99.6663 - 2.6287P_2 + 0.5802P_2^2 - 0.04212P_2^3 \quad (4.14)$$

$$\dot{m}_{total} = 44.333 - 0.3363P_2 - 0.1357P_2^2 \quad (4.15)$$

where $\dot{m}$ is mass flow rate and P is pressure.

Algorithms Representing Figure 4.7

Method `massFlow(`*pressure*`)`**:**
    while *error>acceptableError* **do**
        weight=random(-0.5,0.5)
        bias=random(-0.5,0.5)
        Compute massFlow=m
        Compute error=ma-mp
        Propagate the error to adjust the weight
    end
    return massFlow=m
End massFlow

Algorithm 7: Machine learning algorithm for the mass flow rate

.

The backpropagation artificial neural network of the mass flow rate is represented in algorithm 7. In this algorithm, we enter the pressure as input and the output is mass flow rate. Random and bias are set between -0.5 to 0.5 with the acceptable error. The algorithm computes the error from the subtraction of the actual mass flow rate to the predicted mass flow rate. If the error is greater than acceptable error, the algorithm train again until the error is less. When the error is less, the algorithm produces the output of mass flow rate. Target outputs and the sample used to verify our trained Neural Network are set accordingly. The training function used here is TRAINLM, The adaption learning function chosen is LEARNGDM, the performance function is MSE and the transfer function is PURELIN. The number of inputs, layers and output are one, ten, and one respectively.

The general algorithms for single flash is presented below

Method `singleFlash(` *temp,flowRate,grad,powerOut,satLiq,satEvap,satVap,pressure*`)` **:**

<d,l>=wellProcessell(temp,flowRate,grad,powerOut)
<h2,h3,h4,h5,h6,h7>=flashEnthalpy(temp,satLiq,satEvap,satVap)
<s4,s6,s7>=flashEntropy(temp,satLiq,satEvap,satVap)
<m>=massFlow(pressure)
Compute x2:dryness fraction using equation (4.3)
Compute wt:workturbine using equation (4.4)
Compute nt:turbine efficiency using equation (4.5)
Compute Wt:turbinePower using equation (4.6)
Compute We:powerGrid using equation (4.7)
Compute h5s:enthalpy using equation (4.9)
Compute h5:enthalpy using equation (4.10)
Compute mcw:massflow condenser using equation (4.12)
Compute mtot:total massflowrate using equation (4.14)

End singleFlash

Algorithm 8: Machine learning algorithm for the Single Flash

.

The geothermal single flash process is represented in algorithm 8. In this algorithm, we enter the data from the well process, enthalpy, entropy, and mass flow rate as inputs and the output results compute the given equations. Then the power output is achieved. The details of well process, enthalpy, entropy, and mass flow rate methods are presented in algorithms 2, 5, 6 and 7 respectively

4.4.4 Turbine Module

At the turbine, the work produced is computed by equation (5.3), turbine efficiency in equation (4.5), the power produced by the turbine is computed using equation (4.6) the value of dryness fraction, mass flow rate produced by fig.4.7, and the work produced by the turbine is used to determine power produced by the turbine.

The quality of power depends on enthalpies which in turn determine the dryness fraction. The mass flow rate in the non-choked well is determined by using the second-order equation (4.15) which can be modeled using machine learning on its own.

4.4.5 Grid module

The power estimated at the turbine is gross mechanical power. The gross electric power is estimated by equation (4.7). The efficiency of the generator should not be less than 85%. Otherwise, the power produced will not be sufficient.

4.5 Conclusion

In our model we have modeled the single flash component using machine learning. The model component includes the well process, flash enthalpy, and flash entropy. In the well process we have modeled the depth and lifespan. In the flash, we have modeled the thermodynamic property(enthalpy, entropy), and mass flow rate. From the model we able to predict power produced by the flash system at a given temperature of brine. Results of this model presented in chapter 5.

Chapter 5

Experimental Setting, Results, and Discussion

In this chapter, we present the result of simulation as a result of machine learning configuration presented in chapter 4. In our model, we predict power output to the grid with at most efficiency. Our methods use entropy and enthalpy in isobaric conditions.

5.1 Simulation Environment

Table 2 shows the items and specifications of the simulation environment we used to design, develop, and implement the simulation experiment.

