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Deep Learning in Energy Modeling: Application in Smart Buildings with Distributed Energy Generation

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ABSTRACT Over 33% of final energy consumption is used in buildings which leads to nearly 40% of total direct and indirect CO_2 emissions in the world. While energy consumption is steadily rising globally, managing building energy utilization by on-site renewable energy generation can help responding this demand. This paper proposes a deep learning method based on a discrete wavelet transformation and long short-term memory method (DWT-LSTM) and a scheduling framework for the integrated modelling and management of energy demand and supply for buildings. This method considers several factors including a two-step electricity price, uncertainty in climatic factors, availability of renewable energy resources (wind and solar), energy consumption patterns in buildings, and the non-linear relationships between these parameters. This novel method analyzes and continuously learns from data patterns based on hourly, daily, weekly and monthly intervals. The method enables monitoring and controlling renewable energy generation, the share of energy imports from the grid, employment of saving strategy based on the user priority list, and energy storage management. The main objective of the proposed method is to minimize the reliance on the grid and electricity cost, especially during the peak days. The results demonstrate that the proposed method can forecast building energy demand and energy supply with a high level of accuracy, showing a 3.63-8.57% error range in hourly data prediction for one month ahead. The results also show that the method can supply 304 days (83.2%) of a year without reliance on energy grids, decreasing 87.2% in energy demand on one hand and exporting annually 7777 kWh to the grid on the other hand. In addition, the rescheduling framework decreased the imported electricity cost with the higher electricity tariff by 98 %. The combination of the deep learning forecasting, energy storage, and scheduling algorithm enables reducing annual energy import from the grid from 6709 to 858 kWh (84.3%).

INDEX TERMS Smart Active Buildings; AI-based Energy Model; Deep Learning; LSTM; Artificial Neural Network; Energy System Modeling; Building energy management; Discrete Wavelet Transformation; Load Scheduling.

I. INTRODUCTION

The growth of energy consumption in residential and commercial buildings leads to substantial greenhouse gas (GHG) emissions. Building energy accounts for 33% of the world's energy consumption and 40% of the world's direct and indirect GHG emissions [1], [2]. Providing reliable and green energy sources improve the building energy supply, which enhances the life quality [2]. For example, smart active buildings and net-zero energy buildings aim to preserve interior thermal convenience and minimize energy consumption in order to mitigate the building energy consumption, and GHG emission [3], [4]. Indeed, smart active building modelling has a pivotal role in improving energy efficiency, Energy Storage (ES) measures and the development of renewable

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energy systems in buildings [5], [6]. Using Renewable Energy Resources (RER) requires an efficient management and planning model for achieving a high-performance model [7], [8].

To enable smart active buildings, building energy modelling and forecasting is applied [9], which is a multi-criterion problem. The modelling depends on a wide range of variables, including consumption patterns, temperature, humidity, cloud cover, wind speed, air pressure, and ES capacity. Moreover, energy demand and supply in buildings are time-dependent, varying hourly, weekly, and seasonally [10]. Smart building energy modelling systems include demand-side models, supply-side models, as well as hybridization of demand and supply models for building energy management [11].

As building energy consumption increases and when renewable energy systems are available, therefore, to minimize the energy cost, building an energy management system requires considering the energy consumption and generation simultaneously [12]. For example, the capacity of Photo-Voltaic (PV) energy generation as a promising renewable energy (RE) technology has increased from 7 Gigawatt in 2017 to 17 Gigawatt in 2019 [13]. However, PV outputs fluctuate due to variation of solar irradiance and temperature [14] which is the main challenge associated with the technology [8]. Wind energy is also another greatest progressing renewable energy resource (RER) with high potentials [15]. Moreover, there are hybrid RERs that combine different energy generation sources such as wind-solar, solar-hydro, and wind-hydro hybrids [16]. For instance, integrating wind energy with solar PV can significantly increase the renewable energy supply system's sustainability as wind energy is available during cloudy hours and the nighttime, unlike solar PV [17].

The main drivers for developing smart active buildings include energy efficiency, energy price, and environmental concerns. However, the main challenges are the efficient integration of RERs and removal of energy conversion losses. These challenges require a smart integrated energy system (SIES) that considers the energy generation-consumption system as a unit [18] as shown in Figure 1. A SIES schedules various energy supply resources to optimize the energy supply package (renewable and non-renewable energy resources). A SIES continuously compares the energy demand and supply levels to minimize the energy supply by the non-renewable energy sources [19]. To enable SIES, smart active building energy management needs high granularity of energy consumption and energy generation datasets, for example, the hourly or half-hourly datasets. Indeed, the energy modelling of the smart building equipped with RE sources involves a high level of complexity and non-linearity. Because, RE involves the intermittency of meteorological information and uncertainty in energy generation patterns during the day and across the seasons [20].

This paper develops an AI-based SIES to anticipate the hourly, daily, and weekly building energy demand and supply. We model energy demand and energy supply using Long Short-Term Memory (LSTM) neural network and Discrete Wavelet Decomposition (DWT) methods. As a case study, we use a dataset from five residential buildings in the British Columbia province in Canada. We use the average value of the five buildings' energy demand to eliminate the effects of accidental disturbances. In addition, unlike HEMS scheduling methods which are mostly focused on scheduling appliances to decrease energy costs [21], we develop a novel framework to evaluate the energy demand and RE generation. We also make decisions about the reliance share on the energy grid, and schedule building energy supply based on the Deep Learning (DL) predictions of energy demand, RE supply, energy price, and a pre-chosen energy saving strategy. We consider the buildings as a black-box unit in forecasting, and scheduling energy supply and demand. As a result, we consider the user convenience, energy price, and energy sustainability; and we achieve the RE sources' maximum penetration.

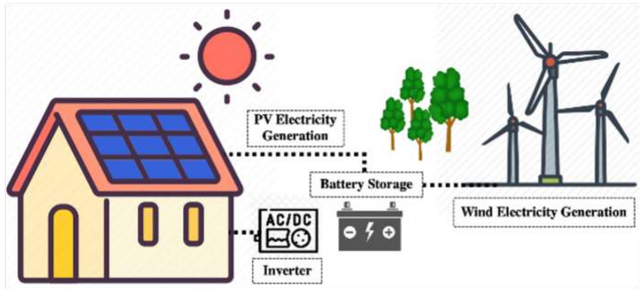

FIGURE 1. The schematic of an integrated smart active building with renewable energy resources.

II. RELATED WORK

An efficient building energy management necessitates precise energy demand and supply forecasting. This is due to its importance in building energy planning and policymaking as it enables policymakers to make critical decisions [22]. An efficient building energy management system needs accurate prediction of distributed energy resources such as wind or solar PV energy. On this basis, numerous methodologies have been developed comprising physical models, statistical methods, artificial intelligence techniques, and hybrid models to increase the prediction accuracy.

In the last decade, substantial research has been performed on building energy forecasting due to its potential for demand-side management and smart power grids penetration [23]. In residential building energy management, two main factors for building convenience are the energy demand profile and renewable energy generation. Appropriate renewable energy generation allows efficient use of energy storage and less reliance on energy exchange with the grid [24].

Based on recent research, 20%–30% of building energy consumption can be saved through optimized operation and management without changing the building structure and the

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TABLE 1. Summary of Abbreviations.

