Smart EDGE Based Tensor Flow Quantum Learning Model for Rural Electrification of Smart Nation

Preethi Nanjundan[a], Chandrasekaran Subramaniam[b], C. Mallika Arjun[c], Ayan Datta[d]

[a]Department of Data Science, Christ (Deemed to be University), Lavasa, Pune, India. E-mail: preethi.n@christuniversity.in
[b]Department of Computer Science and Engineering, (Retired) Anna University, Chennai, India.
E-mail: chandrasekaran_s@msn.com
[c]Consultant, Trifecta Projects Pvt Ltd., Bangalore, India. E-mail: mallikaarjun837@gmail.com
[d]Department of Data Science, Christ (Deemed to be University, Lavasa, Pune, India.
E-mail: ayan.datta@science.christuniversity.in

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Abstract: The objective of the research paper is to propose a tensor quantum neural model with a smart EDGE (Evolving Dimension and Gradient Enlargement) technique. The conventional machine learning technique like recurrent deep learning addresses the vanishing gradient problem using layer wise learning techniques. When the dimensionality of learning changes a greater number of layers are to be included to completely cover the full level of knowledge across the domain. The paper addresses this critical issue and modify the layer wise learning into an EDGE centred tenser flow quantum based neural model. The application of the model is validated on the generated data set through towards rural electrification processes for a smart nation, India. This energy domain involves energy losses, infrastructure facility, feasibility of electrification and environmental issues to determine an amicable solution for the inter-twined complexities towards social reform need. An EDGE Tensor Flow approach in Keras platform towards quantum level processing is modelled and executed with python programming.

Keywords: Tensor Flow Quantum, Recurrent Deep Learning, Gradient Enlargement, Dimensionality.

1. Introduction

Artificial neural networks (ANNs) are important machine learning approaches that have wide applications in pattern recognition, medical diagnosis, system identification and control [1,2,3]. The first algorithmically described ANN is perceptron, which was invented by Rosenblatt [4]. It was also the simplest form of ANNs used for the (supervised) classification of patterns that is promised to be linearly separable. Quantum computing is a highly proposing new field of computer science that can efficiently manipulate high- dimensional data [5]. As integration of ANN and quantum computing, quantum neural networks (QNNs) are promised to be powerful computing devices [6] to solve real-world problems. The idea of the quantum neural network (QNN) was first set forth in [7]. It unites the concept of the ordinary neural network with a quantum computation paradigm. In 1997 A. Lasor came up with a hypothetical model of the quantum neural network using optical interference [10]. Quantum artificial neural networks (QANNs) were first systematically considered by T. Menneer in his PhD thesis. Afterwards, a lot of works were published that generalized well developed tools for classical ANNs to the quantum case. In the year 2000, D. Ventura and T. Martinez proposed a quantum implementation of the associative memory model [9] based on Grover's algorithm, and E. Behrman with co-workers came up with the idea of physical implementation of the quantum neural network as an array of quantum dots [8]. Now most of the proposed quantum neural networks are self-organized networks, i.e., "networks without a teacher," where weight factors are determined by the parameters of the problem to be solved. The "network with a teacher" model of the quantum perceptron was proposed by Altaisky in 2001 [11]. Implementation of this weight updating algorithm is discussed in [12–14]. The algorithm is based on qubit neural networks [15, 16]. Among unsupervised non learning networks are neural networks with quantum gated nodes [17] and currently employed DWave quantum processors [18].

The organization of the paper is as follows: Section 2 starts with the need of smart techniques for a smart nation to gain self- sufficiency and sustainability against the geo political and socio-cultural variations. Section 3 discusses about a framework of Tensor Flow Quantum Learning Techniques towards rural electrification and focuses on data set generation in cooperating all the social economic and environmental issues of the selected geo locations. Section 4 describes the Various Computational Deep Learning techniques along with Tensor Flow Quantum Phased and Classical Transformations. Section 5 state models of the electrification problem into an EDGE- based tensor flow quantum model and its essential components and also focuses on the result obtained and concludes the research work with its limitations and its drawback when applied to different domain issues and its corresponding modifications.