Items	Specification
Processor	Intel Core i3-3217U CPU @1.8GHz
Operating System	Windows 10 64 bits O/S
Hard Disk	500 GB
RAM	4.00 GB
Simulation Environment	MATLAB 2015

Table 5.1: Showing items and specification of the experiment

5.2 Simulation Setup

Our simulation follows the setup as visualized in fig.5.1. We start by imputing temperature and pressure at a given point. From temperature and pressure enthalpies and entropies are generated as described in section 4.4.2. From the same inputs, the system generates the mass flow rate as described in section 4.4.3. The depth and the life of the well are predicted as described in section 4.4.1. The power produced at both the turbine and the grid is predicted based on section 4.4.4 and 4.4.5.

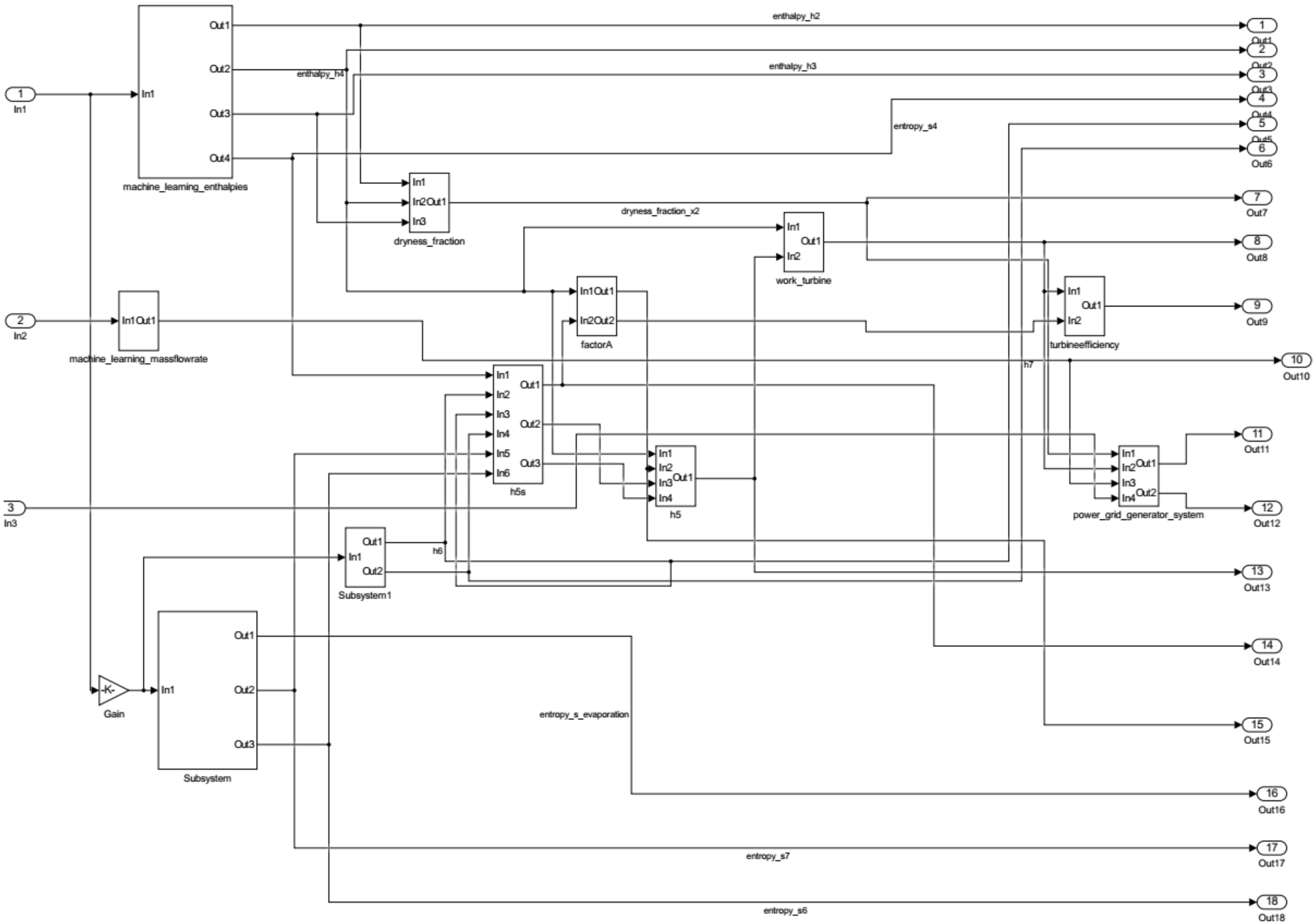

Figure 5.1: Shows simulink model for geothermal power prediction

5.3 Presentation of results

In this section, we present the results of the simulation experiment in Table 5.2