Notation	Description	Notation	Description
GHG	Green House Gas	DWT	Discrete Wavelet Decomposition
ES	Energy Storage	DL	Deep Learning
PV	Photo-Voltaic	BED	Building Energy Demand
RE	Renewable Energy	DBN	Deep Belief Network
RER	Renewable Energy Resources	HDBN	Hierarchical Deep Belief Network
SIES	Smart Integrated Energy System	FNN	Feedforward Neural Network
MAPE	Mean Average Percentage Error	CFNN	Convolutional Neural Network
LCA	Life Cycle Assessment	RBF	Radial Basis Function
TEA	Techno-Economic Analysis	SVR	Support Vector Regression
IOT-BS	Internet Of Thing Based Method	PSO	Particle Swarm Optimization
EDE-ANN	Enhanced Differential Evolution-Artificial Neural Network	ELM	Elman
CNN	Convolutional Neural Network	MILP	Mixed Integer Linear Programming
LP	Linear Programming	DR	Demand Response
GA	Genetic Algorithm	DRNN	Deep Recurrent Neural Network
RNN	Recurrent Neural Network	MLP	Multi Linear Programming
ESS	Energy Storage System	SVM	Support Vector Machine
WT-ANN	Wavelet Transform-Artificial Neural Network	EV	Electric Vehicles
BPNN	Back Propagation Neural Network	ARIMA	Autoregressive Integrated Moving Average
LSTM	Long Short-Term Memory	ARIMAX	Auto Regressive Integrated Moving Average With Exogenous Input
HP	High Pass	HVAC	Heating Ventilation And Air Conditioning
LP	Low Pass	BWC	Bergey Windpower Company
RMSE	Root Mean Square Error	MSE	Mean Squared Error
O&M	Operation and Maintenance	SDI	Supply to Demand Index

energy supply system's hardware configuration. Therefore, there is considerable potential for improving building energy efficiency through effective processes, and predictions [25].

Indeed, building energy demand modeling is significantly essential in decision-making to reduce energy consumption and CO2 emissions, as it helps improving building energy efficiency and enhancing demand and supply management. However, building energy demand (BED) prediction is still a challenging task due to the variety of factors' effect on the consumption, such as the physical characteristics of the building, the installed facilities, the weather conditions such as temperature and daylight [6], [26], and the energy-use patterns of the building residents [27].

On the other hand, according to the global population's growth and rapid economic development, the energy supply has become an essential human concern [28]. As a result of limited conventional energy sources and their harmful effects on the environment, RER such as wind and solar have become essential in energy system development according to their sustainability, and environmentally friendly characteristics [29]. For example, to increase PV operators' expected efficiency and PV facility systems' effective operations, thus, the prediction of PV energy production has become important [20]. Moreover, one of the most critical challenges in renewable energy forecasting is the uncertainty of the renewable energy resources and building energy load [30]. In practice, wind power and solar PV's intermittent nature makes accurate and reliable predictions very challenging. The power output fluctuations of RERs may substantially restrict the ability to cover the demand load, thereby reducing the system reliability and consequently leading to financial losses [31].

Predicting energy consumption and energy production in buildings through forecasting methods significantly improves active buildings management systems' efficiency. However, to achieve this efficiency, first, there is a need to decrease fluctuations and schedule the power peaks and RER supply in buildings; and second, it is crucial to decrease the energy exchange with the grid [32]. However, the study by Molina-Solana et al. concluded that the energy supply scheduling and forecasting approach as well as evaluating the influences of the distributed renewable energy sources penetration on building energy management is a challenging problem that needs more considerations [33].

In this section, we review the state-of-the-art research on building energy management. We categorize the previous studies into three main groups. First, the forecasting methods represents the developed methods to predict building energy consumption and energy generation. Second, the scheduling methods aim to find the energy consumption, price, and generation patterns in buildings and optimize buildings energy by scheduling the energy demand and supply. Third, the combination of forecasting and scheduling methods that implement a hybridization of both approaches improves building energy management efficiency. This is achieved by forecasting energy consumption/generation and scheduling energy demand.

We have presented these classifications in Figure 2. In this classification, the building energy management methods are categorized into three sub-categories. Each sub-category is divided into three groups: machine learning methods, deep learning methods, and engineering methods. Due to the paramount role of deep learning in building energy forecasting and management, we categorize this method separately from machine learning. These groups are further divided based on the intended applications. We present the summary of abbreviations used in this paper in Table 1. The reviewed articles that consider the forecasting methods are

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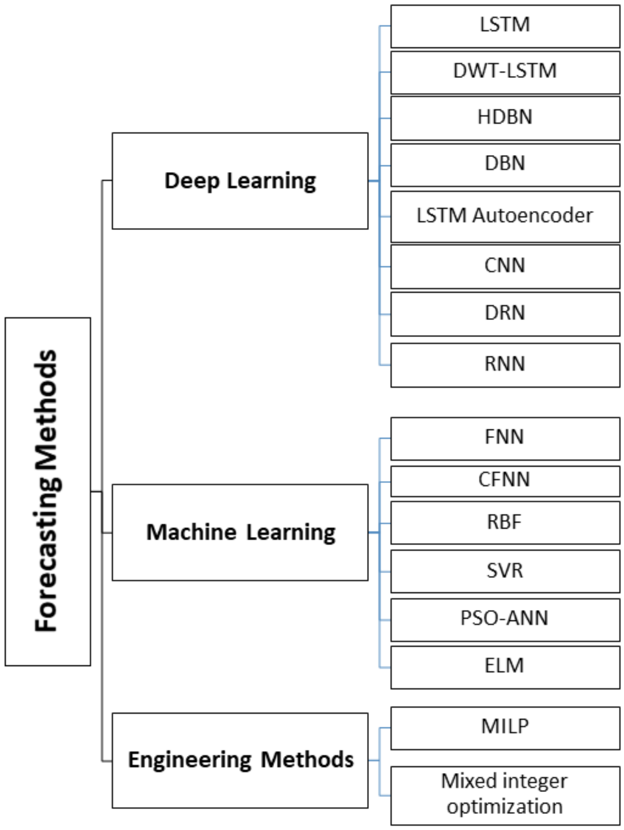

FIGURE 2. Classification of forecasting methods.

summarized in Table 2 and the articles that apply different optimization and scheduling methods, hybridization of forecasting and scheduling methods, and deep learning methods for buildings energy consumption are summarized in Table 3.

A. FORECASTING METHODS

However, in literature, the forecasting methods are divided into three groups, including statistical methods, engineering methods, and data-driven methods [34]. Whereas the data-driven forecasting methods refer to the ensemble machine learning approaches and deep learning methods [35]. Therefore, in this paper, as presented in Figure 2, we divide the forecasting methods into Engineering methods, Machine learning (ML) methods and Deep learning (DL) methods.

Engineering methods are among the popular building energy modelling approaches. These methods estimate energy consumption and energy supply of the buildings considering environmental interactions, building conditioning, occupants consumption, energy demands, energy tariffs, on-site dispatchable, and non-dispatchable generation [36], [37].

Although, in practice, engineering methods are effective and accurate, they are complex to be modelled as these methods are based on physical principles. Thus, to develop a model, the engineering methods require precise details about buildings such as environmental parameters for their input data. These parameters are hard to obtain in many cases; for example, the physical characteristic of each room in a large building is hard (if not impossible) to retrieve. The lack of precise details will thus lead to achieving low accuracy. Hence, implementing engineering methods require experts (professional engineering knowledge) and high computational resources (powerful computers), which makes them cost-inefficient and hard to use [38].

