EAFIT University
Master in Data Science and Analytics

Automatic meters forecasting: a benchmarking between quantum machine learning and classical machine learning

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Abstract

Quantum machine learning has become an edge topic in the last 15 years. It takes advantage of several algorithms in quantum computing that allows to perform complicated and huge operations that reduce time complexity due to the power of quantum mechanics such as superposition. Applications in the medicine, industry and science context have been made but the majority in the context of classification problems. In the supervised learning forecasting is well known that artificial neural networks and Variational Quantum circuits, for the classical and quantum machine learning respectively, work well in terms of accuracy. This research aims to show a benchmarking between classical and quantum supervised machine learning applied to automatic meters of the company EPM services in order to choose the best models in terms of time and accuracy metrics. VQC will be based on the parameter shifted rule as optimization of parameters in the quantum circuit and for the quantum machine learning approach. This will allow identity sectors in which is urgent and necessary to attend by the company.

1 Introduction

Forecasting the reading of public services, be it water, electricity and gas in periods of time is the basis for important decisions in companies in the electricity sector. The objective is to implement, for EPM, a predictive model and an architecture that allows to obtain measurements and predictions when the client wishes. For this company in the electricity sector, these predictive models must be totally reliable and fast in order to identify users who may present problems and thus, seek reviews and solutions in a more efficient way and, if possible, before a damage in the network occurs. This is where, in terms of algorithmic speed and therefore prediction, a cutting-edge topic comes in: quantum machine learning. However, recent research and applications on this topic have not shown, in some cases, superiority in terms of model accuracy. One example is the case Study of heart disease in which a quantum machine learning algorithm in SVM to classify artery disease was made. The results are presented in fig 1, [**6**] in terms of precision and accuracy. Therefore, it is necessary, for our research problem, to make a comparison table between classical and quantum machine learning algorithms in terms of precision.

Technique	Accuracy	Precision_0	Precision_1	Recall_0	Recall_1	F1-Score_0	F1-Score_1
SVM	80.25%	82.30%	78.40%	77.50%	83.05%	79.83%	80.66%
Naive Bayes	78.99%	83.19%	75.20%	75.20%	83.19%	78.99%	78.99%
Logistic Regression	78.99%	81.42%	76.80%	76.03%	82.05%	78.63%	79.34%
Decision Tree	85.29%	84.07%	86.40%	84.82%	85.71%	84.44%	86.06%
Random Forest	88.24%	91.15%	85.60%	85.12%	91.45%	88.03%	88.43%
XGBoost	84.03%	87.61%	80.80%	80.49%	87.83%	83.90%	84.17%
QSVM	77.73%	75.00%	80.51%	79.65%	76.00%	77.25%	78.19%
VQC	73.95%	72.57%	75.20%	72.57%	75.20%	72.57%	75.20%

Figure 1: Comparison in the artery disease study between classical and quantum algorithms.

Different methods of classic time series will be necessary to implement as a first stage of research applying seasonal, additive, multiplicative decomposition techniques, trend elimination, among others. This to compare with machine learning models for time series, more precisely applying FNN artificial neural networks with backpropagation to have a comparison chart in the same classical field and choose the best algorithm for our prediction problem.

It is necessary to make a short introduction with our other framework for comparison of our classic machine learning models, Quantum Machine Learning (QML). Quantum machine learning is the combination between machine learning and quantum computing. It is based on the next idea: If quantum processors are capable of producing statistical patterns that are computationally difficult for a classical computer to produce, then it is very likely that they can also recognize patterns on such information that are equally difficult to find classically. Quantum machine learning can be summarized in the fig 2

The encoding, one of the most important steps can be done by amplitude encoding, basis encoding or time encoding, which are procedures to transform data stored in a classical memory into a quantum state. For example, encoding a vector $\vec{x}$ in qubit base vector. After the encoding step it is important to select the properly QML algorithm

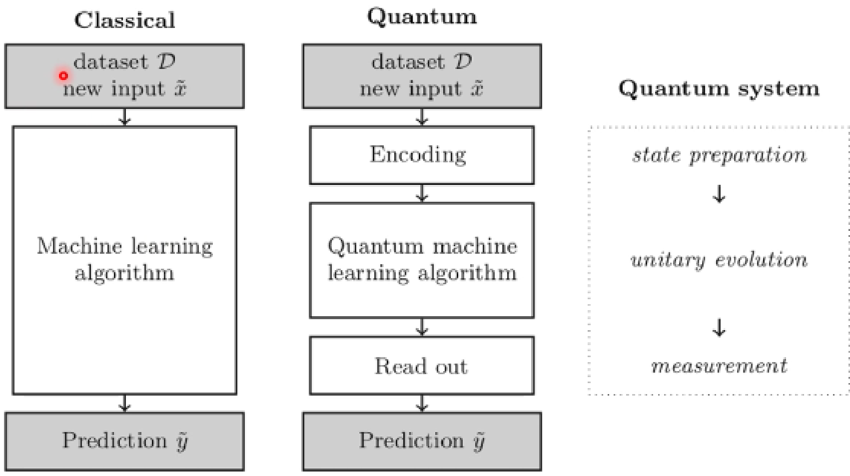

Figure 2: Diagram of Quantum Machine Learning steps.