$Temp(C)$	$Pres(Bar.a)$	$Dry(x_2)$	$Work(kJ)$	$Effi.(n_t)$	$PTur(kW)$	$PGrid(kW)$
100	1.01	0.81	77.3	0.84	6170	6108
120	1.99	0.77	86.1	0.83	6466	6401
140	3.61	0.72	93.4	0.83	6555	6489
160	6.18	0.66	99.1	0.83	6404	6340
165	7.00	0.66	100.3	0.84	6310	6247
170	7.92	0.65	101.5	0.83	6173	6112
175	8.93	0.64	102.6	0.83	5970	5910
180	10.02	0.62	103.6	0.83	5678	5622
185	11.23	0.60	104.6	0.83	5250	5198
190	12.55	0.59	105.4	0.83	4636	4589
195	13.98	0.57	106.2	0.83	3770	3732
200	15.54	0.56	106.8	0.83	2486	2461
205	17.24	0.54	109.3	0.83	680	673

Table 5.2: Showing a variation of temperature and geothermal parameters in a single flash

5.4 Discussion of Results

5.4.1 Dryness Fraction

The graph in fig. 5.2 shows dryness fraction against temperature. From the graph higher temperatures results in low dryness fraction. As the temperature is increased from 100 towards 205°C, the dryness fraction drops from 0.81 to 0.54. Consequently, the work done as a result increase from 77.3 kJ to 109.3kJ. Moreover, the pressure is observed to increase with temperature. The dryness fraction at low temperature is high because of the liquid content in brine. As the temperature increase, the liquid content reduces creating low dryness fraction hence increase in work. These results imply that the flash achieved better performance when the dryness fraction is between 0.68 and 0.77 in the temperature range of 120 to 155°C.

5.4.2 Turbine work

The graph in fig. 5.3 shows the effect of temperature on the work done by the turbine. As the temperature increases the work done increases gradually with a low gradient. This implies that at high-temperature work done is high therefore the power output is low. At temperature above 205°C, the work done is more than 109 kJ beyond which there is no power output at the turbine. At very high temperatures the pressure is very

