Classical-quantum neural networks for monitoring home appliances from power readings

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Index Terms—**Classical neural networks, Green function, power consumption, quantum neural networks.**

I. Introduction

As energy conservation becomes more important due to the rising cost of electricity and the growing popularity of home automation, many consumers are turning to smart meter devices. These devices can measure and record a household's overall power usage, and an electric utility provider may notify consumers if it detects that refrigerator door has been left open or if irrigation system turns on unexpectedly. However, the data produced by the devices have atypical data patterns similar to data generated from quantum experiments, so classical machine learning cannot accurately predict the behavior of individual appliances.

One promising machine learning in terms of processing atypical data patterns is quantum machine learning [1]. Quantum machine learning is a machine learning paradigm that enables learning of immense quantities of data by using quantum operations and qubits. A primary goal of quantum machine learning is complex data are executed faster on a quantum computer. However, qubits that bring data cannot be initialized to arbitrary values. Quantum simulator [2] can cope with this problem by manipulating quantum systems so that one can mimic the behavior of other quantum systems. The simulator is able to run both classical and quantum neural networks.

Several studies have been undertaken to investigate classical and quantum neural networks [3], [4]. In classical neural networks, particularly physics-informed neural networks (PINNs), some focus on Fourier networks [5][6][7], whereas others on Fourier features [8], [9]. These works explain frequency representations of input data, and each architecture is suited to different types of data and tasks. Other works on Fourier neural operators solve partial differential equations using deep learning techniques [10], [11]. PINNs have limitations when it comes to approximating functions with highly oscillatory behavior, and can struggle with problems involving translation [12]. PINNs can also pose a multi-objective optimization problem if Dirichlet and Neumann boundary conditions are soft-constraining [13].

On the other hand, quantum neural networks offer efficient algorithms to reduce computation steps [14], [15]. Some focus on feed-forward and recurrent algorithms [16][17][18], whereas others on Boltzmann machines [19], [20]. These works use quantum annealing to find the global minimum of a cost function. Other works on variational quantum circuits solve optimization problems using variational quantum algorithms [21][22][23]. Quantum computers are not yet fully developed, so most of the quantum neural networks are only theoretical ideas that need to be tested in real experiments.

The goal of this research is to investigate the combined role of PINNs induced by Laplace-Fourier neural operator with quantum neural networks under variational quantum circuits. The Laplace-Fourier neural operator aims to provide an alternative layer in PINNs to replace incomplete and inefficient Fourier neural operator. There are two benefits if the Laplace-Fourier neural operator algorithm can determine the operating status of an appliance:

- Habit-improving recommendations: Users can view the usage trends of household appliances in their local area at an aggregate level, allowing them to consult these trends and optimize the usage of their own appliances.
- Anomaly detection: Typically, when no one is home, the TV is switched off. If the TV is turned on at an unusual or unexpected time, an application can notify the user.

The remainder of this proposal is organized as follows. Section 2 provides a research question and its goal. Section 3 specifies and motivates the Laplace-Fourier neural operator while contrasting it with the Fourier neural operator. Section 4 provides the research timeline and the preliminary results together with its expected outcomes while Section 5 concludes.

II. Objectives

The primary research question is expressed in this manner:

How can we precisely determine the operating status of household appliances such as electric kettles and washing machines using classical-quantum neural networks, solely based on smart power readings?

To answer this question, we design two studies:

A. A study to identify the on/off state of every appliance at each timestamp.

B. A study to derive an activation function using quantum mechanics.

This research argues that classical-quantum neural networks offer an accurately predictions to understand the behavior of individual appliances.

III. METHODOLOGY

A. Learning classes

A training dataset can specify quantum states in various ways. There are different learning classes based on the training dataset's form, the learner's technological abilities, and their learning objective. For learning class $L_{goal}^{context}$ [24], the subscript goal represents the learning objective, while the superscript context represents the training dataset and/or the learner's abilities. The goal can be either c for classical machine learning or q for quantum machine learning. The context can be c for classical or q for quantum. Other context values can be used for more specificity:

- L_c^c represents the traditional form of machine learning, where classical methods are used to learn about classical objects from classical dataset.
- L_c^q means using a quantum computer (or a quantum simulator) to assist with a classical machine learning task. The computer could potentially accelerate the machine learning process, even though the goal remains classical.
- L_q^c is the quantum learning class where all quantum state descriptions in the training dataset $D_n = \{(\psi_1, y_1), \ldots, (\psi_n, y_n)\}$ are provided classically.
- L_q^q is the learning class where k copies of each training quantum state are provided.