On the other hand, the ML methods can handle large amounts of data with accurate forecasting analysis. Therefore, these methods have a high potential to be applied for modelling building energy management.

For example, a comparative study in a short-term energy forecasting of anomalous days was implemented using different ML methods, including an ensemble forecast framework (ENFF), Elman neural network (ELM), Feedforward Neural Network (FNN), and Radial Basis Function (RBF) neural network [39]. The work in [40] that evaluates the performance of SVR and MLP in building energy forecasting proves the effectiveness of these machine learning-based methods in building energy modelling. A hybridization of lower-upper bound estimation and neural networks as an ensemble of ML methods are also applied to calculate potential uncertainties associated with forecasting wind and solar power and energy load [30]. A combination of the Grid-GA searching algorithm and Support Vector Regression (SVR) model to forecast renewable energy generation (wind and solar energy) and energy demand load is also presented in [41]. In addition, an ANN method is implemented to forecast energy generation and consumption for a hotel building for the next 24 hours based on daily weather forecasts [42].

Fortunately, Deep learning (DL) methods are promising approaches for learning the intrinsic non-linear characteristics and constant data patterns [43], [44]. DL methods are highly accurate energy forecasting models for modelling energy demand and supply due to their high performance in dealing with solid data regularity, and periodicity [14], [45]–[47]. In addition, DL methods are reliable for learning long-term dependencies of energy data, leading to accurate forecasting results. Thereby, DL methods outperform other alternative ML approaches [48]. Moreover, the performance of DL methods are comparable and, in some cases, superior to engineering methods such as expert-based models [49], [50], fuzzy logic [51], mixed-integer linear programming [52]. As a result, DL methods have attracted significant attention in recent studies in building's energy management modelling.

For example, the work in [53] employs a convolutional neural network approach to forecast solar PV energy generation. This work highlights the superiority of the DL forecasting method over SVR, ANN, and deep belief networks.

Another example in [54] implements a deep belief network to solve short-term load forecasting problems in demand-side management. The results show the high performance of the DL model through the input data and the developed DL model.

Furthermore, another study in [55] applies recurrent neu-

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ral network (RNN) to model energy demand and supply forecasting. Indeed, the RNN uses its internal state (i.e., memory) for processing sequences of inputs, and thus it shapes a directed graph along with the sequences of inputs. In particular, LSTM is a special type of RNN that provides better performance than other DL models in energy demand modelling [50]. For instance, the research in [56] develops a combination of deep RNN with LSTM methods (DRNN-LSTM) to forecast aggregated power load and the photovoltaic (PV) power output in a community micro-grid. The research demonstrated that the DRNN-LSTM model outperforms other ML models such as MLP and SVM methods. Another example that highlight the performance of LSTM in energy forecasting is presented in [57] that forecasts 3-day ahead energy demand across each month in a year.

B. OPTIMIZATION AND SCHEDULING METHODS

Optimization and scheduling (OS) methods is a sub-category of building energy management methods that try to optimize energy consumption, and generation using energy consumption patterns, RE generation patterns, energy storage capacity and energy cost [62]. The OS methods mainly focus on minimizing the overall cost of energy (financially and environmentally) and reliance on the grid by producing as much as possible the renewable energy resources. For example, the study in [66] implements an intelligent load scheduling model for residential load. This study aims to minimize the user intervention by considering the degradation cost of the battery pack in the vehicle-to-grid mode. This addresses the necessity of managing and optimizing the energy consumption in smart buildings, and fully utilizing solar energy or wind energy, and electrical storage operation [25], [58], [60].

Indeed, energy OS methods and renewable resources have a crucial role in moving toward an independent and low-cost smart building. The efficiency of integrating RE sources and energy storage in a smart active building also can be significantly increased through an optimizing and scheduling approach. For example, the study in [59] developed an OS method based on demand response and time of consumption pricing to optimize the integration of a solar PV system and an energy storage system (ESS) in smart homes. The results showed that the energy consumption decreased by 48% and the renewable energy share increased to 65% of the total energy consumption.

Moreover, the uncertainty of various environmental and psycho-economic factors such as the residents' energy consumption patterns are among the main challenges in scheduling building energy consumption. For example, the data-driven machine learning methods proves to be an efficient approach in tackling these types of challenges [67].

Another study in [68] integrates solar PV and an OS model, leading to the reduction of more than 43% of electricity consumption in an official building supplied by the grid. Besides, the OS model decreased the per-unit cost of PV/Grid system electricity by almost 10% comparing with the grid tariff. It also minimized over 90% emission compared with the study site's total emission.

Implementing an OS method in a smart building has also shown that an integrated OS model with a PV system covers 16.02% of the annual load energy at 0.5252 $/kWh energy cost, while an integrated OS model with a PV-wind system covers 53.65% of the annual load at the lowest energy cost; 0.1251 $/kWh. In addition, adding battery storage to the integration of the OS model and solar-wind system improves the annual average load cover ratio and self-consumption ratio by 14.08% and 16.56%, respectively. The OS-PV-wind-battery system also covers 81.29% of the annual load at an affordable energy cost (0.2230 $/kWh) [69].

The work in [58] uses a fuzzy decision support method as an OS method to optimize the integration of ground source heat pump and solar PV in a smart building. As a result, the integration of OS, ground source heat pump and solar PV covers 44% smart building energy demand and reduces 11.4% of the life cycle environmental impacts at the building level. Furthermore, the hybridization of an OS method and IoT-based techniques demonstrate efficiency in scheduling energy consumption and generation simultaneously. For example, the IoT-based approach is used to collect the real-time information of energy consumption [70]. The data is then analyzed to optimize the energy scheduling and to control the home energy consumption patterns in order to decrease the energy cost [12].

Fortunately, deep learning methods have shown potentials in optimizing and scheduling smart home energy management. For example, the study in [71] applies a hierarchical deep reinforcement learning method for scheduling smart home appliances' energy consumption and distributed energy resources. The method utilizes an energy storage system (ESS) and an electric vehicle (EV) based on weather conditions, the driving patterns of the EV, cost of electricity, state of energy of the ESS and EV, and consumer preferences. As a result, implementing deep learning and solar PV in building energy management has decreased energy costs by 11%.

C. COMBINATION OF FORECASTING AND SCHEDULING METHODS

Combination of forecasting and scheduling methods (CFS) is among the efficient approaches that simultaneously implement forecasting and scheduling approaches. These methods forecast energy generation, energy consumption and energy price; and then schedule the energy demand and supply in order to optimize and schedule the share of RERs, energy price, environmental emission, and reliance on the grid due to the forecasting results [61]–[63], [72]. For example, the work in [61] develops a method to forecast and schedule the electricity pricing, electricity consuming tasks, and renewable energy generation. The implementation results of the method demonstrate the energy reduction in smart homes due to the optimization of distributed energy resources operation and electricity-consuming household tasks.

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TABLE 2. A summary and classification of different forecasting methods for buildings energy consumption.