2. Need for a Smart Technique for a Smart Nation

The democratic republic of India, as a nation of united multi-lingual nations is one of many developing nations with a highly specific issue of rural electrification across its vast landscape. The issue of electric power generation at mountain or river sides and transmission across the deserts or dense forests pose many challenges including bio-centric and plantation centric problems. The renewable energy sources like wind energy and solar energy are to be carefully spotted and erected as the government economy has faced many ups and downs in recent pre and post-pandemic periods. The attainment of a minimum specific basic energy requirement for every citizen in this ancient nation lies in the socio-cultural aspects of the people an also on the co-operative psychology of the people. The success of the government policies and planning also depends on the rightful fulfilment of the poor living in the dense forests and in the hill tops as tribal people. The digitization of the life style including e-currency and internet facilities are based on the time driven fundamental infra-structural energy need of the citizen paying all forms of taxes. The specific need that is time driven and an attainable fundamental right to consume electrical energy is a “SMART” demand for people who live in Sea-shore, Mountain and Regional Territories (SMART).

The other side of the issue concentrated by the self- sufficiency of the local areas with the help of local or state government budget cost and maintained by the energy consumption charges. Many geo-located tribal areas can be electrified by proper design of the generation of electrical power. This can be accomplished by firing the waste trees with abundant forest wood and solar panel across the vast desert plain. In some other local places, nearby waterfalls and small dams can be erected and utilized towards hydroelectric power stations within a reasonable cost of generation and distribution. Many plain areas and valleys can be flooded with bio chemical energy plant with sugar cane juices and algae fields with a careful compliance monitoring of eco cyclic carbon emission into atmosphere. Similarly, the tidal energy or wave energy can be converted into electrical energy through multiple transformations and stored in a riskier storage cell or alternator. The other important factor in the generation of electrical energy through a mammoth number of automotive like the use of cyber-connected passenger vehicles. The wind energy can be utilized to generate a considerable quantity of electrical charge and stored in the discharge stations which then be utilized for the nation to be smart within the local budget cost. The design for sustainability can be achieved through successful maintenance of the multiple resources with minimum loss and rate of change of electrical energy production through predictable seasonal changes, and especially during risky pandemic periods. The selection of correct renewable energy resources for the correct region forces a smart electrification technique to enhance the sustainability of the generation and transmission of energy according to national and local constraints for a smart nation like India.

3. Socio Economic and Environment Issues in Electrification in India

Rural Electrification is a process of bringing electrical power to rural and remote areas. Electricity is not only used for household purposes but it also allows mechanization of many farming operations, such as threshing, milking, hoisting grain for storage. A famous program New Deal’s Rural Electrification Administration in the United States pioneered many of the schemes still practiced in other countries. India adopted rural electrification programmes and build new ones in order to provide 400 million Indians electricity in rural India. In today's context, rural electrification has five major facets.

- Setting up of rural electricity infrastructure.
- Providing connectivity to households.
- Adequate supply of desired quality of power.
- Supply of electricity at affordable rates.
- Providing clean, environmentally benign and sustainable power in efficient way.

India has always had a rural economy and since independence successive governments have tried to improve the rural infrastructure including energy infrastructure. However, a lot is yet to be achieved to give a real impetus to rural economy. In spite of launching of ambitious schemes to achieve 100% rural electrification, India has achieved only 67.3% overall electrification (urban and rural together). More than 75 million households (45% of the total rural households) are yet to be electrified (Census of India, 201a). As per latest data, about 19,909 villages are yet to be electrified (Progress report of village electrification as on 31-01-2015 as per 2011).

Table I. Data of unelectrified houses in multiple states

Status of un-electrified households in India as reported by the Indian states according to the date mentioned in

the table below:

Sl. No.	Date	States in India	Number of Rural Households (in Lakhs)	Households Electrified (in Lakhs)	Remaining Unelectrified Households (in Lakhs)	Percentage
1	30.04.2017	Assam	51.85	27.49	24.36	53.01 %
	10.10.2017	Assam	51.88	27.78	24.10	53.54 %
	31.03.2011	Assam	9.92	8.34	1.58	84.08 %
2	30.04.2017	Bihar	122.56	55.19	67.37	45,03 %
	10.10.2017	Bihar	123.46	58.76	64.70	47.59 %
	31.032011	Bihar	20.13	13.43	6.7	66.73 %
3	30.04.2017	Kerala	70.97	70.79	0.18	99.74 %
	10.10.2017	Kerala	71.04	71.04	0.00	100 %
	31.032011	Kerala	36.2	35.12	1.08	97.01 %
4	30.04.2017	Kashmir	12.88	10.18	2.70	79.03 %
	10.10.2017	Kashmir	12.91	10.21	2.70	79.08 %
	31.032011	Kashmir	5.17	5.07	0.1	98.04 %
5	30.04.2017	MP	113.61	67.77	45.85	59.65
	10.10.2017	MP	114,00	69.05	44.95	60.57 %
	31.032011	MP	38.45	35.65	2.8	92.73 %
6	30.04.2017	UP	305.18	149.12	156.07	48.86 %
	10.10.2017	UP	302.34	155.87	146.47	51.55 %
	31.032011	UP	74.49	60.65	13.84	81.42 %