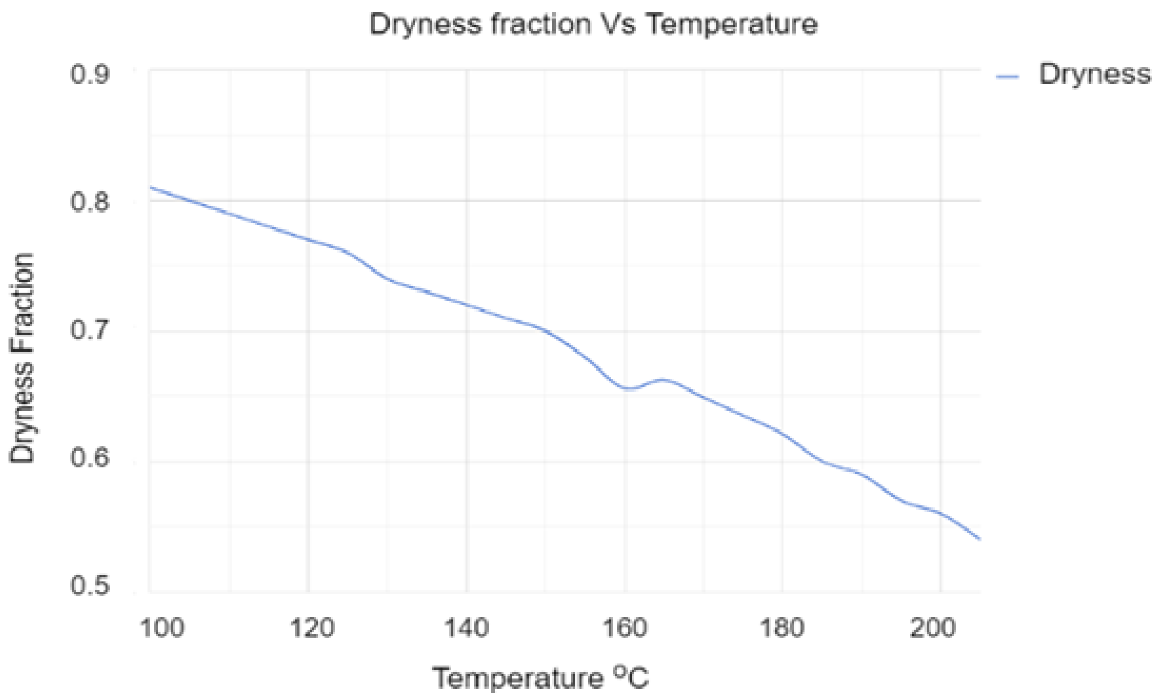

Figure 5.2: dryness fraction

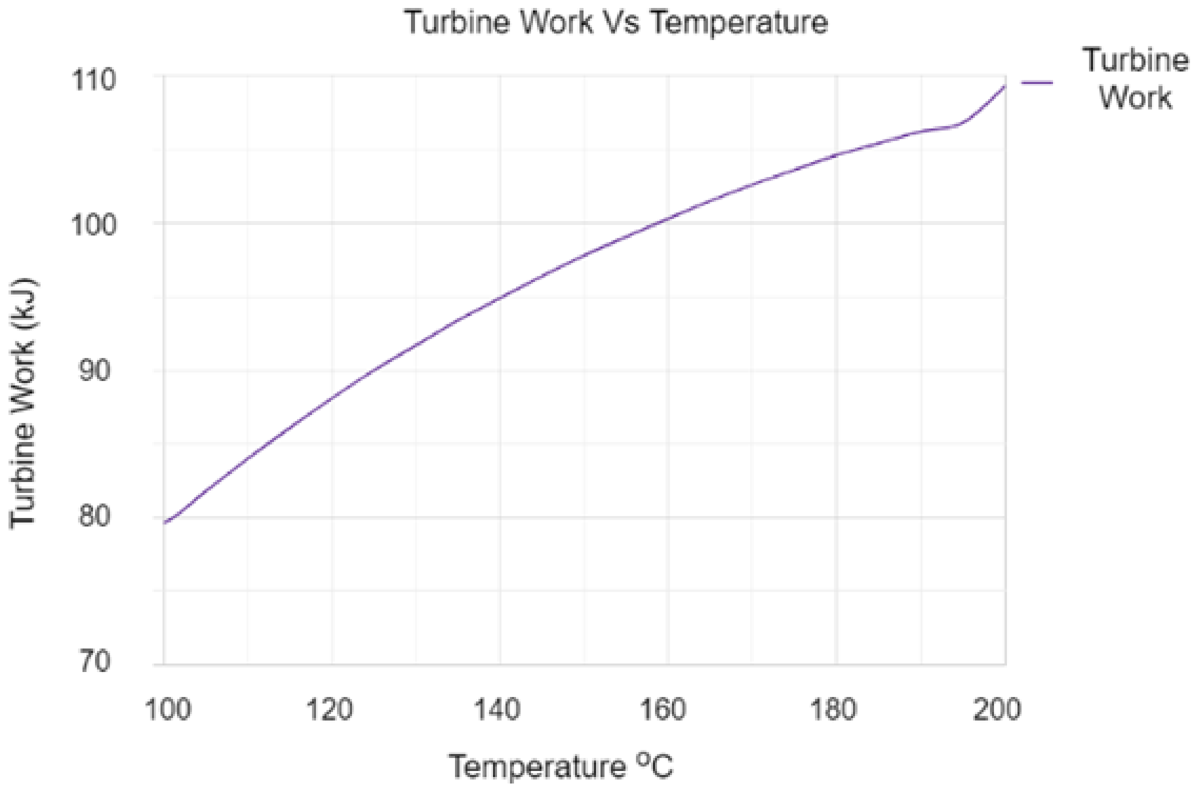

Figure 5.3: work turbine

high and the liquid content in the vapor is very low, this is not supported by the single flash technology. For that reason, if the well temperature is found to be beyond 200°C is better to use other technologies such as dry steam.