In this context, the dataset from power meter devices can be categorized into the L_q^c class, because ψ_{time} is the classical description of quantum state $|\psi_{time}\rangle$, and y_{time} is the electrical power from smart meter readings.

B. Theoretical formulation in quantum mechanics

The kernel integral operator is defined by [10]:

$$(K(a;\phi)v_t)(x) = \int_D k(x,y,a(x),a(y);\phi)v_t(y)\,dy\,, \forall x \in D \quad (1)$$

By letting $k_\phi\big(x,y,a(x),a(y)\big) = k_\phi(x-y)$ and applying the convolution theorem, [10] find that

$$(K(a;\phi)v_t)(x) = F^{-1}\Big(F\big(k_\phi\big)\cdot F(v_t)\Big)(x), \forall x \in D \quad (2)$$

Here F^{-1} is the inverse Fourier transform, and F is the Fourier transform.

Time evolution is not defined in (1), and the kernel integral operator $(K(a;\phi)v_t)(x)$ is just an output function $u_t(x)$. We propose a 3D propagator in space and time by

$$K(\vec{r}'', t; \vec{r}', t_0) = \sum_j \langle \vec{r}''|j\rangle\langle j|\vec{r}'\rangle e^{\frac{-iE_j(t-t_0)}{\hbar}} \quad (3)$$

The propagator is acting on the initial function $v(\vec{r}', t_0)$ to yield the final function:

$$u(\vec{r}'', t) = \int dr'\, K(\vec{r}'', t; \vec{r}', t_0) v(\vec{r}', t_0) \quad (4)$$

In case of $t_0 = 0$ and $\vec{r}'' = \vec{r}'$, we have

$$G(t) = \int dr'\, K(\vec{r}'', t; \vec{r}', t_0) = \int dr'\, K(\vec{r}', t; \vec{r}', 0) = \int dr' \sum_j \langle \vec{r}'|j\rangle\langle j|\vec{r}'\rangle e^{\frac{-iE_j(t-0)}{\hbar}} = \int dr' \sum_j |\langle \vec{r}'|j\rangle|^2 e^{\frac{-iE_jt}{\hbar}} = \sum_j e^{\frac{-iE_jt}{\hbar}} \quad (5)$$

The time-dependent function $G(t)$ is once again acting on the initial function $v(\vec{r}', 0)$ to yield the final function:

$$u(\vec{r}', t) = G(t)v(\vec{r}', 0) \quad (6)$$

Taking the Laplace-Fourier transform of $G(t)$:

$$G(E) = \frac{-i}{\hbar}\int_0^\infty dt\, G(t)e^{\frac{iEt}{\hbar}} = \frac{-i}{\hbar}\int_0^\infty dt \sum_j e^{\frac{-iE_jt}{\hbar}} e^{\frac{iEt}{\hbar}} = \lim_{\varepsilon\to 0}\frac{-i}{\hbar}\int_0^\infty dt \sum_j e^{\frac{-iE_jt}{\hbar}} e^{\frac{i(E+i\varepsilon)t}{\hbar}} = \lim_{\varepsilon\to 0}\frac{-i}{\hbar}\int_0^\infty dt \sum_j e^{\frac{-iE_jt}{\hbar}} e^{\frac{iEt}{\hbar}} e^{\frac{-\varepsilon t}{\hbar}} = \lim_{\varepsilon\to 0}\frac{-i}{\hbar}\int_0^\infty dt \sum_j e^{\frac{i(E-E_j)t}{\hbar}} e^{\frac{-\varepsilon t}{\hbar}} = \sum_j \frac{1}{E-E_j} \quad (7)$$

We obtain the final function:

$$u(\vec{r}', E) = G(E)v(\vec{r}') \quad (8)$$

Equation (7) – the Laplace-Fourier neural operator – suggests that one can inspect the energy spectrum E of a quantum system by calculating the Green-like function $G(E)$ algebraically, instead of convoluting functions and transforming it back to the real space.

C. Architecture of the system

A system that covers all stages, from the operating status of home appliances (on/off) inferred from power readings collected by a smart meter, to the use of proposed machine learning techniques (classical-quantum neural networks), is depicted in Figure 1. The system is a simplified version of the single input multiple output method. The process starts with the recording of power demand for each appliance by a smart meter, and the recording data are collected every 6 seconds. The data are ingested into the hybrid neural networks. The classical part (PINN) of the hybrid contains the proposed layer which is the Laplace-Fourier neural operator, while the quantum part serves as a front end. Output of the networks is visualized for real-time monitoring.