However, not all electrified villages are getting quality power and it is estimated that nearly 33% of the population may be facing under-electrification, accessing less than 50kWh of electricity per month/household.

4. Various Computational Deep Learning Techniques

Classical Computational Learning - The classical conditioning theory is based on the assumption that learning is developed through the interactions with the environment. Also, the environment shapes the behavior and internal mental state such as thoughts, feelings, emotions do not explain the human behavior. The computational classical learning sees more data points, their positions, directions of vectors, intensities of their values into supervised and unsupervised learning.

Deep Machine Learning - Deep learning is an artificial intelligence (AI) function that imitates the workings of the human brain in processing data and creating patterns for use in decision making. It is also known as deep neural learning or deep neural network with large amounts of data and its varieties.

Quantum Machine Learning - Quantum Learning is a powerful and engaging teaching and learning methodology that integrates quantum processing utilizing qubits and quantum operations. It has been proven to incorporate hybrid methods that involve both classical and quantum processing toward the learning process. Quantum computing focuses on algorithms on the states instead of data.

Layer-wise Learning – It is an enhanced version of deep learning or otherwise called as Greedy layer-wise learning. The training layers are sequentially starting from bottom as input layer. It accepts an unsupervised technique where each layer learns a higher-level representation of the layer below. The training criterion does not depend on the labels used in the layers or in the network.

Tenser Flow Quantum Learning: It is a combination of quantum computing with qubits and machine learning through tensor operations across data. The state vector and a parameterized quantum circuit are used to get bigger state vector. TensorFlow Quantum (TFQ) is a quantum machine learning library for rapid prototyping of hybrid quantum-classical ML models.

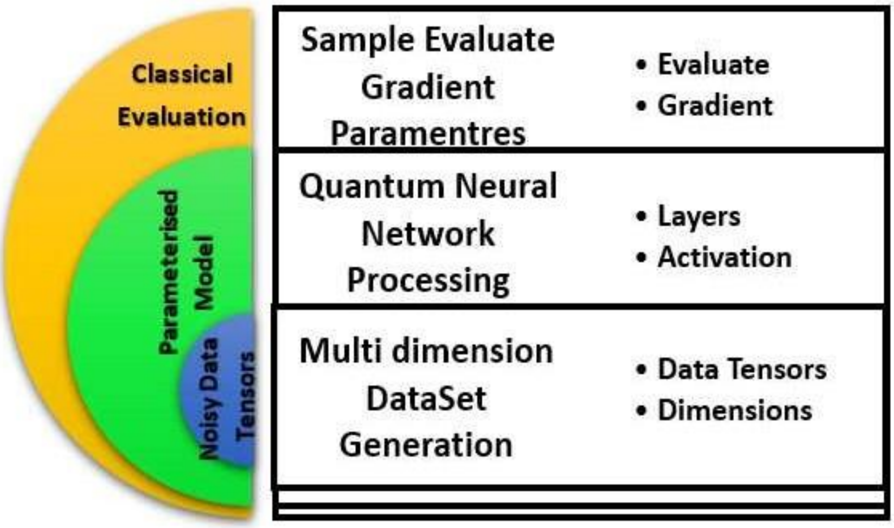

Fig. 1. Tensor Flow Quantum Phased and Classical Transformations

The above model consists of three different layers starting with classical evaluation which consists of sample evaluate gradient parameters, whose main function is to evaluate and gradient. Nevertheless, it moves towards the inner layer parameterized model which contains of quantum neural network processing, which contains of layers and activation. Finally, the last part is of noisy data tensors, whose main function is multi-dimension data set generation whose main parts are data tensors and dimensions. The Table shown below shows an enumeration and a comparison among different learning techniques based on multiple features.