	Reference	Forecasting Criteria	Method	Findings
Forecasting methods	Elma et al. [37]	Wind speed, solar irradiance temperature	WT-ANN	Very short term (5-75 min) forecasting of building energy demand, solar PV and wind energy generation
	Raza et al [39]	Anomalous days short-term load forecasting	Ensemble feed forward, Elman Feedforward, and RBF neural network	Proved the ENFF has a higher accuracy than BPNN and ARIMA
	H. Quan et al. [30]	Uncertainty estimation in forecasting wind and solar power, energy load	Hybridization of lower upper bound estimation, Particle swarm optimization, and neural network	Increase the coverage of wide-based criteria by 60%
	Y. Li et al. [41]	Forecast wind and solar energy generation and energy demand load	Grid-GA searching algorithm and SVR	Grid-GA searching method is compared with Grid-searching and GA-searching. The Grid-GA searching is less time-consuming, and suitable for the short-time forecasting of renewable generations and energy loads in smart community
	N. Ayoub et al. [42]	Forecast energy demand solar and wind energy generation for the next 24 hours	Artificial neural network	ANN models are among the most accurate methods in forecasting energy demand and supply
	X. Kong et al. [54]	Short-term load forecasting problems in demand-side management	Deep belief network	Deep belief network is more accurate than ARMA, SVR, PM and ARIMA in load forecasting
	M. Cai et al. [44]	Day-ahead building load forecasts	RNN, CNN, and ARIMAX	RNN has a higher accuracy than CNN and ARIMAX
	L. Du et al. [53]	Forecast solar PV energy generation	CNN, SVR, and ANN	CNN has a higher accuracy than SVR and ANN
	L. Wen et al. [56]	Forecast aggregated power load and the photovoltaic (PV) power output	DRNN-LSTM	DRNN-LSTM has a higher accuracy than MLP, and SVM
	N. Al Khafaf et al. [57]	Forecast 3-day ahead energy demand	LSTM	—
	X. Guan et al. [25]	Scheduling building energy supplies and demand	Mixed-integer optimization	7.54%, 6.24, 10.67 reduced costs for sunny, cloudy, and rainy weather

Another work in [62] applies a CFS method to forecast wind speed and solar radiation and schedule smart appliances and charging/discharging of electric vehicles (EVs) using the MILP method. The results of the method show that the CFS method can optimally mitigate the energy and increase the RE penetration.

In addition, coupling forecasting methods with an experimental simulation to monitor energy supply and energy consumption of the smart building leads to a reduction in electricity cost, reduction of peak power, and increase in comfort levels [72].

The deep learning forecasting methods have recently been coupled with Linear Programming (LP) methods to schedule energy-consuming appliances based on demand response. For instance, the work in [63] establish a deep learning method to achieve an optimal operation of smart home appliances. This method uses an annual dataset to forecast day-ahead energy consumption by smart building appliances. The forecast results were coupled with an LP-based optimization model to manage and schedule the appliance for a suitable demand response considering price limits, demand, and equipment rating. The results demonstrate a significant reduction in energy bills.

The studies mentioned above highlight that developing a smart building energy management framework is necessary to decrease reliance on energy grid and energy cost; as well as to increase renewable energy share in the energy supply in buildings and power grids.

D. OUR PROPOSED METHOD

In the literature, there are limited studies that have focused on the smart active building energy consumption and generation using scheduling and forecasting methods, battery management, RE generation management, and consumption scheduling based on the forecast patterns. Using these considerations, our proposed method forecasts energy supply and demand using hybridization of LSTM and DWT methods suitable for modelling non-linear and complex problems such as solar and wind energy generation and energy demand forecasting problems. Based on the results of forecasting, we then propose the scheduling algorithm which reschedules energy demand to minimize electricity import from the grid and consequently energy costs during the peak days. Therefore, we can achieve the lowest level of dependency on the energy grid and the highest level of RE penetration.

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TABLE 3. A summary and classification of different optimization and scheduling methods, hybridization of forecasting and scheduling methods, and deep learning methods for buildings energy consumption.

	Reference	Forecasting Criteria	Method	Findings
Optimization and scheduling methods	H. Karunathilake et al. [58]	Integration of ground source heat pump and solar PV	Fuzzy logic, Life cycle assessment	Covers 44% of the building energy demand
	Y. Ma et al. [59]	Integration of solar energy and energy storage	Scheduling energy demand based on demand response and time of consumption pricing	48% decrease of energy increased and 65% coverage of energy consumption by renewable energy
	S. Lee [20]	Scheduling energy consumption of smart home appliances and distributed energy resources, energy storage system, and an electric vehicle	Hierarchical deep reinforcement learning	11% cost decrease with PV integration
	Han et al. [12]	Scheduling energy consumption and generation simultaneously to decrease the energy cost	EMD model, CFNN, and IoT-based scheduling	Decrements of 14.60% and 15.35% of the energy costs occurred in February and August
	Dadashi-Rad et al. [7]	Scheduling energy consumption and renewable energy generation simultaneously to decrease the energy cost	PSO model and KNX protocol	25-30% reduction in consumption
	Jin et al. [60]	Scheduling day-ahead energy consumption and distributed energy resources simultaneously to decrease the energy cost	model predictive control	reduction in daily energy costs
Hybridization of forecasting and scheduling methods	D. Zhang et al. [61]	optimal scheduling of smart homes' energy consumption	Scheduling mixed-integer linear programming, day-ahead forecasted energy consumption, renewable energy supply	Total peak demand over the threshold has been reduced from 1566 kWh in the RMO scenario to 1191 kWh. 11% reduction of the total electricity demand
	S. Aslam et al. [62]	Scheduling and forecasting energy demand and supply to mitigate energy costs	MILP to schedule appliances and EVs. EDE-ANN for day-ahead energy prediction	45% and 80% of electricity cost reduction without and with microgrid integration
	T. Hossen et al. [63]	Forecast day-ahead energy consumption and manage and schedule the appliance demand response	Deep learning, Linear Programming optimization model	Energy consuming appliance has a great role on energy forecasting accuracy as lights are easily forecasted in comparison with Duct Heater due to their predictable patterns
	S. A. Adewuyi et al. [43]	Short-term load forecasting	LSTM, CNN, and MLP	LSTM has a significantly higher accuracy comparing with MLP
Deep Learning methods	J. Zhang et al. [47]	Predicting the short-term power output of a photovoltaic panel	MLP, CNN, and a LSTM	Improved RMSE skill score of 7% for MLP and 12% for CNN-based network and LSTM achieved a 21% RMSE skill score
	F. Wang et al. [14]	Photovoltaic (PV) power generation	LSTM-RNN	LSTM-RNN has a higher accuracy than BPNN SVM
	G. Li et al. [46]	Photovoltaic Power Forecasting	RNN, BPNN, RBF neural network, SVM, and LSTM	Deep learning models (RNN, and LSTM) have a significantly higher accuracy in comparison with Persistence model, RBF, BPNN, and SVM
	B. Kermanshahi [55]	Long-term load forecasting	RNN and feed-forward back-propagation (BP)	RNN has a higher level of accuracy than BP
	J. Yang et al. [64]	Generation representative scenarios in an integrated hydro-photovoltaic (PV) power generation system	LSTM auto-encoder	LSTM auto encoder method is highly potential in building energy forecasting
	Y. Liu et al. [65]	Wind Power Short-Term Prediction	LSTM and Discrete Wavelet Transform	LSTM-DWT has a higher accuracy in comparison with RNN-DWT, LSTM, RNN, SVR and BP
	J. Ku et al. [15]	Wind Speed Forecasting	Wavelet Transform, LSTM, and SVR	Equipping LSTM with DWT significantly increases the forecasting accuracy

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III. MATERIALS AND METHODS

In this section, we firstly model the energy demand and RE energy supply of the building using long short-term memory neural network and wavelet decomposition transformation (DWT) methods. The historical datasets of the energy demand and energy supply, temperature, humidity, and air pressure are the input to the DWT. The DWT decomposes each input into three levels of frequencies. The decomposed signals are inserted into LSTM models to predict energy demand and energy supply based on the temperature, humidity, pressure, day of the week, and hour of the day. The energy demand and energy supply models represent the energy consumption patterns of the building and energy generation of the RE sources and their responses to the climatic patterns, time of the day, and day of the week.