The Laplace-Fourier neural operator is shown in Figure 2. In this simplified figure, an input dataset sequence of length n, represented by v, is processed by the Green-like function G to make a prediction, represented by u, for all m appliances.

D. Data source

Since we involve time evolution in the formalism, we use data of power consumption that change every time. The data is retrieved from UKERC Energy Data Centre [25]. The UK-DALE dataset captures the power consumption of individual appliances and the entire house every 6 seconds from 5 households. We use data from house #2, which includes 19 appliances' power usage. Due to the dataset's sample rate of ⅙ Hz, it is challenging to estimate low-power appliances. After analyzing the data, we choose eight

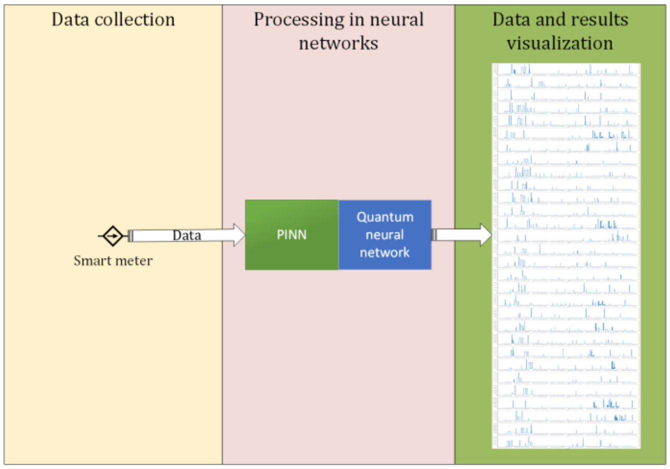

Fig. 1. System architecture

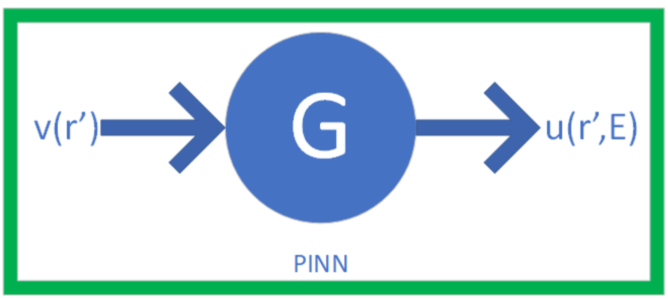

Fig. 2. A layer of Laplace-Fourier neural operator in Physics-Informed Neural Networks

target appliances: a treadmill, washing machine, dishwasher, microwave, toaster, electric kettle, rice cooker, and electric stovetop (cooker).

The power consumption histograms for eight appliances are displayed in Figure 3. As the appliances are mostly turned off, the majority of the readings are close to zero.

In Figure 4, the power usage of eight individual appliances is compared to the total power usage of the entire house. The input to system is the overall consumption (represented by the blue curve), as this data is easily accessible and can even be measured from outside the home.

The data for House #2 covers the period from late February to early October 2013, with data from March to July being used in system. A summary of eight appliances is shown in Table 1. The data is highly imbalanced in terms of both the "on" and "off" states of each appliance and the power consumption scale of each appliance, which presents a significant challenge for prediction.

One important step in preparing the UK-DALE data is to determine the on/off status of each appliance at every timestamp since this information was not recorded. An appliance is considered to be "on" if its power usage exceeds one standard deviation from the average power readings, as most appliances are off for the majority of the time and their readings are close to zero. We create a notebook - e2e_processed_h2_appliance.ipynb – that contains the code for this data preprocessing step [26].