what will be apply depending on the machine learning problem. As this research aims to make a benchmarking between classical machine learning and quantum machine learning, it is necessary to choose the same algorithm in the two worlds. Quantum variational circuits (QVC) are implemented as the form of artificial neural network in quantum computing [**1**],[**2**],[**8**]. This will be the type of quantum neural network used in the benchmarking to compare, based on MAPE and MSE error and test metrics, to the classical analogue and choose the best forecasting model to predict in less time and high accuracy the measurement in the automatic meters.

2 General Objective

Carry out a comparative framework of the prediction models between classical and quantum algorithms, more specifically, between classical and quantum machine learning supervised models to predict the measurements in the EPM service network meters.

2.1 Specific Objectives

1. Apply a time series analysis and implement a classical time series method for the forecasting of the service network meters.
2. Use quantum computing to predict future values. Create a forecasting model by a Variational Quantum Circuit or QNN.

3. Benchmarking between metrics of the classical and quantum machine learning forecasting models.

4. Publish two research articles: one of the review of the context of quantum machine learning and another about this research.

3 Theoretical background: classical and quantum machine learning

3.1 Classical Forecasting

Our research problem is based on a prediction problem, i.e, a prediction of the future based on the past. It is for that very reason that we can conclude so far that is a time series model problem for different times in which a measurement of any public service by EPM is taken for different temporalities. As a relevance analysis it will be important to make a detrended and deseasonalized a time series that has a dependency between the past and future data and the stochastic rule does not change. It will be very important in our analysis to determine if the stochastic process is strictly stationary, i.e, the first two moments, $E[\phi_t] = \mu_t$ and $Var[\phi_t]$, of the serie are finite and the covariance depends only on the lag $k = t_2 - t_1$, or weak stationary, i.e, its mean is constant and its auto covariance function depends only on the lag [**9**]. From utter importance is to evaluate the sort of process of the data in terms of time series, i.e, stochastic process, autoregressive process of order n, i.e, AR(n), in which the relationship between the past and the future is linear [**9**]., or Nonlinear Auto Regressive (NAR). It is expected that in terms of consumption (energy, water, gas) the relations between variables and time has to be linear of the form

$$\phi_t = \alpha_1\phi_{t-1} + \ldots + \alpha_p\phi_{t-n} + w_t,$$

where ϕ_i are the lags of the model an which the parameters α's can be found in terms of the Least-squares estimation:

$$\hat{\alpha} = (X^T X)^{-1} X^T Y. \tag{1}$$

X matrix has rows and columns that formally are the embedding vectors

$$x = \ [\phi_{t-1}, \phi_{t-2}, \ldots, \phi_{t-n}\ ] \tag{2}$$

that satisfies the equation $y = f(x) + w$, the latter as an extension of the form $\phi_t = f(\phi_{t-1}, \phi_{t-2}, \ldots, \phi_{t-n}) + w(t)$ for the extension of a AR formulation to a Nonlinear

Auto Regressive formulation [**10**]. We have to take into consideration the number of lags that the the autocorrelation function (ACF) gives us to take into account for the forecasting depending on the chosen model that we are going to choose related with the data. Lags are the predictor variables, the α are the weights to find in terms of the lags. ARIMA model as a generalization of the AM and MA (Moving Average) with a differentiation degree in order to have a stationary time series.Test Dickey-Fuller will allow us to test for ARIMA model $y_t = \phi_1 y_{t-1} + \epsilon_t$ the stationarity of the serie $|\phi_1| < 1$.

There are 11 different classical time series forecasting methods [**10**]: AR, MA, ARMA, ARIMA, SARIMA, SARIMAX, VAR, VARMA, VARMAX, SES, HWES. The first aim of this researching is to find the methods that fit our data, these depending on the exogenous variables that we might take into consideration: weather, climate events such El Niño, elections, importan holidays, etc. For the test error, a test data set will be set to compare and get the MAPE metric in our supervised model.

3.2 Classical Machine learning forecasting

In terms of a classical machine learning (not quantum) it is considered for our researching purpose a supervised learning problem, where we have to infer from historical data the possibly nonlinear dependance between the input (past embedding vector 2 and the output (future value), see figure 3, [**9**].