Moreover, a novel framework is developed to forecast and control energy demand, energy supply, RE generation, reliance on the grid, electricity price, the level of ES, and activation of energy-saving strategy. Figure 3 illustrates a schematic of the proposed framework.

In general, the proposed method in this study includes integration of DWT and LSTM methods applied to forecast energy demand and energy supply and a scheduling framework to reschedule the energy supply to minimize energy costs, reliance on the grid. The wind energy generation, solar energy generation, energy demand, and the imported electricity from the grid based on the electricity price are forecasted for the next week. The proposed rescheduling method is used for rescheduling energy supply based on a week-ahead prediction of energy demand, energy supply, reliance on the grid, exported electricity to the grid, cost of imported electricity from the grid, and the level of saved energy in the energy storage. The first objective of the proposed framework is to minimize the imported electricity from the grid, especially during the peak days (days with more than 22.1918 kWh net imported energy from the grid) by saving the RE supply in the energy storage or importing electricity from the grid during the non-peak days (until the boundary limit), if RE is not available and energy storage can not supply the week ahead energy demand.

The structure of this framework is presented in Figure 3. In this structure, the oval cells are the inputs to the framework. The rhomboid cells are decision functions, and the rectangle cells are simple functions for recording and subtracting.

A. SCHEDULING FRAMEWORK

In the proposed framework, we defined an index to represent the ratio of renewable energy supply and available supplied energy by ES to energy demand called Supply to Demand Index (SDI). The SDI is estimated as follows:

$$SDI = \frac{E_{RE}}{E_D} \tag{1}$$

In Equation 1, the SDI, E_E, E_{RE}, and E_{ES} represent supply to demand index, energy demand, available RE energy supply, and available energy supply by the energy storage, respectively. The SDI is the measure of energy balance in the building. The SDI shows the relationship between energy demand and the sum of RE supply and energy storage as follows:

$$SDI = \begin{cases} > 1, & \text{If } E_D < E_{RE} + E_{ES} \\ 1, & \text{If } E_D = E_{RE} + E_{ES} \\ < 1, & \text{If } E_D > E_{RE} + E_{ES} \end{cases} \tag{2}$$

To help the framework better understand the necessity to rely on the grid or not, we define α as an index to show when the building needs to import electricity from the grid and when it can recharge the energy storage or export electricity to the grid. α is a binary index defined as follows:

$$\alpha = \begin{cases} 1, & \text{If } 1 \leqslant \text{SDI} \\ 0, & \text{If } 0 \leqslant \text{SDI} < 1 \end{cases} \tag{3}$$

In Eq. 3, α returns zero for SDI value lower than 1 and 1 for SDI more than 1.

In British Columbia, the electricity price has two tariffs based on daily electricity consumption; 0.0941 \$/kWh for lower than the boundary value of electricity consumption (22.1918 kWh per day) and 0.141\$/kWh for more than 22.1918 kWh per day. The ratio of net electricity demand to the boundary value reflects that the imported electricity is calculated based on which tariff as presented in the following equation:

$$EP = \frac{E_D - E_{RE}}{22.1918} \tag{4}$$

In Eq. 4, E_{RE} and EP are the amount of the electricity load supplied by RE resources and the index of imported electricity cost.

$$\beta = \begin{cases} 1, & \text{If } 1 \leqslant \text{EP} \\ 0, & \text{If } 0 \leqslant \text{EP} < 1 \end{cases} \tag{5}$$

In Eq. 5, EP is the ratio of the electricity demand to the electricity demand boundary, and β determines whether the electricity load is higher than the boundary demand in a binary state. β is zero when the electricity demand is lower than the boundary load and one for higher than the boundary load. The proposed scheduling method considers week-ahead energy demand and energy supply predictions to monitor the combination of the RE supply, import from the grid, and the saved energy in the energy storage. Based on the estimated β and EP value, the reliance on the grid during the peak days and the amount of imported electricity during the peak days are estimated and accordingly the lower boundary for the energy storage is estimated to minimize the reliance on the grid with the higher tariff. The amount of the electricity that is necessary to import from the grid with the higher tariff is estimated as follows:

$$ES_{Min} = \sum (EP_i - 22.1918) \times \beta \tag{6}$$

In Eq. 6, the EP_i, ES_{Min} are respectively, imported electricity from the grid with the higher electricity tariff and

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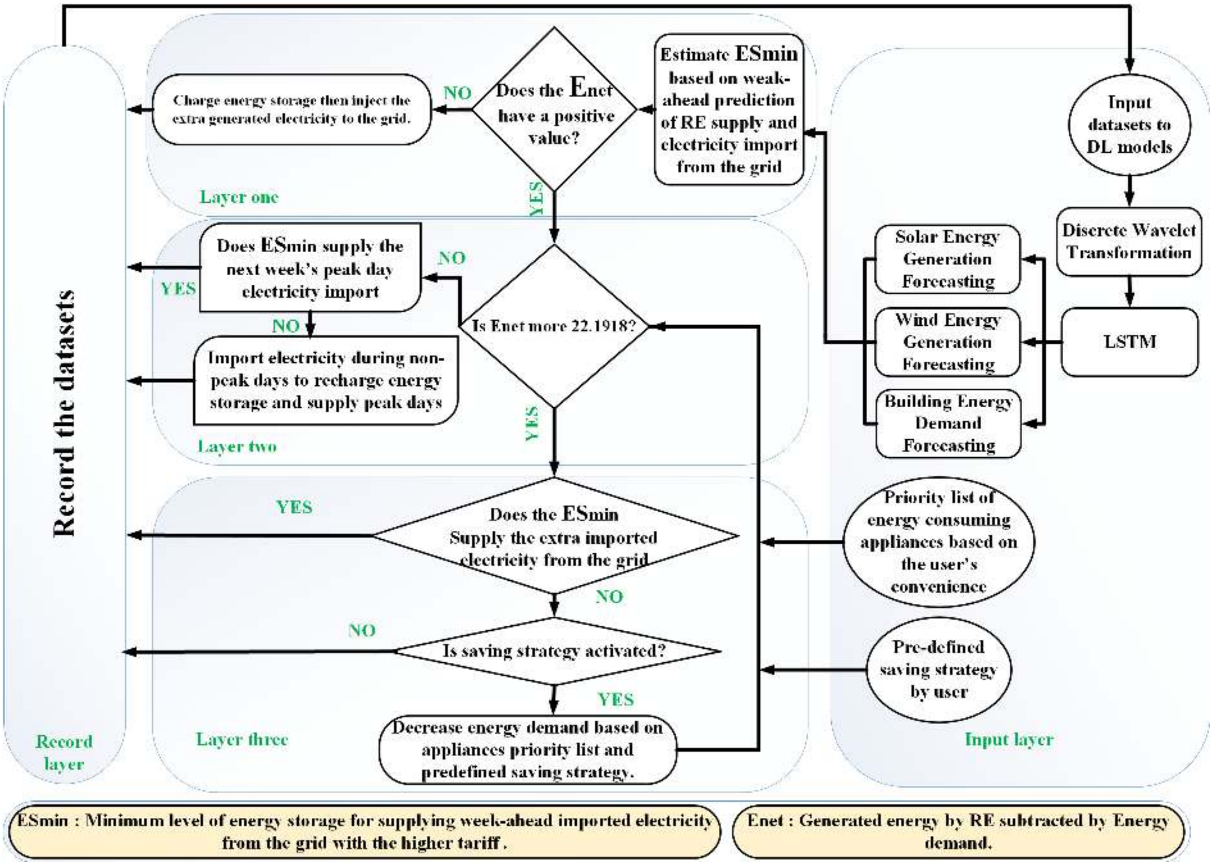

FIGURE 3. Integrated energy system structure.

minimum level of the saved energy in the energy storage to supply the imported electricity from the grid with the higher electricity tariff.