5.4.3 Power generated

The graph is shown in fig. 5.4 shows power produced by the turbine as well as power generated on the grid. From the simulation, maximum power is observed when the temperature is 140°C, dryness fraction is 0.72, the pressure is 3.61 bar, and generator efficiency of 99% maximum power observed is 6.489 MW per well. From our observation, the power generated at the turbine is parabolic. At low temperatures, power production is low, at moderate temperature especially above 120°C and below 190°C power produces is considerably high. At very high temperatures, the power produced is very low using flash technology. For example, at 195 the power produce is 3 MW, at 200 the power reduces by up to 65%, at 205°C the power reduces to less than 1 MW, beyond 205°C there is no power produced at the turbine. Therefore, if a well is observed to have initial temperatures exceeding 180°C it is rational to use other technologies than single flash. The power on the grid follows the same trajectory with the power by turbine, and mainly depend on generator efficiency.

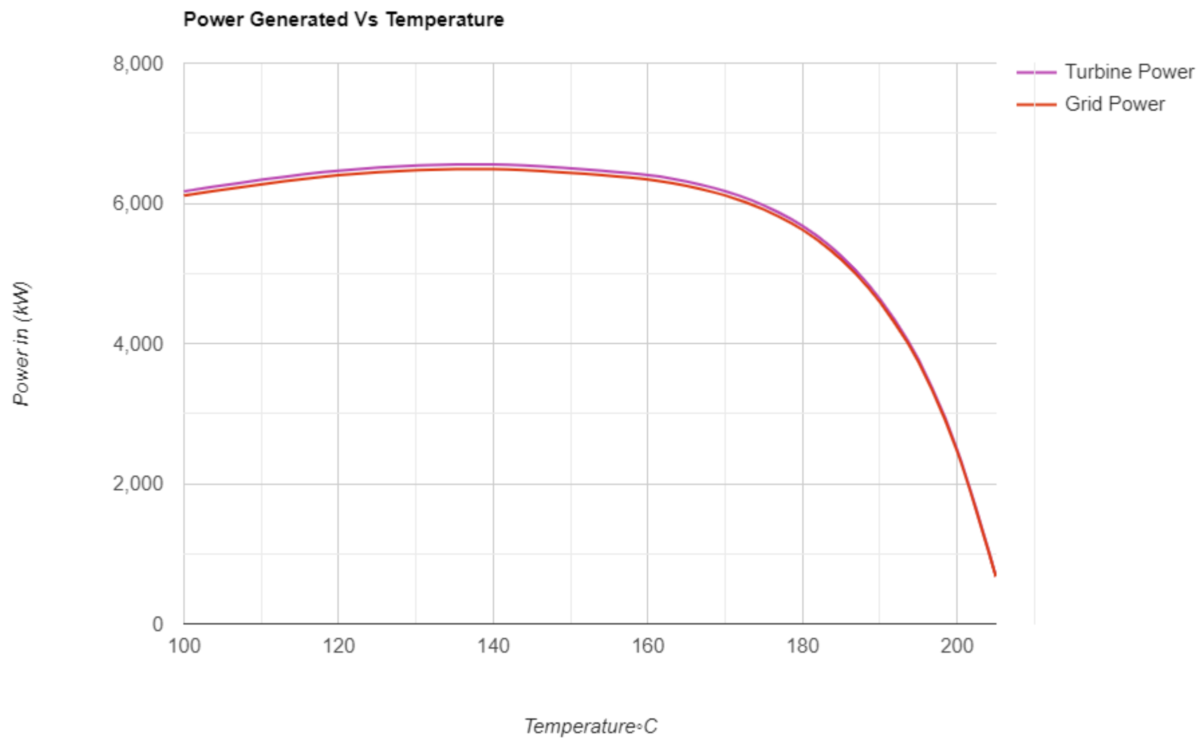

Figure 5.4: power generated

In this section, we have presented the result of our simulation experiment in Table 5.2. We have presented graphical results specifically on dryness fraction, work produced by a turbine in fig. 5.2 and 5.3, which are the major factors that determine the performance of a geothermal are setting in single flash technology. The results show that machine learning can effectively be used in the operations of a single flash. Generally speaking, embedding machine learning in a geothermal environment can improve operations.

5.5 Conclusion

Conclusively, our result portrays that the use of machine learning can improve performance prediction in a single flash ecosystem. At given temperature (T) and pressure (P), we can tell how much power can be produced at both the turbine and the grid. Secondly, it is possible to predict the depth of the well and its lifespan. Also, from the model, it is possible to observe other parameters that determine the quality of the power produced. These parameters include dryness fraction, turbine work and turbine efficiency.