Table II. Different Computational Learning Models

Features / Attributes / Parameters	**Classical Computational Learning**	**Deep Machine Learning**	**Quantum Machine Learning**	**Layer- wise Learning**	**Tenser Flow Quantum Learning**
Number of Layers	2	>3	2	n	8
Learning Rate	0.1	(0.0to1. 0)	(0.0to1.0)	(0.0to1. 0)	(0.0to1.0)
Activation Function	Softmax and Sigmoid	ReLU	Softmax and ReLU	Sigmoid, TanH and ReLU	QReLU and m- QReLU
Supervised(S) / Unsupervised(U)	Supervise d	Supervised & Unsupervised	Supervise d & Unsupervised	Unsupervised	Supervise d & Unsupervised
Entanglement	Entangled	Entangled	Entangled	Entangled	Entangled
Evolving Dimension	PCA	PCA & SVD	PCA & SVD	SVD & PCA	PCA & SVD
Gradient Enlargement	Yes possible	Yes possible	Yes possible	Yes possible	Yes possible

5. Tensor Flow Quantum with Edge Strategy

The Tensor Flow Quantum (TFQ) contains the basic structures, such as qubits, gates, circuits, and measurement operators that are required for specifying quantum computations. User-specified quantum computations can then be executed in simulation or on real hardware. Cirq also contains substantial machinery that helps users design efficient algorithms for NISQ machines, such as compilers and schedulers, and enables the implementation of hybrid quantum- classical algorithms to run on quantum circuit simulators, and eventually on quantum processors.

The TensorFlow Quantum approach is used for hybrid quantum-classical convolutional neural networks, machine learning for quantum control, layer-wise learning for quantum neural networks, quantum dynamics learning, generative modelling of mixed quantum states, and learning to learn with quantum neural networks via classical recurrent neural networks. A review of these quantum applications in the TFQ white paper is referred and each example can be run in-browser via Colab from the domain research repository.

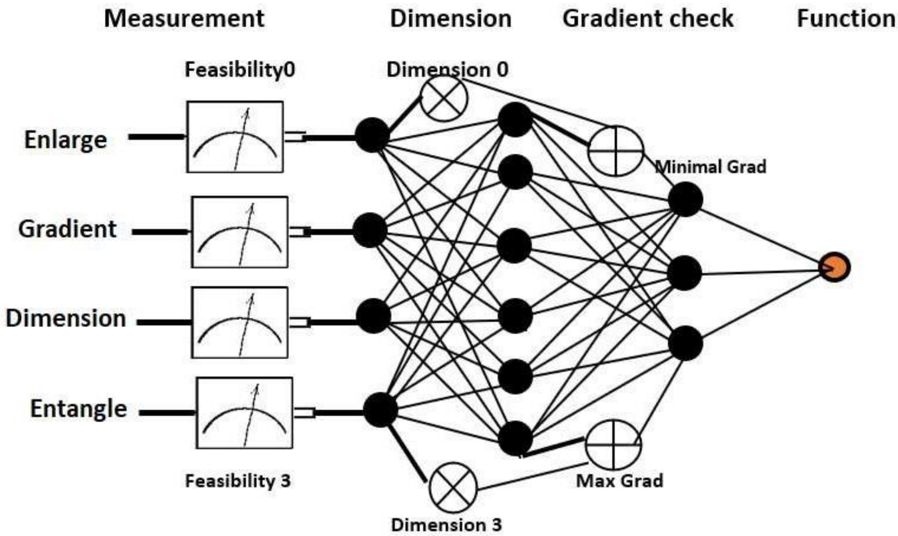

Fig. 2. Evolving Dimension Gradient Enlarge Sample Classical Cost Optimized Model

The quantum circuit can be modelled with the help of input factors matrix for electrification process E, Environment like Hamiltonian matrix with factors that determine the feasibility of electrification, Ψ is state vector and F is the feasibility vector.

$$E \mid \Psi > \; = \; F \mid \Psi >$$

The quantum processing of operation from the left the same environment matrix become the expected feasibility F of E

$$< \Psi \mid E \mid \Psi > = < \Psi \mid F \mid \Psi > = F < \Psi \mid\mid \Psi > = F$$

where **< Ψ |** is the conjugate of **| Ψ >**.