The proposed framework makes the following decision for minimizing the reliance on the grid during the peak time:

- Specify the week ahead energy demand and supply based on the predictions. Accordingly, the peak days, non-peak days and net-zero days are determined for the next week.
- The minimum level of energy storage is defined as ES_{min} to save energy for the peak days during the next week using the extra supply RE in net-zero days and imported electricity during the not-peak days (if extra RE supply is not able to supply the peak-days extra energy demand). In this way, the reliance on the grid will be decreased during the peak days. The minimum level of energy storage is defined as ES_{min} to save energy for the peak days during the next week. In this way, the reliance on the grid will be decreased during the peak days. The possibility of recharging the energy storage and maintaining its charge level at ES_{min} by E_{RE} is evaluated. When the $\sum E_{RE}$ during the next week is less than ES_{min}, the framework imports electricity from the grid during the non-peak days to recharge the energy storage up to the amount of ES_{min}.
- Based on ES_{min}, the possibility of recharging the energy storage and maintaining its charge level at ES_{min} by E_{RE} is evaluated. When the $\sum E_{RE}$ during the next week is less than ES_{min}, the framework imports electricity from the grid during the non-peak days to recharge the energy storage up to the amount of ES_{min}.
- Save the extra generated RE in the energy storage when E_{RE} is higher than the E_D until the energy storage is fully charged and then export the extra E_{RE} to the grid.
- Export $(E_{Net} - 40.5)$ to the grid when $E_{RE} - E_D$ is positive and higher the ES_{Max} (40.5 kWh).

$$E_{SG} = \sum(\alpha) \times ((E_{RE} - (E_{ES_{max}} - E_{ES}) - E_D)) \quad (7)$$

In Eq. 7, the extra supplied electricity is firstly used to recharge the energy storage and then the surplus electricity is sold to the electricity grid. The E_{RE}, $E_{ES_{max}} - E_{ES}$, and E_D, denotes the amount of the supplied RE energy, the electricity used for charging the energy storage, and the building energy demand, respectively.

As it is demonstrated in Figure 4(a), the daily energy costs are estimated based on the energy consumption, boundary-value, energy price. Hence, rescheduling the imported electricity from the grid has a significant role in reliance and the grid and energy costs.

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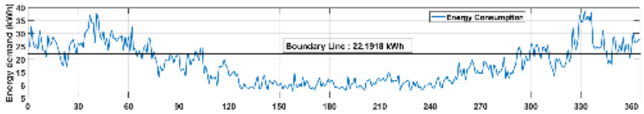
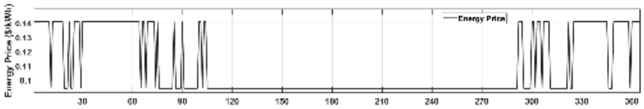
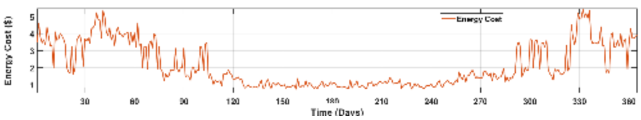


(a) Energy demand in 2019.



(b) Energy price in 2019.



(c) Energy cost in 2019.

FIGURE 4. Daily energy demand and Energy cost in 2019.

In this paper, the scheduling framework tries to reduce the reliance on the electricity grid during the higher tariff. Moreover, a cost function is defined to estimate the final energy costs of the building. These costs are composed of imported electricity from the grid during the high consumption days and the net income from the injected electricity to the grid during the high RE supply. The C_t is estimated based on the two electricity tariffs and a hypothetical selling price to the grid, equal to the lower electricity tariffs. The total electricity cost is estimated as follows:

$$C_t = \sum (E_{SG} \times P_s) - \sum (E_{BG} \times (|\beta - 1|) \times P_{b_1}) + (E_{BG} \times (\beta) \times P_{b_2}) \tag{8}$$

subjected to:

$$\beta = \begin{cases} E_D(i) \leqslant E_{RE}(i) + E_S(i) + E_{BG}(i) \\ 0 \leqslant E_S(i) \ \leqslant 40.5 \\ E_{BG}(i) \ \leqslant 22.1918 \end{cases} \tag{9}$$

In Eq. 8 and E_{SG}, E_{BG}, P_{b_1}, P_{b_2}, and P_s represent the amount of the injected electricity to the grid, the amount of the imported electricity from the grid, the electricity price in the first tariff, the electricity price in the second tariff, and the price of the sold electricity to the grid, respectively. The constraints of the proposed scheduling framework are presented in Eq. 9. In Eq. 9, $E_D(i)$, $E_{RE}(i)$, $E_S(i)$, and $E_{BG}(i)$ are energy demand, renewable energy supply, energy storage level, and imported electricity from the grid at moment i, respectively.

When the energy demand, RE energy supply, imported energy from the grid, and injected energy to the grid are estimated for a given time interval based on the predictions of the DL models.

In this study, in order to lessen the reliance on the grid, especially when the electricity price is high and moving toward a net-zero building, we developed a saving strategy in which the users choose a saving scenario based on the $alpha$ and $beta$ factors and their financial plans to reduce reliance on the grid on the one hand and decrease the energy costs on the other hand. The users can modify the saving strategy to attain the best saving scenario with the highest convenience.

B. DISCRETE WAVELET DECOMPOSITION

Discrete Wavelet Transform (DWT) methodology is a functional approach to derive valuable characteristics from the non-stationary time-series data analysis. DWT method decomposes a signal in a time-scaled way. The buildings energy demand, wind energy generation, and solar PV energy generation have a high level of intermittency and non-linearity. The DWT denoising approach tries to remove the redundant noises and prevents the LSTM model from being occupied with intermittent noises resulting from uncertainty and intermittency in the input dataset. DWT is a well-accomplished method in extracting meaningful information from the non-linear and intermittent datasets such as building energy demand, wind and solar PV energy generation [73]. Moreover, the non-stationary decomposition of time series into multidimensional components by DWT can effectively reduce the volatility of the original time series and make them more stable and predictable. Accordingly, the integration of DL models, specifically LSTM models with DWT, proved to be powerful tools for modelling energy demand [74], PV energy generation [75], and wind speed [76]. Recently, hybridization of LSTM and Wavelet Decomposition methods proved to be high-performance tools in the prediction of wind power generation [65], wind speed [15], and energy consumption [34].

