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Unification of Geothermal Plants with National Grids Using Artificial Intelligence (AI)

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ABSTRACT

Geothermal energy, a considerably underutilized resource compared to other renewable energy sources provides relatively cleaner and safer energy with minimal environmental impact. It is estimated that geothermal can produce 8.3% of the total electricity generated globally, sufficing 17.3% of the population reaping ecological and economic benefits. With our ever-growing energy demands and need for energy security, using geothermal potential to generate electricity is judicious. Further, integrating such plants with national grids will pave way to a unified, trust worthy energy system. But, managing such an enormous system with contribution from diverse energy sources is a mammoth task. However, with the advent of better storage technology, improved sensors, big data, artificial intelligence and the like it is easier than ever to undertake such intensive projects. Newer, efficient algorithms will simplify gathering of billions of bits of data, processing this data to better manage power production, co-ordinate power distribution and detect faults and anomalies in a smart grid. From production of power to its distribution to consumers optimal use of AI can help increase contribution of geothermal energy to any nation's energy supply. This paper aims to provide artificial intelligence-based solutions to unify and coordinate geothermal plants with interconnected national smart grid.

1. INTRODUCTION

Today, more than 940 million people (13% of world population) have no access to electricity [Fig 1]. Changes in the climate are detectable in our day-to-day life without the use of any scientific instrument [Sippel et.al, 2020]. To mitigate these harmful effects we have two options- to reduce Co2 emissions or to move towards sustainable energy options. As shown in Fig 2, low carbon energy constitutes a large part of the abatement strategy.