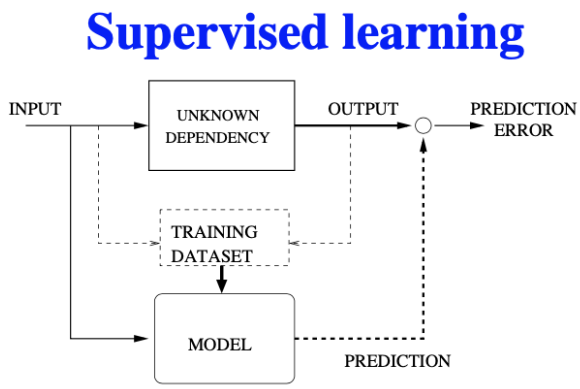

Figure 3: Supervised classical machine learning scheme

For the aim of forecasting with this ML technique it is important to choose a complexity of the model that satisfies a good bias/variance trade-off, which we can see in figure 4 which refers for a MISE, i.e, mean-squared-error decomposed in three terms:

$$MISE = \sigma_w^2 + squared\ bias + variance,$$

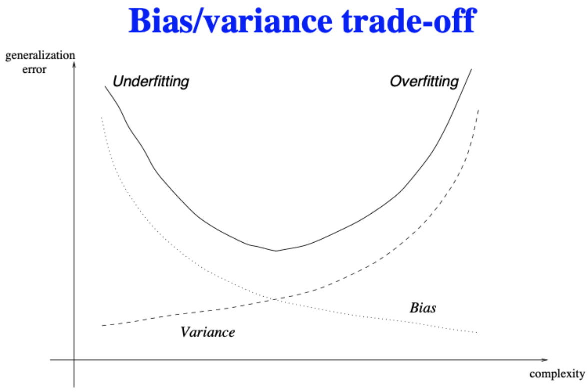

Figure 4: Bias/variance trade-off

Where σ represents the noise or fandom error of the regression model $y = f(x + w)$. The following task will be the chosen functional $\hat{f}(x, \alpha)$ that depends on the degree of the functional (linear or nonlinear), and the hiperparameters.

For the feature engineering of the data in this forecasting problem, the research will be based on backward step-wise selection removing variables and making an input such as exogenous variables if is the case, with the aim of getting the best R^2 and BIC metrics for the models in which the point that optimize the MSE is precisely in the optimization point to avoid underfitting and overfitting in terms of the training data set, this can be seen in figure 4.

In order to make the benchmarking between the Quantum Neural Network in the framework of quantum machine learning and the quantum variational circuit the prediction of the time series will be based on a recursive multi-step forecasting in a iterated prediction, figures 5 and 6 show the scheme of this sort of forecasting structure. This because Recurrent Neural Networks belong to such class, their recurrent architecture and the associated training algorithm (temporal backpropagation) are suitable to handle the time-dependent nature of the data [**3**],[**5**], and this problem aims to be analyzed and implemented in the quantum RNN or FNN versions using the same quantum circuits that represents a neural network and with the back propagation we will evaluate the competition with the shifted-parameter rule in quantum variational circuits, something that will be explained latter in the next subsection.

Iterated modeling of dependencies will be used for the modeling dependencies in the RNN or FNN, image 7 shows the structure of this modeling,[**12**]. Metrics to use in this machine learning problem will be the NMSE (Normalizaed Mean Squared Error) and MAPE.

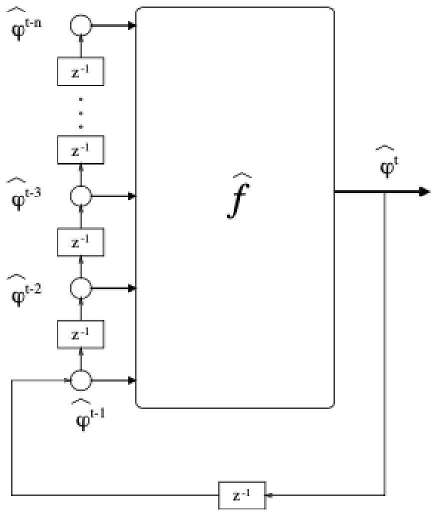

Figure 5: The approximator $\hat{f}$ returns the prediction of the value of the time series at time $t+1$ by iterating the predictions obtained in the previous steps. The rectangular box containing z^{-1} represents a unit delay operator $\hat{\phi}^{t-1} = z^{-1}\hat{\phi}^{t}$.

3.3 Quantum Machine Learning Forecasting

Quantum Machine Learning (QML) is a research area and a computational paradigm that takes advantage of Quantum Physics and Machine Learning (ML) through the use of quantum computers, with which it exploits the properties of superposition, quantum parallelism, entanglement and tunneling, to develop processes with high calculation, simplicity, fast application of algorithms, and lesser query complexity, in which performance and computational speed are significantly improved compared to classical computing [**1**], [**2**]. It is important to add that unlike the classical information that is storaged in bits, quantum information processing uses superposition states of photons or atoms to process, store, and transmit data, this is summarized in the figure 8 [1], which quantum states (Qubit) are schematic drawn in a Bloch Sphere, which is represented by the states $|0\rangle$, $|1\rangle$ or a normalized complex linear superposition of the two. The states contain information obtained from some physical process such as quantum sensing, quantum metrology [**12**], quantum networks [**13**], quantum control [**14**] or even quantum analog–digital transduction.