In a simple sense, it is possible to consider all the impinging factors as qubits and apply tensor products with their average probabilities. The tensors are important data structure to navigate across vector models and matrix models in order to train the machine towards deep and recurrent learning techniques. Generally, vectors are first order tensors and a matrix representation is a second order tensor. The feasibility factors for each state can be arranged in a matrix form with rows as states and factors as columns. To tune the problem further, towards more refined solutions, each column will be again turned into multiple rows with parameters or features representing the Electrification Feasibility Matrices of State (EFMS).

$$\left.\begin{matrix}\textbf{Mountain}\\ \textbf{Budget}\end{matrix}\right] \otimes \begin{matrix}\textbf{Rainfall}\\ \textbf{Soil}\end{matrix} \; = \; \begin{matrix}\textbf{mountain-rainfall} & \textbf{mountain-soil}\\ \textbf{budget-rainfall} & \textbf{budget-soil}\end{matrix}$$

The bigger size matrices can be built with more numbers of environmental reasons are treated as qubits with a greater number of state vectors. As a sample of two single column with quantum states are shown and their tensor products of their average expected values is shown above. In quantum computing models, the quantum gates are basic building blocks which are reversible. This property is worth mentioning for the quantum computing for the given rural electrification problem as there are many choices in the real implementation of physical erection and installation works. Quantum circuit models the above process through quantum gates in many different ways. Quantum logic gates like Quantum NOT gate is acting linearly with the input factor in the soil variable which may be loose grainy state rather than tough and rough state. NOT Gate operation needs the state of the soil is to be inverted by the operation as

| loose > → ***| hard >*** and ***| hard >*** → ***| loose >*** and so on. With superposition to be applied between the variables, the inversion can be done linearly.

$$\boldsymbol{Soil \mid loose > + \, Hill \mid high > \;\rightarrow\; Soil \mid hard > + \, Hill \mid low >}$$

The matrix representation Loose Hard of a NOT Gate and measured. Hard Loose

Uniform superposition of feasibilities and possibilities can be done by the Hadamard gate can be visualized as the basic gate to map the quantum states of the factors in the electrification processes and their uniform superpositions. These can be represented as the following set of transformations.

$$|\,\textbf{loose}> \;= \mathbf{1}/|\boldsymbol{loose}> + \quad |\boldsymbol{hard}>/\sqrt{\mathbf{2}}$$
$$|\,\textbf{hard}> \;= \mathbf{1}/|\boldsymbol{loose}> \;-\; |\boldsymbol{hard}>/\sqrt{\mathbf{2}}$$
$$\textbf{dimension}\;\;|\,\textbf{low}> \;= \mathbf{1}/|\boldsymbol{low}> \;-\; |\boldsymbol{high}>/\sqrt{\mathbf{2}}.$$

More number of Hadamard gates can be used to describe the exact nature of the data available regarding a village to be electrified possible or effectively or not. The controlled NOT gates can also be used to control the EDGE of the of the quantum circuit based on their values. If in the proposed EDGE approach, the E, D, G, E are the control bits for the circuit to adjust according to the data. If the enlarge bit is zero, and like any other control bits, they will allow the quantum tensor to pass through measurements. If the EDGE bits are in one state, the feasibility bit will be inverted. This inversion makes the learning across the full span of the state vectors.

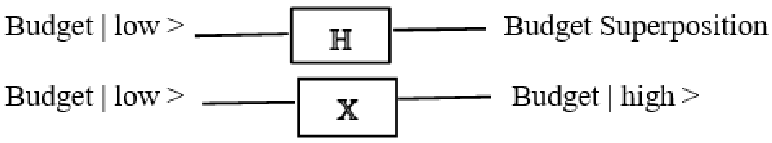

Fig. 3a. Quantum NOT and Hadamard Gate representations

In deciding the electrification of rural village, the feasibility and plausibility have to be analyzed through the budget as the controlling factor. Similarly, when many high mountains based tribal villages are considered during the same power distribution processes, the rainfall factor may be the control bit in the state vectors.