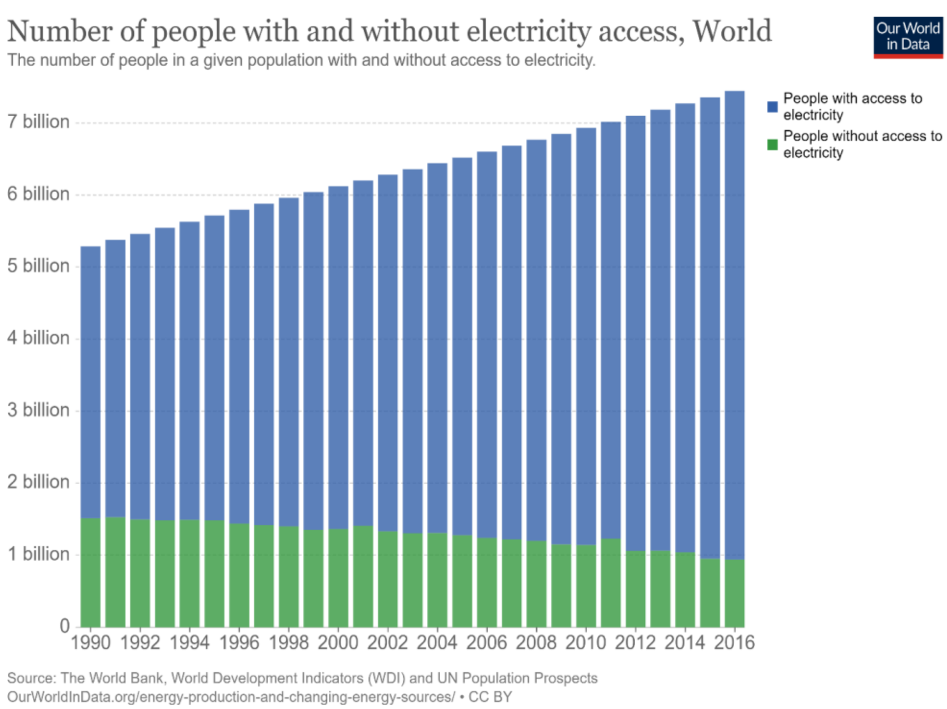

Fig 1: Global population with access to electricity

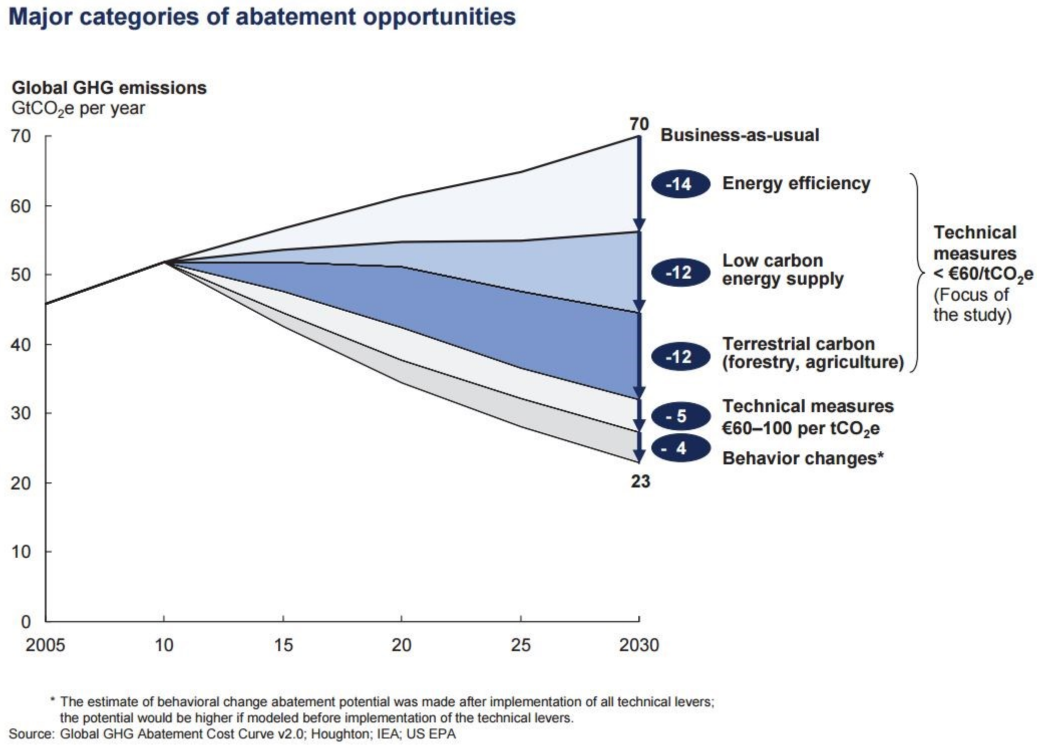

Fig 2: Greenhouse gas abatement opportunities

With climate change and rapidly exhausting fossil fuel wells, the whole world is leaning towards renewable energy sources. Wind, solar and tidal energy are extensively utilized resources. A relatively cleaner source of energy is geothermal power obtained by extracting heat from the depths of the Earth. It has been estimated that by 2024, upto 12.2% of CAGR growth will be observed in global geothermal energy market [1]. It has the potential to meet 3-5% of global energy demand by 2050. From fig 3, we can ascertain that installed geothermal energy capacity has risen from 8000 MW in 2000 to 12,000 MW in 2016. This rise is due to technological innovations and increased awareness among the general public. Geothermal energy is used for cooking, bathing, drying crops and melting snow directly from hot springs and dry sources. Electrical power generation, industrial processes and space heating require use of certain technological equipments [Lund,..; Friedleifsson, 2001].

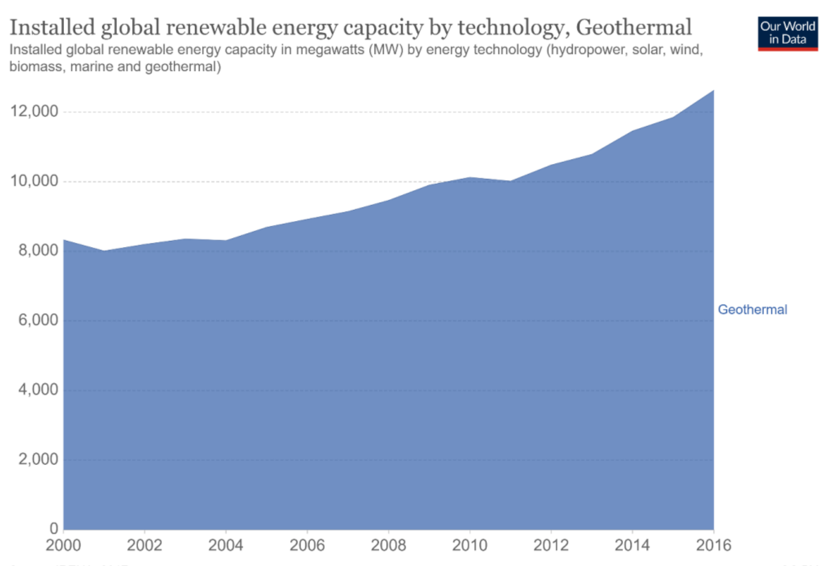

Fig 3: Installed global geothermal energy capacity.