It is important to mention that classical bitstring can be easily encoded into n qubits, but the converse is not possible in a efficiently encoding way due to the fact that n-qubits system requieres $(2^n - 1)$ complex numbers to be specified. Figure 9 shows the different QML tasks depending on the kind of data and the algorithm to use, [[**3**]. This research will be based on classical data type using a quantum algorithm type, aiming for one of

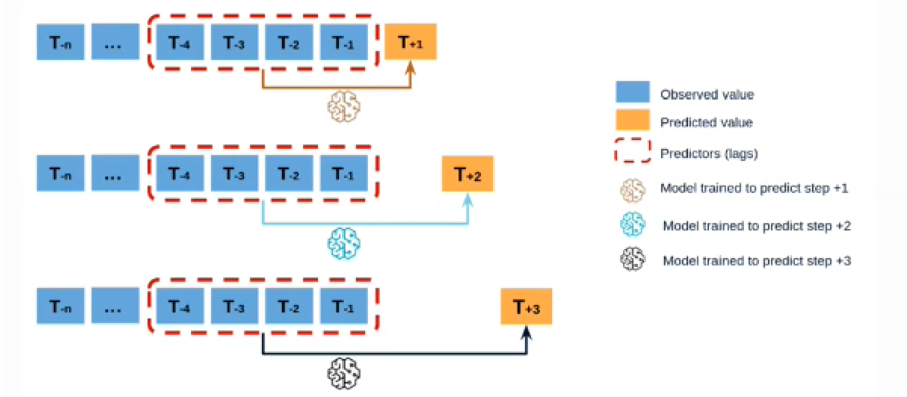

Figure 6: Direct multi-step prediction process diagram to predict 3 steps into the future using the last 4 lags of the series as predictors. Figure taken from [**11**].

the QML key applications: Classical data analysis, more precisely, speed up optimization in supervised ML task [**2**]. The first step is that our classical data x which represents the measurements of the meters in our time series for the forecasting has to be encoded in a quantum system through some embedding mapping $x_j \rightarrow |\psi(x_j)\rangle$, with $|\psi(x_j)\rangle$ in a Hilbert space $\mathcal{H}$. This issue is explained in the first part of the methodology section 4.

According to [**3**], a second more ambitious definition of QML focuses on problems in which data is difficult to generate or store classically and refers to the use of a quantum device to classify or extract features from quantum states. The aim of QML is to reduce the complexity in terms of either samples (sample complexity) or the number of operations needed in order to train the model and classify a test vector [**3**], something known as quantum supremacy. This reduction in the $\mathcal{O}(n)$ is summarized in the table of the figure 10 [**1**]. It is the aim of this research to take advantage of the quantum properties, circuits and algorithms to estimate the measurements of the automatic meters in a more real time and with greater precision, where what one wants to implement is to look at the measurement whenever one wants.

3.4 QML paradigms and algorithms: state of the art

Like ML, QML paradigms are supervised learning or task based, unsupervised learning or data based, and reinforced learning or reward based. Due to its resilience to noise, good generalization properties, and in a broad sense, its potential to achieve a quantum advantage, supervised learning has received special attention in recent years [**2**]. QML algorithms speed up quantum systems to improve ML regression or classification tasks, for example, through the Quantum Support Vector Machine, Quantum PCA, Variational Quantum Classifier, Quantum Boltzmann Machine, Quantum Neural Network (QNN),

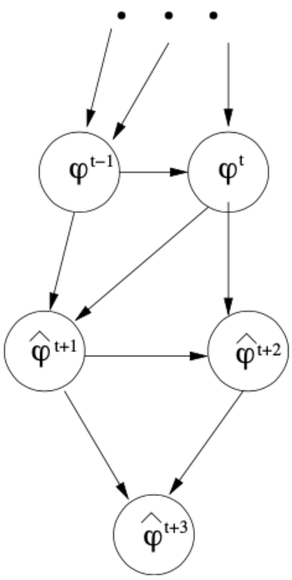

Figure 7: Iterated modeling of dependencies

Quantum Convolutional Neural Network, and Quantum Deep Neural Network [**1**].
QNNs refer to the application in a data science problem of parameterized quantum circuits, which are a sequence of unitary gates acting on the quantum data states, some of which have free parameters that will be trained to solve a problem. This algorithm deserves special attention since it is used in all three QML paradigms. For instance, the goal of a QNN in a supervised classification task may be to map states in different classes to distinguishable regions of Hilbert space. In the unsupervised learning case, a clustering task can be mapped to a MAXCUT problem and solved by training a QNN to maximize the distance between classes, while in a reinforced learning task, a QNN can be used as a Q-function approximator to establish the best action of an agent given its current state [**2**].
In some cases, hybrid approaches are used with models that have classical and quantum neural networks, which seek to distribute representational capacity and computational complexity across classical and quantum computing. In other cases, researchers have proposed quantum versions of kernel methods, which map each input to a vector and learn a linear function in the reproducing kernel Hilbert space, which has a dimension that could be infinite and makes the kernel method be potent in terms of its expressiveness [**2**].
The inductive bias refers to the bias generated by the assumptions made in the model design and limits the search space of potential features to a subset of all possible features. Since this bias and the training process define the feasibility of a ML model, and