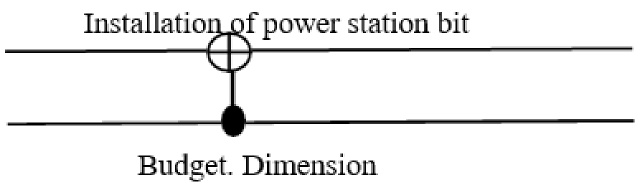

Fig. 3b. Controlled NOT Quantum Operations in TFQ

The control qubits are connected in parallel in the quantum circuit with suitable number of Hadamard gates to the respective environment factor qubits. Most of the uniform superposition of states respond to the feasibility and plausibility of the electrification process in India. Multiple qubits with minimum four control NOT bits and suitable number of Hadamard gates are to be connected with measurements for a complete quantum circuit.

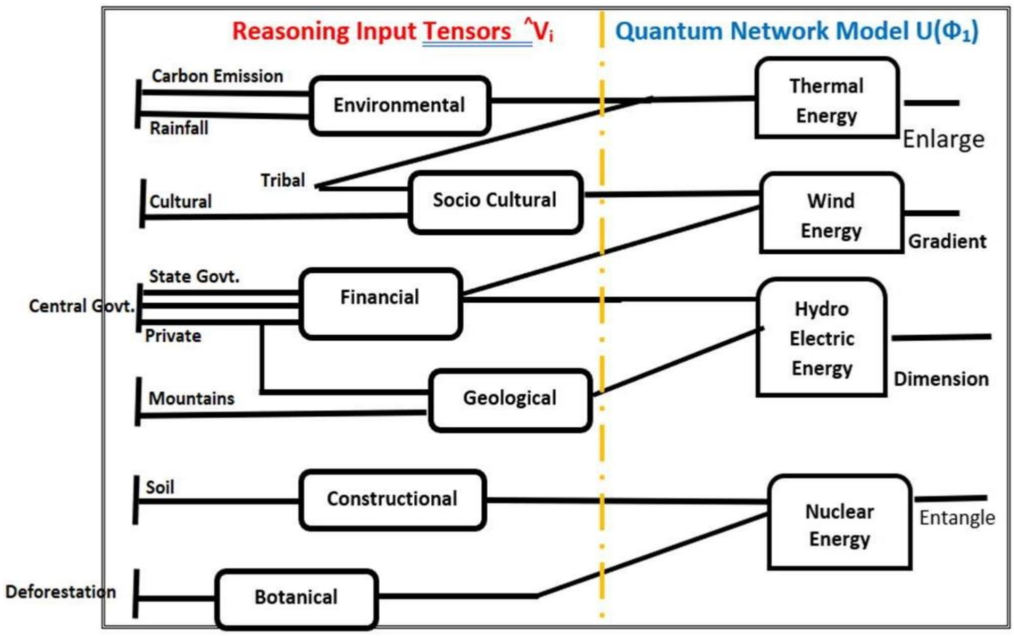

Fig. 4. Tensor Flow Quantum Learning Model

Tensor Flow Quantum models are extremely useful for the fast proto-typing and training of quantum models over quantum data. The rural electrification processes and their data are quantum and Bayesian probability across the bits over Noisy Intermediate Scale Quantum and Quantum Error Correction processors. The arrangements of various quantum logic gates on the number of qubits as a quantum circuit to obtain the desired outcome makes the quantum computing to solve the complex problems. The control bits for the proposed EDGE- TFQ Learning model with each feature are shown below:

E	1 0 0	0	Evolvement Check
D	0 1 0	0	Dimensionality Check
G	0 0 0	1	Gradient Check
E	0 0 1	0	Enlargement Check

The feasibility of electrification processes in each State can be obtained by reasoning all these relevant socio cultural and economic conditions of that particular state as shown below. For example, feasibility matrix of the Electrification for the State of Assam is shown below in table. The model proposes an EDGE driven TFQ learning, the size of the matrix to six-six- dimensional square matrix. The feasibility of electrification of Indian states are highly dependent on various factors but they are different scale for different Indian States. These factors are obtained from the National Information Centre, India which are sampled for two important States, Assam and Uttar Pradesh for the model demonstration purposes. The above model can be simulated using Cirq, an opensource framework for TFQ Learning technique. The learning model must be given the data in such a way to look and behave as per the control bits shown as EDGE in the same sequence.