However, a single source of renewable energy will not save our species. Rather, we require a combination of all available reserves to be integrated into one fully functioning and efficient grid. If we want to find solutions for global energy woes, integration of local energy sources in individual countries and regions into national/regional systems that make use of the best local and imported energy is important. To realize this goal, the existing grid infrastructure needs to be changed, technology upgraded and operational methods improved [2]

2. WHY COMBINE GEOTHERMAL ENERGY WITH SMART TECHNOLOGY?

Geothermal energy has massive potential but is held back by certain obstacles that cannot be overlooked. It has high upfront costs, is location specific, can cause earthquakes in extreme causes and the waste generated from plants requires proper management [Smith, 1973; Li et.al, 2015]. There are other problems that come with integrating renewable sources with power grids. Grid extension and smart grid technology are indispensable. Furthermore, some resources are dispatchable, some are not and many are subject to erratic energy generation [Buscheck et.al, 2014; Colak et.al,2020]. Hence, flexible generation, efficient storage, transportation and distribution of electricity is required.

Smart grid technologies incorporate sophisticated tools to mitigate power collapses and vulnerabilities such as cyber-attacks, motor heating, generator faults and the like. They also control and monitor the grid from generator to consumer, appliances connected to the grid and smart metering. Demand side management, Phasor measurement unit, Fault ride through and Advanced metering infrastructure are some of the techniques used to reduce variability in power systems, thereby, allowing easy integration of renewable sources in the grid. Since geothermal plants are localized, mini-grids and island systems are excellent immediate models that can serve our purpose. These smaller systems can then be unified with the larger grids and then ultimately with the national grid. It is economically attractive, technologically efficient and reliable [Gilding et.al, 2010; IEA-ETSAP and IRENA technology brief, 2015]

3. ARTIFICIAL INTELLIGENCE SOLUTIONS FOR OBSTACLES FACED BY GEOTHERMAL PLANTS

Nowadays, geothermal suitability assessments require invasive inspections, high costs, and legal permissions. Since, geothermal reservoirs are location specific, knowing the suitable hotspots will save time and money whilst providing useful knowledge during prior assessments. Plant effectiveness is governed by complex, unknown combinations of variables. Providing a solution to this, Coroy and Trumpy [2020] created a geospatial map of all existing and probable geothermal plants globally and tested the model against currently active and planned plants. A machine learning model known as Maximum Entropy (MaxEnt) was trained on data collected by the said team. Upto 65% accuracy was obtained by their approach. Compared with other studies using Support vector machines and Random forests the results are stunning.

Geothermal electricity is obtained using steam to rotate a turbine activating a generator connected to it which generates electricity. There are three types of power plants- dry steam, flash and binary. All these power plants operate at different temperatures. Hence, the next step is to determine the temperature and pressure range of any geothermal reservoir. Gas geothermometers working on multi-criterion decision analysis are used for this purpose. The issues with this equipment are the significant statistical differences in predicted temperatures within a group of these devices and lack of practical computer programs to assist the complicated calculations involved in reaching the final result. Recently, artificial neural networks had been employed for optimal evaluation and efficient coordination amongst many such geothermometers working in synchronization. Different networks with various weights and connections had been used. Excellent results were obtained with upto 96% accuracy in vapor dominated and 85% accuracy in liquid dominated reservoirs. [Anicasio et.al, 2021]

Demand and load side management require proper load and energy generated forecasting. Fuzzy neural networks, deep learning networks and a combination of three or four machine learning models in one algorithm provide accurate short- and long-term load forecasting. Time series modelling to forecast short term load by Amjady[2001] provides predictions with less than 2% error. Pandian et.al [2006] has used fuzzy neural nets with 2.75% maximum error. Short term-load forecasting with support vector machines by Mohandes [2002], neural networks and ensemble approach by Wang et.al [2018] and convolution neural networks by Sadaei et.al [2019] perform with errors less than 4-5%. Similar models are in use to forecast long term loads, heat loss, weather conditions and machine health in power plants.

Speaking of forecasting on plant side, geothermal system equipped with absorption refrigeration capable of working in unison with other sources such as solar or wind energy is modelled using deep learning networks by Khosravi and Syri[2020] with only 2.41% error. Considering regulations provided by classical plants, this model can be put to practice with enough capital available.