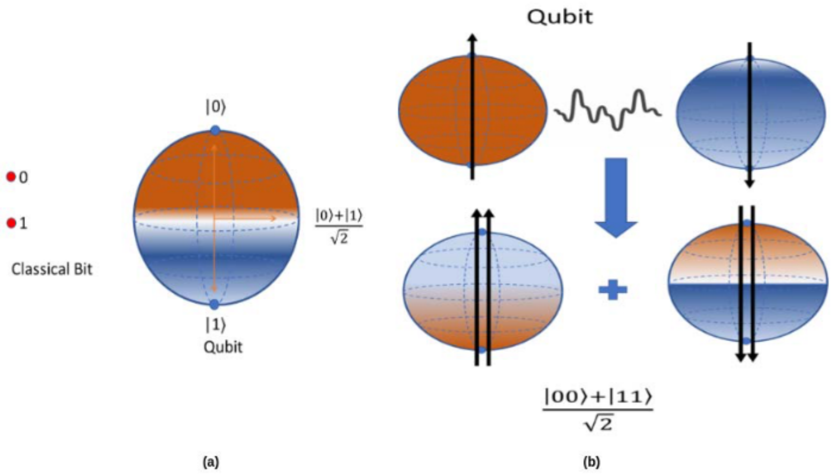

Figure 8: (a) classical and quantum state (b) Quantum Superposition and entanglement

considering the importance of QNNs in QML, the development of QNN architectures that have sharp priors is an active research topic in the area. Some works have shown that reaching a helpful inductive bias is fundamental to improve the trainability in QML models, which is given thanks to a notable reduction in the expressivity and the parameter space dimension; in this case, a theory of quantum geometric deep learning could be crucial to generate consistent methods to create a QML model architectures that ensures trainability and generalization [**2**] .

3.5 Current QML research areas

At present, QML is used in different areas or research domains. For example, it is used in chemistry for drug design, in materials science to predict properties of new materials, in quantum computing to learn how to correct errors and design quantum algorithms, in sensing and metrology, to extract hidden parameters from quantum systems, and speed up classical data analysis in supervised and unsupervised ML tasks [2]. However, Biomedical application is one of the areas in which QML algorithms are currently massively used, mostly Quantum support vector Machine, Variational Quantum Classifier, and Quantum neural network [**1**]. The importance of implementing QML in Biomedical lies in identifying the complexity and severity of diseases through data processing and analysis, to reduce errors in diagnosis, prediction and classification of these and design more effective treatments. Biomedical is divided into four main areas: Omics (bioinformatics or biomedicine), biomedical images, Biosignals, and medical healthcare records (MHRs). The first one studies human diagnostic images and QML works seek to clas-

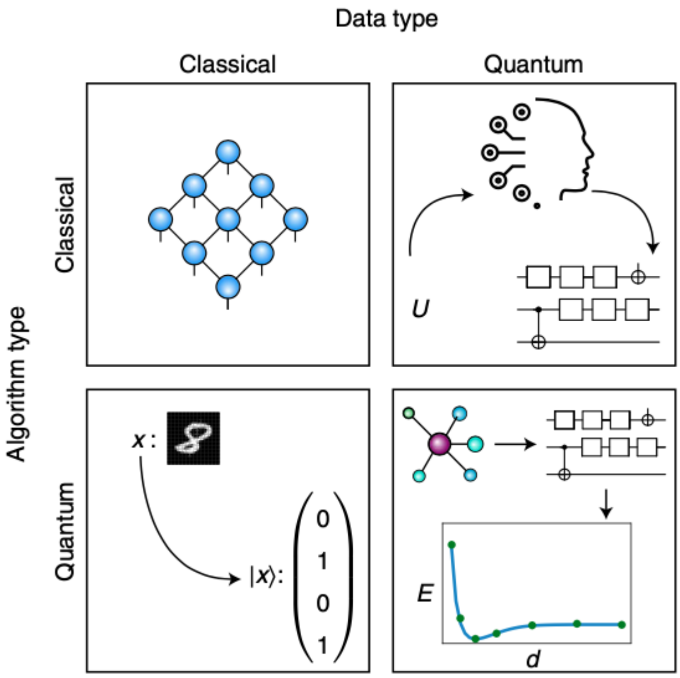

Figure 9: QML tasks. This researching will be based on classical data type using a quantum algorithm type.

sify colon, breast, prostate, brain, among others, cancers, and tumors. In biomedical imaging, researchers have recently been implementing QML algorithms to classify and diagnose accurately Cervical Cancer and COVID-19 through X-ray images of the lungs [**1**]. For this area, in [**1**] authors state that QML models have gotten outstanding results compared to their classical versions in ML.
Biosignals refers to the electrical signals generated by neurons, brain and muscles tissues, which are detected through biomedical sensors. In this research line, work has been carried out to predict future cognitive responses and improve the performance of the brain-computer interface. As for the MHRs, they are developed to evaluate large medical data that contain information on clinical test results, drug history, treatments, etc. In this area, QML models have been implemented for the classification of diabetes [**1**].