The discrete version of Wavelet Transform (WT) is common in reducing continuous wavelet computation load. It passes the signal through serial filters, including High Pass (HP) filters and Low Pass (LP) filters. Equation 10 and 11 represent the HP and LP. The DWT decomposition coefficients are computed through the passing process [77]:

$$x_1(n) = \sum_{k=0}^{L-1} c_k x(k-n) \tag{10}$$

$$x_2(n) = \sum_{k=0}^{L-1} d_k x(k-n) \tag{11}$$

The LP and HP components are $x_1(n)$ and $x_2(n)$, respectively. The c_k and d_k are the coefficients of the LP and HP filters, respectively. The k also indicates the decomposition level, and n is the translating constant, which are integers. It is worth noting that DWT is a transformation function that decomposes a signal into several levels. These levels are time series of coefficients. Each set of coefficients demonstrates the given signal's evolution in a specific frequency band [78]. This study compared a two-layer DWT and three-layer DWT in decomposing the variables into two and three layers of frequency bands. As it is noticeable in Figure 5, the DWT

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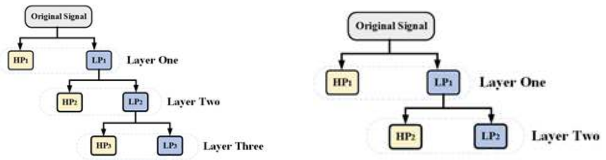
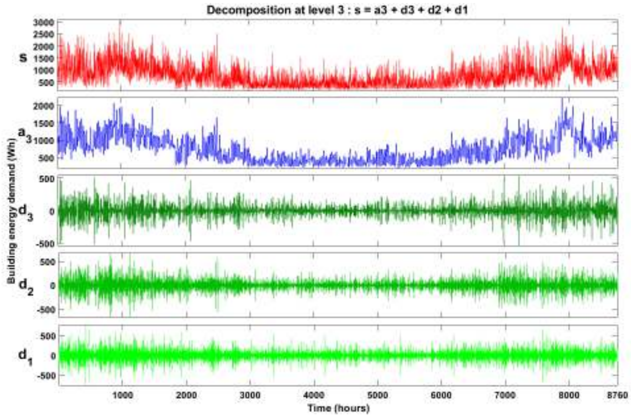
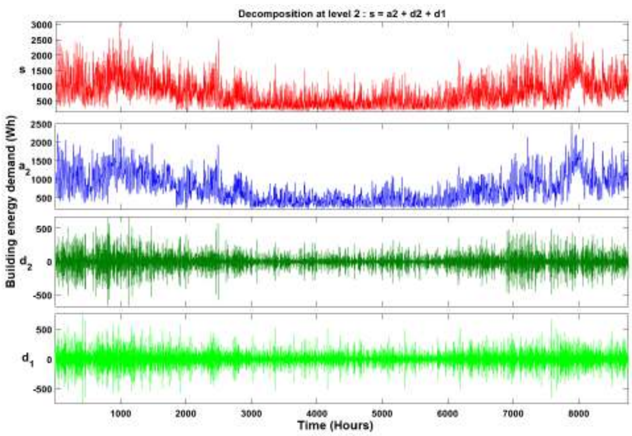


(a) A three layer-DWT structure. (b) A three layer-DWT structure.

FIGURE 5. Block diagram of the proposed DWT denoising methods.

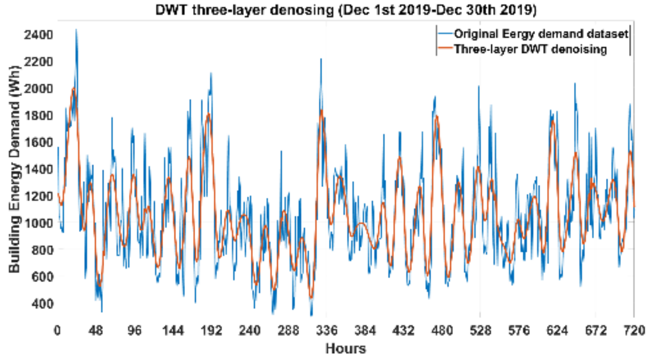


(a) A three layer-DWT decomposition.

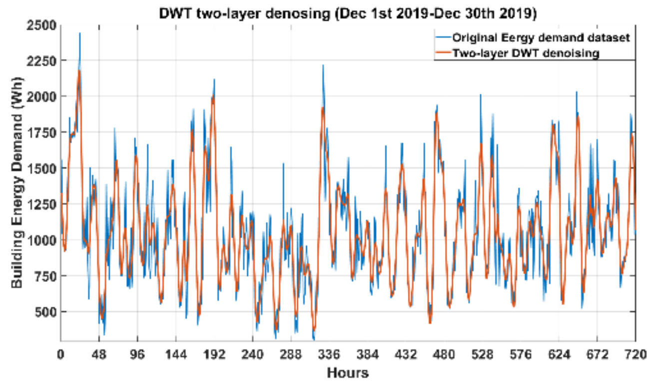


(b) A two layer-DWT decomposition.

FIGURE 6. The denoising results of the proposed DWT denoising methods.



(a) Two-layer Denoised Building Energy Demand.



(b) Three-layer Denoised Building Energy Demand.

FIGURE 7. DWT Denoising of Building Energy demand.

method decomposes the original data (signal) into layers. In each layer, the input frequency is divided into Low Pass and High Pass. In the next layer, the LP signal of the previous layer is decomposed into high and low passes. The DWT method helps to extract long-term and short-term time series characteristics of the variables. Accordingly, using the DWT outputs improves the LSTM models' accuracy in forecasting the energy demand and the energy supply. In Figure 5, the block diagram of the implemented DWT in this study is presented.

The number of the DWT layers plays a significant role in the level of denoising. As the number of layers increases, the long-term patterns remain, and the short-term patterns vanish. Figure 6 compares a two-layer and three-layer DWT denoising process on building energy demand. As it is noticeable in Figure 7(a), the daily patterns remained in the three-layer DWT while the hourly patterns are almost removed. On the contrary, the hourly patterns still remain in the two-layer DWT in Figure 7(b), and the redundant noises are removed. With the increase of the layers, the capability of the LSTM increases in accurately modelling the denoised signals (target variable and input variables). However, increasing the number of layers may remove important short-term patterns, which decreases the model's reliability as it is not capable of short-term modelling.

C. LSTM NEURAL NETWORK DEEP LEARNING

Artificial Neural Networks (ANN) are AI-based models inspired by biological neural networks. Commonly, ANN models are implemented in the modelling of complex and non-linear problems [79]. ANN models are potential approaches with a high level of self-learning, flexibility, and non-linearity. ANN finds patterns among datasets by its neurons. ANN includes interconnected neurons, the input layer, hidden layers, output layer, iterations, connection weights, learning algorithms, and transfer function. It uses the learned patterns from datasets to apply this knowledge in upcoming situations [80]. Although neural networks are potential methods, they have drawbacks regarding learning speed, error convergence, and accuracy due to long-term dependencies. In the Back Propagation learning algorithm, long-term dependencies face exploding and vanishing gradients. Deep learning methodology has attracted attention during the last

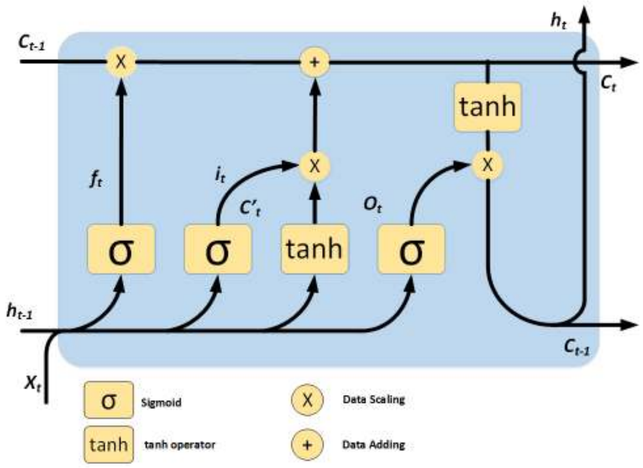


FIGURE 8. Structure of a LSTM cell.

few years as a result of its potentials in non-linear modelling issues with long-term dependencies precisely [81].