As mentioned earlier, earthquakes can be caused in extreme cases near reservoirs. This disaster not only harms the humans in and around the plant, but is also accompanied by huge economic losses, environmental degradation and potential disruptions in power line which if not controlled may lead to destruction of all machines connected with said power line. To avoid such catastrophes, earthquake predictions using deep learning models is feasible. Plenty of data related to earthquakes has been amassed by seismologists over decades. However, the complexity of calculations involved cannot be matched by existing computer algorithms. On the other hand, deep learning models are intricate, interconnected, work on probabilistic mathematical ideas and provide extremely accurate results. Wang et.al [2020] used LSTM (long-short term memory) networks to predict earthquakes. Simultaneous magnitude prediction and phase detection is also possible using deep neural nets [Mousavi et.al, 2020; Kuang et.al, 2020; Panakkat and Adeli, 2007]. Machine learning models will work well too. However, error rate and complexity handling of machine learning models is poor compared to deep learning networks. Hence, they are not preferred for applications involving thousands of compound calculations.

4. ARTIFICIAL INTELLIGENCE SOLUTIONS FOR NATIONAL GRIDS

This paper cumulated the empirical formulas to design a geo solar coupled cooling system can be used in any climatic conditions where there is appropriate amount of solar insolation. If there is less than 8-10 hours of solar irradiance then the amount of solar power generated will be less and it would not be enough to power the connected systems. Countries and cities that are near the equator will get good solar irradiance but as we move south or north from the equator then the amount of solar irradiance decreases. The coupled system's main components are the vertical heat exchanger and the PV panels. Most amount of the heat that enters into the building block through conductance and radiation is considered in cooling load. If more complex cooling system is to be designed then more finesse can be incorporated to calculate the cooling load with exact amount of heat by human activity, air infiltration, building block leaks. These are very small in amount but could affect the cooling load if the conditions are harsh. The length of the vertical heat exchanger can vary according the load and the type of the material of the pipe. The total length obtained from the above empirical relations must be divided by the number of the pair of vertical bore that we need to install. This can be calculated by estimating the drill depth by soil testing of the strata. Calculation for daily load will lead to the erroneous heat exchanger length, annual load data should be considered for better design.

If smart interconnected grids are put to practice the biggest problem to arise will be synchronizing grids and protecting the system from cyber-attacks. Moreover, mini-grids means distributed systems which are highly prone to damage. Traditionally, non-linear approaches were used to overcome these obstacles. But classic power controllers and system protection are made to respond passively. Below is a table listing various AI techniques used to optimize and synchronize smart grids.

Author/s	Year of publication	Method/s used	Objective
Utkarsh et.al	2016	Distributed computational intelligent algorithm	Reduce power losses in systems
Neves et.al	2018	Linear programming	Optimization of isolated grid
Darab et al	2019	ANN, support vector machine, fuzzy logic, genetic algorithm, Traveling wave method, impedance based method	Lighting strike detection, fault location detection, and islanding
Changsong et al.	2009	ANN	Energy trading and coordination of DERs
Sun et,al.	2014	fast iterative shrinkage-thresholding algorithm (FISTA), Lagrange dual decomposition	Using Distributed ESS to provide real-time power balancing service for an electric power grid

5. CHALLENGES

We have given plenty of literature to support the idea of integration of geothermal plants with national grid. However, there are many unsolved problems to be resolved.

- With the changing input variables of the distributed agents, the system learns and adopts the required operation. Every node is responsive to changes in input variables. Deep learning algorithms are self-learning once trained. Hence, gathering as much relevant data as possible should be the next step forward.

- Automation of current power system and geothermal plant architecture will yield efficient, self-reliable systems. Remote device monitoring, fault detection, voltage regulation are some areas still struggling to be automated. Replacing current gadgets with IOT devices in the depths of the plants is bound to reduce the risks.

- Cyber security protocols need to be updates to as applying them to such as smart system is not possible in their current state. Also, such upgradation demands a skilled workforce to maintain and improve it in coming years.

- Reducing burden on grid engineers and consumers can be done by installing automated sensors, temperature, voltage and current controllers. The problem with existing electronic devices is that they require a human operator to take the final step. In case, the anomaly is detected late, the whole system can blow up and its devastating effects can destroy power lines for several miles.

- Geothermal plants have high initial costs so finding potential investors is an arduous task. The energy finance market is expanding to incorporate sustainable energy projects. No doubt it is fitting to exploit this wave.

- Lastly, there is plenty of research to be done on deep learning algorithms and their efficacy. More and better workforce, technology and financial support is required before its methods can be applied to curb our energy woes completely.

6 CONCLUSION

In conclusion, we looked at the need for geothermal energy and the expected contributions it will make in coming years. Next, we listed out the problems limiting geothermal usage and solutions artificial intelligence models can provide. Different machine learning, deep learning, ensemble models and their performances were listed out and compared. Furthermore, AI based answers to obstacles facing unified national grid realisation were given due credit. Lastly, other issues still plaguing smart grids that need consideration have been put forth.

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