3.6 QML Algorithm for the Time series Forecasting

Since our classical machine learning problem will be covered by artificial neural networks (ANNs), our comparison framework with QML has to be in the quantum version of ANNs, called Quantum Neural Network (QNN) [**1**]. It has been demonstrated that

Method	Speedup
Bayesian Inference	$O(\sqrt{N})$
Online Perceptron	$O(\sqrt{N})$
Least-squares fitting	$O(logN)$
Classical Boltzmann Machine	$O(\sqrt{N})$
Quantum Boltzmann Machine	$O(logN)$
Quantum PCA	$O(logN)$
Quantum Support Vector Machine	$O(logN)$
Quantum Reinforcement learning	$O(\sqrt{N})$

Figure 10: Speedup technique for QML [**7**]

classical neural networks can be embedded into a parameterized quantum circuits (PQC) [**2**] also known as Variational Quantum Circuit. These are a sequence of unitary gates acting on the quantum data states $|\psi_j\rangle$ some of which have free parameters θ that will be trained to solve an optimization problem [**2**]. Fig 11 shows one example of a VQC [**1**]. In fig 12 [**2**], we can see the schematic version of feedforward neural network FNN in the quantum computation world in which each node corresponds to a qubit, while lines connecting qubits are unitary operations, table of the figure 13 from [**1**] summarizes this correspondence.

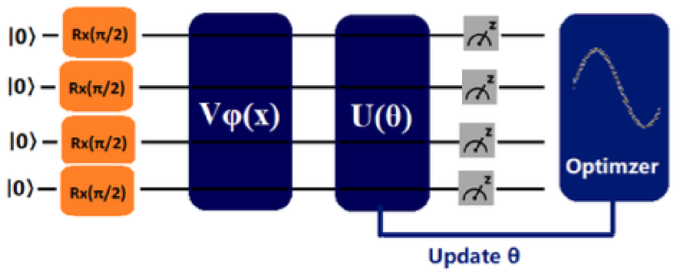

Figure 11: Variational Quantum Circuit.

Both in the quantum world and in the classical one, the FNN uses the backpropagation algorithm that is based on the gradient descends [**3**],[**4**]. Is the aim of this research to use the back propagation algorithm and the parameter-shifted rule for QVC to make a benchmarking in terms of complexity, times and accuracy in the forecasting problem. We believe that for the latter the time complexity is improved because of the use of the same circuit and gates with a shift in the parameter θ of the unitary gate that we use to find the derivative of an expectation value to optimize the parameter in our QVC as a

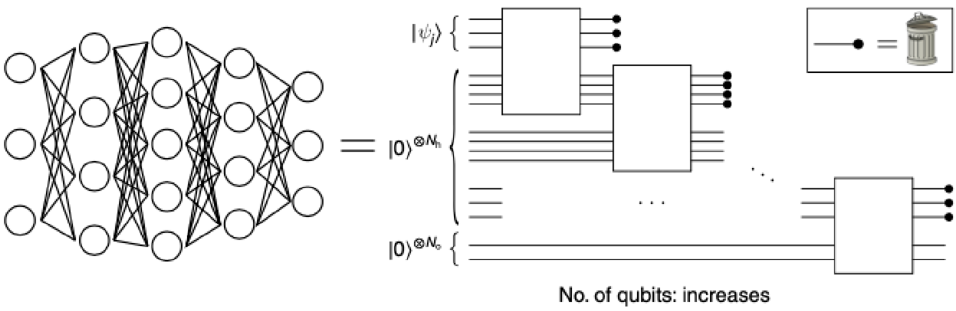

Figure 12: Quantum circuit representation of a FNN. The circuit is initialized in a product state

Quantum Mechanics	Neural networks
Wave function	Neurons
Superposition (Coherence)	Interconnections (weights)
Measurement (De-coherence)	Evolution to attractor
Entanglement	Learning rule
Unitary transformation	Gain function

Figure 13: Correspondence between the quantum mechanics elements in a VQC with a classical Neural network.

representation of the FNN. This demonstration is made on the annex page based on the article [**4**]. Several works such as [5] use this analytic gradients on quantum hardware for hybrid quantum-classical algorithm. Given that even quantum algorithms used to estimate the gradient of a model with D parameters acting on n-qubits require $O(\sqrt{D}/\epsilon)$ queries to estimate the gradient within error ϵ (in the infinity-norm), it implies that with high probability the gradient will require $O(poly(2^n))$ applications of the model to even learn the sign of any component of the gradient accurately [**3**].