Table III. Feasibility Matix of Electrification for State 1

Feasibility Matrix of Electrification for Assam (FMEA)						
Feasibility Deciding Factors	***Environmental***	***Socio Cultural***	***Financial***	***Geological***	***Constructional***	***Botanical***
Population	0. 12	0.45	0.82	0.54	0.75	0.85
Size	0.75	0.50	0.80	0.35	0.65	0.60
Area	0.85	0.35	0.72	0.10	0.15	0.65
Culture	0.90	0.45	0.55	0.25	0.58	0.80
Electrification Need	0.80	0.50	0.64	0.42	0.60	0.55
Climate	0.77	0.60	0.85	0.40	0.75	0.90

Table IV. Feasibility Matix of Electrification for State 2

Feasibility Matrix of Electrification for Uttar Pradesh (FMEU)						
Feasibility Deciding Factors	***Environmental***	***Socio Cultural***	***Financial***	***Geological***	***Constructional***	***Botanical***
Population	0.90	0.50	0.65	0.80	0.90	0.75
Size	0.45	0.20	0.47	070	0.72	0.50
Area	0.65	030	076	0.65	0.82	0.75
Culture	0.50	0.65	0.88	0.84	0.64	0.65
Electrification Need	030	0.70	0.80	0.35	0.42	0.30
Climate	085	0.65	0.92	0.62	0.84	0.45

The normalized values in the above Tables III and IV are vectors where each column is a cluster of other factors within it. Hilbert space is a vector space over either the field of real or complex numbers equipped with an inner product and it is known that a qubit is a Hilbert space. That is the feasibility values are state space in the feasibility sphere a shown in Fig.5.

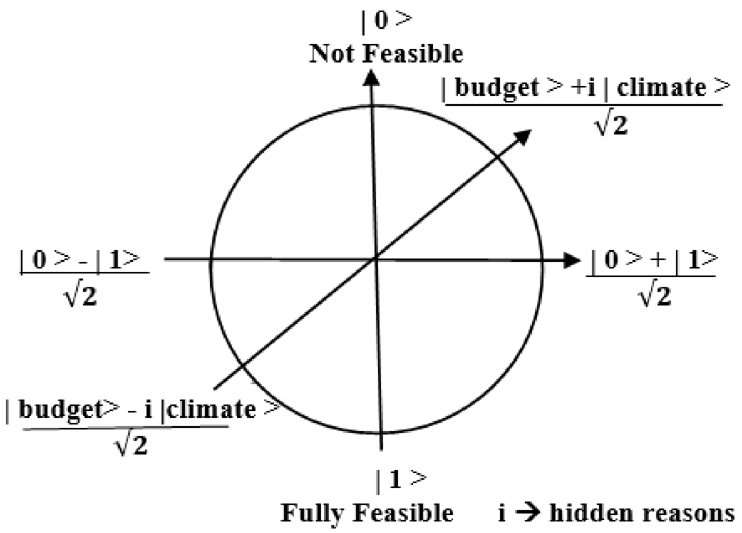

Fig. 5. Feasibility Sphere for Indian State Electrification

6. Conclusion

The research work addresses the rural electrification problem that is multi-dimensional and complex based on the inter-twining issues and challenges. The data set is a multitude of statistics of various features of the individual states incorporating the socio-economic cultural diversities of India. The data is considered to be a vector and varying in the direction of consideration. The classical computing may not give an amicable solution through a mammoth information processing in various state level and center government policy level regulations. The number of qubits needed for a low-level budget is from 10 to 50 but a greater number of qubits may be needed if the deciding factors are more and their states. The proposed model addresses the learning improvisation due to vanishing gradient problem and it is solved by introducing suitable modification in the model. The control bits are sequentially activated to determine the number of quantum gates needed to solve the above specified social demand issue. The actual data are to be obtained from the respective governments of state governments and ecological departments to apply across various learning models. The EDGE-TFQ model outputs the feasibility state vector and learn from the sample states. The actual limitation of the work is to enhance the size of the quantum circuit to a full span to cover all the states of all the factors from all the states. The size of the quantum circuit will be very big to incorporate the state spaces of all factors towards the feasibility of electrification. The performance of this model can be enhanced by considering the entanglement feature in the quantum circuit and error correction due to noisy data. These EDGE- TFQ enhancement options will be considered in the future work and extended to all other national issues that are homogeneous to the process considered.

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