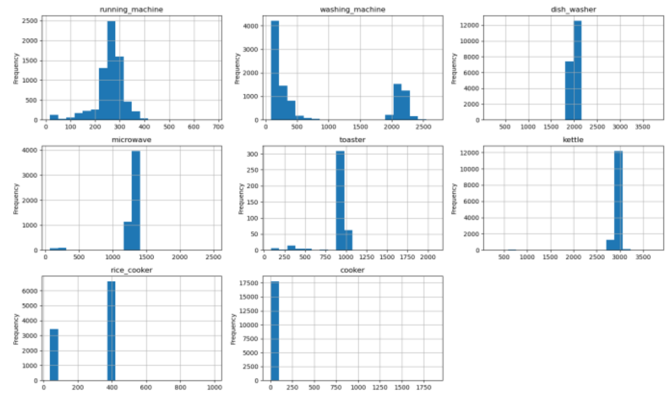

Fig. 3. Demand histograms of eight appliances

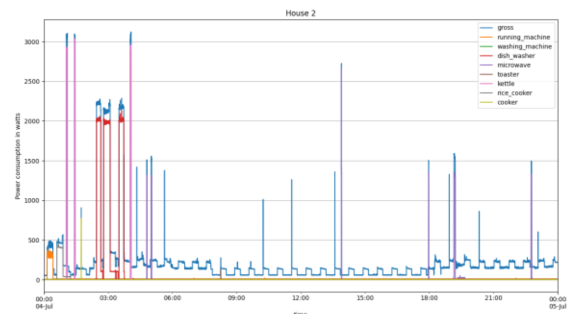

Fig. 4. Data sample from house #2 on 2013-07-04 UTC

TABLE I

DESCRIPTIVE SUMMARY OF POWER CONSUMPTION

	cooker	rice_cooker	kettle	toaster	microwave	running_machine	washing_machine	dish_washer
count	2190874	2190874	2190874	2190874	2190874	2190874	2190874	2190874
mean	0.082431	2.285429924	19.48569	0.302918	3.228323947	5.654346621	6.841747631	19.53853713
std	3.315511	22.3474211	233.1883	12.85732	63.26168798	15.38121911	82.42392368	189.6412709
min	0	0	0	0	0	0	0	0
25%	0	1	1	0	0	1	3	1
50%	0	1	1	0	0	1	3	1
75%	0	1	1	0	0	10	3	1
max	3532	1017	3996	2364	2668	718	2974	3964

IV. RESEARCH TIMELINE AND PRELIMINARY RESULTS

We use a long short-term memory (LSTM) based network as a base comparison to the proposed layer, the Laplace-Fourier neural operator. Some learning parameters that are used by these layers can be seen in Table 2.

The precision and recall of each appliance are shown in Table 3. The cooker and toaster are challenging to predict using LSTM due to their significantly lower peak power consumption compared to other appliances. We provide a script - LSTM.sh – so one can use the script to reconstruct the results [26].

In Table 4, we are doing a preliminary study to determine if artificial intelligence can be useful. During the internship, we find a dataset of power consumption. We feed the data into an LSTM model and found that it takes two hours to get predictions for some appliances. We derive a mathematical formula based on quantum mechanics to find a better prediction than LSTM model. We discover the Laplace-Fourier neural operator is computed algebraically, so we expect that the computation is much faster than the Fourier neural operator using by other researchers.

TABLE 2
PARAMETERS OF MACHINE LEARNING

Parameter	Value
Learning rate	8.1729×10^{-5}
Filter probability	0.6827
Size	131
Sequence length	5
Number of epochs	40
Train batch size	64
Dropout rate	0.3204
Layers	4

TABLE 3
PRECISION AND RECALL OF PREDICTIONS FOR INDIVIDUAL APPLIANCES

Appliance	LSTM		Laplace-Fourier neural operator	
	Precision	Recall	Precision	Recall
Cooker	0.00	0.00	Research in progress	
Rice cooker	0.81	0.43		
Kettle	0.72	0.96		
Toaster	0.00	0.00		
Micro wave	0.86	0.53		
Dish washer	0.86	0.80		
Washing machine	0.96	0.02		
Running machine	0.31	0.72		

TABLE 4
TIMELINE OF THE RESEARCH

Activity	2022	2023	2024	2025
Preliminary study				
Internship				
Writing proposal				
Submit articles to conferences				
Submit articles to journals				
Writing doctoral thesis				

V. COMPANY INTERNSHIP

This research has been running in Techvisory since February 2023. The mission of Techvisory is providing in-depth knowledge in the technological and industrial fields for its customers [27]. Techvisory offers cutting-edge solutions that enable businesses to make well-informed decisions through real-time functionality, data enhancement, and data intelligence.

VI. CONCLUSIONS

It is now possible to monitor and track household's total power consumption using various smart meter devices on the market. An electric utility provider can use classical machine learning to examine meter data and alert customers to unusual behavior from specific appliances. However, classical machine learning cannot predict the behavior of individual appliances accurately. To predict the behavior accurately, this research offers a machine learning hybrid that combines classical and quantum neural networks. The classical neural networks are based on physics-informed neural networks, and we propose a Laplace-Fourier neural operator as the layer in the PINNs. Using single input multiple output method and computing the power consumption algebraically, we expect the hybrid networks can accurately predict the individual appliance behavior.

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