Several researchers such Amin et al [**16**], used QNN to classify COVID desease with high accuracy and precision, implementing 3 dense layers, 500 neurons, ReLU activation, and 02 neurons with SoftMax for feature mapping) with 4 qubits on Pennylane (the quantum computer and simulator from Xanadu) using COVID 19 Pakistani and Chinese patient's lungs CT images [**1**]. Also E. El-Shafeiy et al [**17**] used QNN model with 30 nodes getting 92.334% of accuracy in the prediction of severity of COVID-19. This research in the QML frame can be summarized in 14 [**2**]. In the methodology section each step and times will be explained in detail. Other way to see this process with a circuit scheme is shown in the figure 15 for a convolutional neural network [**1**].

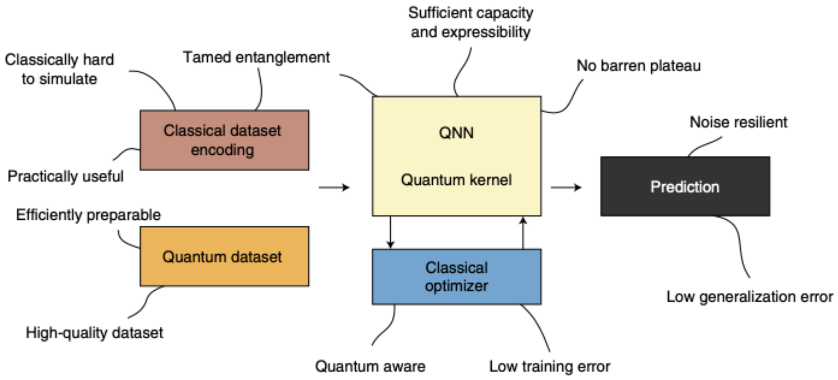

Figure 14: Construction of a QML model.

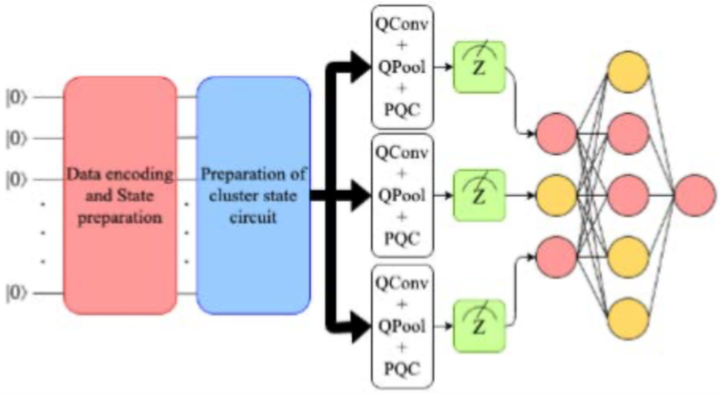

Figure 15: Schematic circuit of quantum convolutional neural network circuit

4 Methodology

4.1 Classical Machine Learning Forecasting

Based on the data given by EPM the first task of this research is the model selection of the classical time series. We will have to estimate the lags and the forecasting method, this methods are explained in the section 3.1. For this aim we firstly have to make the data cleansing in terms of NaN variables and get the correlations between the variables in order to take into account hendoenous or exogenous variables for the forecasting of the meters in terms seasons, temperatures, locations, etc. After the lags, the differential operators to use with the purpose of seasonalizing the series a forecasting will be done in the next semester (2023-02). MSE and MAPE are going to be used as metrics of prediction, bias and variance metrics respectively. An iterative model with RNN or FNN with the back propagation we will be evaluated as a Classical machine learning technique in competition with the shifted-parameter rule in quantum variational circuits. CRISP-DM methodology applies for our classical scope, which is a process model that serves as the base for a data science process and is based on the following steps: business understanding, data understanding, data preparation, modeling, evaluation and deployment. The metrics mentioned previously are our benchmarking metrics so to speak.

4.2 Quantum Machine Learning Forecasting

One of the aims of the research that was settled down with my advisors, is the creation of two scientific articles: one article of review and the other a researching article. For the first article the estimated time is between April and December of 2023. The purpose is to read the majority of articles related with the QML in the frame of QNN. At the same time, is my job to specialize in the Xanadu quantum computer framework: Pennylane. Something that I has been working with Juan Guillermo Lalinde and which is my desire make an internship at this company or at IBM in 2024. Now the steps of the quantum machine learning framework are presented.