Chapter 6

Conclusion and future work

6.1 Conclusion

In this thesis, we study utilization mapping for geothermal energy using machine learning algorithms along with the use case and challenge of geothermal usage.

Chapter 1 presents the motivation, problem statement, objectives, contribution of the thesis, background, related works, and outline of the thesis. The rest of the thesis is organized as follows.

Chapter 2 addressed a review on the geothermal energy of current and prospect in Indonesia. We studied worldwide geothermal energy. Indonesia's geothermal resources on its geological having many volcanoes and her hydrothermal reservoir characteristic which possesses an enormous opportunity for energy production. Promising factors discussed include the cost of access efficiency, most geothermal plants are built at the site of the reservoir. In order to increase economically worthwhile geothermal industry, hybrid power plants are known to be cost-effective than separate power plants. Regarding the air emission, geothermal fields in Indonesia will generally utilize ground-water systems and will have very few air emissions. Lack of technical geothermal experts, the number of geothermal experts in electricity production must be increased due to huge potential which can be self-maintenance by Indonesian experts as the key role person.

Chapter 3 focused on utilization mapping for geothermal energy. Our utilization mapping model based on temperature includes mathematical model of utilization mapping for the geothermal resources and the classes of utilization. The model produces results for the utilization mapping in the three-time zone of Indonesia. It shows that most of geothermal sites are best-fit electricity generation whereas the rest is the best fit for direct uses.

Chapter 4 focused on machine learning model for improving single flash energy production. The model was proposed for the well process and flash process in isobaric conditions. We use machine learning to determine the well depth, well lifespan, enthalpies, entropies, and mass flow rate, turbine work, turbine efficiency, dryness fraction, and grid power. We use Artificial Neural Network. Our model produce result with at most accuracy.

Chapter 5 addressed the experimental setup, simulation setup, results, and discussions. The specification of the simulation environment is MATLAB/Simulink. From our result, it shows the tabular form of dryness fraction, turbine work and power generated. For the dryness fraction, as temperature increases, the dryness fraction is drop. For work produced by turbine, as the temperature increase, the work increases gradually. For power generated, as temperature increases, the maximum power is observed

Chapter 6 present the conclusion of the thesis and future work

6.2 Future work

In the future, we intend to use machine learning to explore other technologies such as double flash. Moreover, the geothermal smart grid is a good candidate for the application of machine learning.

The geothermal power plant produces power from well(s) as a power source. To allocate power produced to the users, geothermal power utilization and distribution process must be efficient. For the aforementioned reason, we need smart grid solution. Smart grid mechanisms are often used to optimize and stabilize electricity from the power plant hence prevent losses. For example, when a blackout occurs, the smart grid accommodates generation options for reducing the downtime. Moreover, the efficiency of electricity distribution needs to minimize the power outage as much as possible.

In a vicinity, for example, a region, the power users have varying power requirements. Some users like industries may need high power, whereas domestic users may need less power. Moreover, domestic power requirements during the day differ from that of the night. In addition, power requirements may depend on season's e.g. in the dry season the power requirement may be higher than the power requirement in the wet season for domestic users. In our proposed visualize smart grid model, we categories users such that we have different classes of power users' e.g. domestic user, industry, government offices, etc. The use of smart grid solution is to provide an efficient distribution for its utilization mapping. The power produced from the plant as the main source is distributed to different regions based on the class of users through the connections organized in the tree structure. The main source of power is placed at the root of the tree. We call this source slack root. The power produced at the slack root must be normally distributed through distribution and intermediate distribution centers, which form branches in our model. The power from the branches is distributed to the user classes, which form the leaves of the tree. Since the needs of users differ from region to region or sub-region to sub-region, there is a need to minimize power distribution and maximize consumption. Therefore the model is formulated in such a way that the main source that is distributed to users depending on their consumption. At peak hours, the distribution should be maximized, whereas at non pick hours distribution must be reserved. In situation where power is not sufficient, the smart grid mechanism should show deficiency. The power distribution represented as the topological treemap shown in fig.6.1 To solve the smart grid utilization and distribution problem above, linear programming, dynamic programming, Bayesian and machine learning it may be used. The possibility of applying machine learning approach is a fit option. The use machine learning tools for example reinforcement learning, fuzzy logic, and genetic algorithms an interesting solution that is left for future studies.