4.2.1 Feature selection: Encoding process.

The first step in our QML forecasting is the step of the encoding. Depending on the nature of the data we have to decide wether to encode our classical data into quantum bits (Qubits) in the two following forms:

1. **Bit Encoding.** With $[v_i]$ representing the bit-string vector of the training vector this bit vector can be accessed on demand through a self inverse quantum oracle of the form [**3**]:

$$O_{data} \left|i\right\rangle \left|b\right\rangle = \left|i\right\rangle \left|b \oplus [v_i]\right\rangle ,$$

known as the coherent bit-oracle [**3**]. With this sort a superposition of queries on the training data of the form

$$O_{data} \left(\sum_x a_x \left|x\right\rangle \left|0\right\rangle \right) = \sum_x a_x \left|x\right\rangle \left|[v_i]\right\rangle ,$$

which allows the achievement of quantum speedup over the size of the data [3]. However, being this one sort of encoding the most similar manner as the data is provided to most of the classcial machine learning algorithm, the number of qubits necessary to store the information can be prohibited, i.e, for MNIST data set is necessary a quantum computer with a minimum of 784 qubits [**3**].

2. **Amplitude Encoding.** In this scheme, the data, i.e, the vectors of the training set, are embedded as unit vectors in the quantum computer [**18**], [**19**] from feature vectors of dimension up to 2^n when using n qubits. With $\{v_i : i = 1, ..., N\}$ and $v_i = \sum_j v_{ij} |j\rangle$ the encoding is then $|v_i\rangle = \sum_j v_{ij}/|v_i| |j\rangle$. There are two main classes of amplitude encoding: coherent and incoherent encoding. In this research, the incoherent version will be used since it is the most commonly used in quantum neural networks [**3**].

4.3 Creation of the QNN

The aim is create a quantum neural network, a FNN quantum version using variational quantum circuits. This will be based on the master course in QML taught by the advisors of this research, their papers in this field and the studies in the quantum architecture in the computer of IBM (Qiskit simulator) and computers from Xanadu. Also the creation of this QNN will be based on the study on paper [**8**].

4.4 Quantum Computers and Simulators

This research is not free from the limits of noisy intermediate-scale quantum devices, the restricted number of quantum bits, and the limited size of sample data. For this very reason we have other benchmarking in terms of the quantum computers to be used, IBM or Xanadu quantum computers. IBM has Qiskit, an environment that allows 127 qubits and an open-source SDK for working with quantum computers at the level of pulses, circuits, and application modules. Xanadu uses simulation fro electromagnetic fields, trapped atoms, harmonic oscillators, Bose-Einstein condensates and phonons [**1**].

4.5 Evaluation and Expected Products

In the evaluation between the metrics, which is more accurate and which one is faster, we suppose that quantum machine learning algorithms. However, depending on the quantum computing capacity and the amount of data, we will decide the sort of encoding and maybe consider splitting the problem in two ways: data and forecasting problems in which not speed up is required we can use classical machine learning algorithms and forecasting problems in which speed is more important, of course with a good accuracy, we will use quantum machine learning algorithms. Is the aim of this research to get a similar table to the one in the figure 16, in which we can compare the forecasting with different classical and quantum machine learning algorithms as gotten in [**18**] in terms of the training error/validation error and MAPE.

	CANCER	SONAR	WINE*	SEMEION*	MNIST256*
Quantum circuit	0.022/**0.058**	0.000/0.195	0.000/0.028	0.031/0.031	0.031/0.033
PERC	0.128/0.137	0.283/0.315	0.067/0.134	0.022/0.038	0.065/0.066
MLPlin	0.060/0.075	0.117/0.263	0.001/**0.039**	0.001/0.025	0.038/0.041
MLPshal	0.064/0.077	0.010/**0.174**	0.029/0.063	0.002/**0.024**	0.011/**0.018**
MLPdeep	0.056/0.076	0.001/**0.174**	0.010/0.063	0.001/0.026	0.014/0.021
SVMpoly1	0.373/0.367	0.452/0.477	0.430/0.466	0.101/0.100	0.092/0.092
SVMpoly2	0.169/0.169	0.334/0.383	0.090/0.099	0.100/0.101	0.091/0.092
Average	0.125/0.136	0.171/0.283	0.090/0.137	0.037/0.049	0.040/0.043

Figure 16: Results of the benchmarking experiments taken from [**18**].The cells are of the format 'training error/validation error'.

4.6 Ethical Considerations

This research project aims to potentiate one of the edge areas in quantum information, quantum computing and machine learning: quantum machine learning. This is the future, there will be a time in future years in which the name machine learning will have two distinctions: classical or quantum. This project provide a way of solution in a forecasting problem in EPM with automatic meters and with the highest precision and speed never seen before in industry context problems by taking advantage quantum computing powers. A commitment to deliver reliable algorithms and results is made.

4.7 Estimated times

The following chart represent the times and deadlines for this research.

Activity	**Temporality**
Data cleansing and feature engineering	July-August 2023
Classical Time series method, lags and forecasting methods	August-September 2023
Classical machine learning forecasting	September-November 2023
Article 1: review about QML and QNN	July 2023- January 2024
Quantum encoding	December 2023 - February 2024
QNN in terms of QVC construction	Februar-April 2024
Benchmarking	April-June 2024
Article 2: Researching problem.	June-July 2024

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