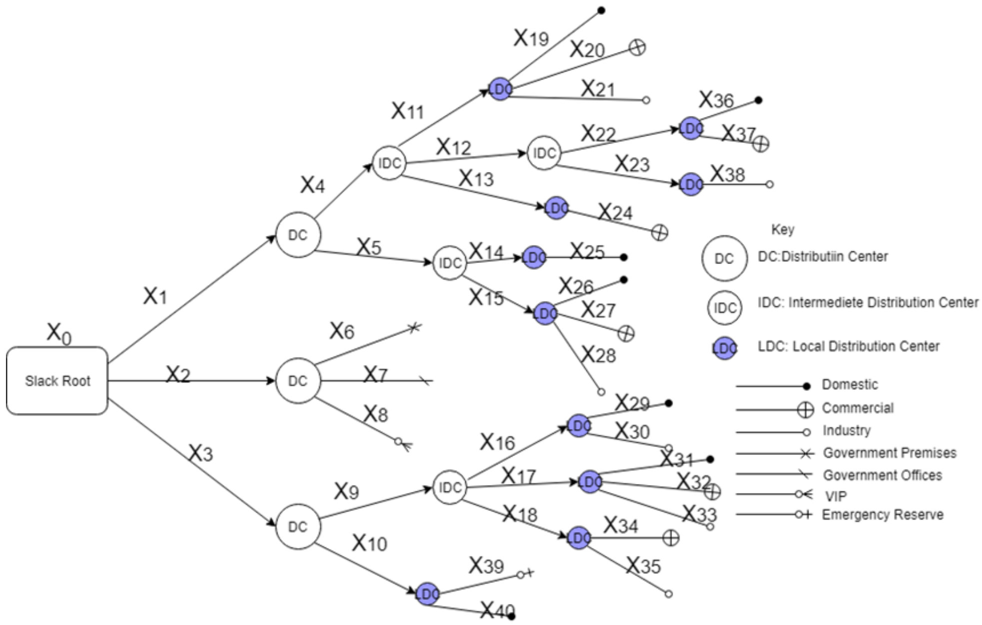

Figure 6.1: Shows geothermal smart grid topological map

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Appendix A

Enthalpies

Enthalpy(kJ/kg)			
Temperature(°C)	Sat.Liquid	Sat.Evaporation	Sat. Vapor
130	546.38	2173.7	2720.1
135	567.75	2159.1	2726.9
140	589.16	2144.3	2733.5
145	610.64	2129.2	2739.8
150	632.18	2113.8	2745.9
155	653.79	2098	2751.8
160	675.47	2082	2757.5
165	697.24	2065.6	2762.8
170	719.08	2048.8	2767.9
175	741.02	2031.7	2772.7
180	763.05	2014.2	2777.2
185	785.19	1996.2	2781.4
190	807.43	1977.9	2785.3
195	829.78	1959	2788.8
200	852.26	1939.8	2792
205	874.87	1920	2794.8

Appendix B

Entropies

Entropy(kJ/(kg.K))			
Temperature(°C)	Sat.Liquid	Sat.Evaporation	Sat. Vapor
135	1.6872	5.2901	6.9773
140	1.7392	5.1901	6.9294
145	1.7908	5.0919	6.8827
150	1.8418	4.9953	6.8371
155	1.8924	4.9002	6.7927
160	1.9426	4.8066	6.7492
165	1.9923	4.7143	6.7067
170	2.0417	4.6233	6.665
175	2.0906	4.5335	6.6242
180	2.1392	4.4448	6.5841
185	2.1875	4.3572	6.5447
190	2.2355	4.2705	6.5059
195	2.2831	4.1847	6.4678
200	2.3305	4.0997	6.4302
205	2.3776	4.0154	6.393

List of Publications

Conference

1. **Aldi Cahya Muhammad**, K. Habibul Kabir,Adam A. Alli "Machine learning model for improving single flash geothermal energy production: A case of Indonesia", PROCEEDINGS, The 7th Indonesia International Geothermal Convention & Exhibition (IIGCE) 2019 Assembly Hall - Jakarta Convention Center Indonesia, August 13 - 15, 2019
   (Best Paper Award-IIGCE 2019)