Recently, by introducing the gate controller, the LSTM gained the ability to significantly resolve the problem of vanishing or exploding gradient that occurs in the back-propagation process; this feature makes the LSTM one of the most popular DL neural networks in recent years [82]. LSTM is a variation of Recurrent Neural Networks proposed by Hochreiter for the first time [83]. The LSTM saves the forward and back-propagated weights in its layers. LSTM combines long-term memory and short-term memories using gate monitoring. Figure 8 demonstrates the structure of an LSTM unit.

An LSTM cell is composed of a forget gate, input gate, memory cell. The forget gate controls the reflection of the previous state on the current state. The input gate governs the updating of the cell state by new data. The output gate monitors the output information according to the cell state. The input gate, output gate, and memory cell are defined as [84], [85]:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \quad (12)$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (13)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (14)$$

$$\hat{C}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c) \quad (15)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \hat{C}_t) \quad (16)$$

$$h_t = o_t \times \tanh(C_t)) \quad (17)$$

In Equation (12) to Equation (17), the $X_t$is the input at time t. The selected set of inputs X_t is saved in the $C_t$by the input gate. On the other hand, $C_{t-1}$is selectively forgotten by forgetting gate. The output gate finally monitors the section of the C_t that is added to the output h_t [85]. Also, W_f, W_i, W_o, and W_c are the forget, input, output gate, and cell state weights, respectively. The forget, input, output, and cell state biases are saved in b_f, b_i, b_o, and b_c, respectively. The Sigmoid function in Equation (12), (13), and (14) prepares the dataset for the forget gate, output gate, and input gate by converting the dataset to a value between 0 and 1. The output of the gates is a function of X_t and h_{t-1} that are the present inputs and previous cell outputs, respectively. If the h_{t-1} and X_t values are equal to 0, and the gates will block them. In contrast, when the values are equal to 1 they will be saved. The cell states, C_t, and C'_t Are defined in Equations (16) and (17).

D. ENERGY DEMAND MODELING

Building energy systems are complex non-linear systems influenced by weather conditions, building operating modes, occupant schedules, and cost limits with a high demand for modelling approach [86]. Energy demand forecasting models are mainly categorized into three groups; Engineering methods in which the thermodynamic and physical rules are implemented based on the building's complex parameters and the environment. Statistical methods are developed based on the energy-related factors correlations. Statistical models generally suffer from a lack of accuracy and flexibility, and finally, the AI-based methods take energy consumption patterns as input and try to find the non-linear relationship among the input datasets and the target datasets. AI-based approaches have higher accuracy and flexibility than engineering and statistical models [34]. Data-driven BED forecasting models do not require data about the simulated building in detail and learn from historical data for forecasting [87].

Modelling energy demand faces two main obstacles that hinder the existing data-driven forecasting methodologies from being widely implemented in the smart grid development process. Firstly, the reliability of data-driven methods in modelling residential households' energy demand is still a source of doubt as the energy demand patterns for every household can be intermittent. Secondly, conventional deep learning neural networks, such as the convolutional neural networks (CNNs), need multidimensional inputs to attain high forecasting precision. Hence, uni-dimensional time-series data, such as energy demand data forecasting, is still challenging even for deep learning methodologies. However, a combination of wavelet transformation and LSTM proved to be a promising method in modelling the BED [73]. The input variables are as follows:

- Building energy demand, including the previous week, day and hour average energy consumption of 5 residential buildings.
- Vacation and weekends: the influence of the weekends and vacations on the building energy demand are considered as a binary value (zero for vacations and weekends and 1 for non-vacations and weekdays).
- Temperature: Hourly deviation of the temperature.
- Hour of the day: introducing the correlation between the hour of the day and building energy demand to the model.

In this study, the implemented LSTM and DWT-LSTM model energy demand based on energy consumption, vacations, temperature, and the hour of the day historical datasets

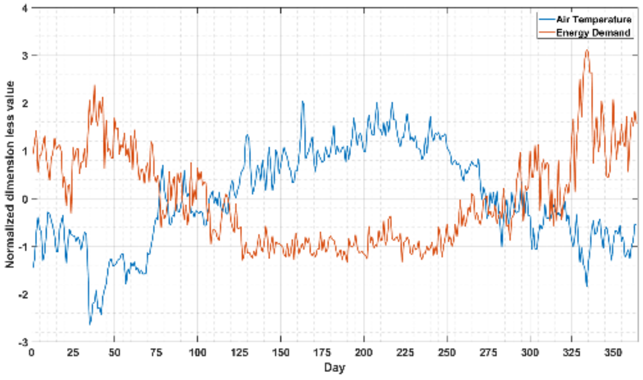


FIGURE 9. Air Temperature and Energy Demand annual trends.

from January 1st 2019 to December 1st 2019 as training inputs. The energy demand is strongly influenced by air temperature, as is noticeable in Figure 9. With the increase in the temperature, the energy demand decreases. The energy demand in the studied buildings has a periodic pattern. It has hourly, daily, weekly, monthly, and annual patterns. Accordingly, we predicted energy consumption for the next thirty days (720) hours and compared the observed energy demand results. Vacations and the weekends also has a significant role in building energy demand as the families usually have different energy consumption patterns due to the effects of gatherings, going on trips and spending more time at home instead of the workplace. The vacations and weekends are considered binary variables (one for vacations and weekends and zero for non-vacations and weekdays). Finally, the hour of the helps the LSTM model to correlate the hourly energy consumption during the day with the consumption hours for more accurate forecasting of hourly energy demand.

The utilized datasets [1] are based on a survey about energy consumption in residential buildings in British Colombia [88]. The characteristics of these buildings which are presented in Table 4 are the last read, coverage of the datasets, house type, facing, region, and HVAC system.

The coverage is the per cent of non-missing readings. The value of 1 is 100%. The missing values are interpolated from neighbouring values. Facing is the direction that the house is facing. The region is defined by a three-letter code of the house's regional weather station. YVR is Vancouver and Lower Mainland area, and WYJ is in Victoria and the surrounding area. The house type is defined based on the age and number of the building levels [88].

E. ENERGY SUPPLY MODELING

The wind and solar energy supply are highly affected by climatic factors (e.g., sunny hours, cloudiness, and wind speed). Accordingly, wind and solar energy sources have the highest uncertainty among these groups. One of the goals of this study is to predict the wind and solar energy generation patterns [14] as the integration of DWT and LSTM proved to be a capable method in modelling this type of time series problem [15], [64]. According to climatic factors, we developed LSTM and DWT-LSTM models to predict wind and solar energy supply on an hourly basis. The solar PV generation in cases where the consumer operates a solar PV system is dependent on the latitude (geographical location) [89].

In our primary analysis, we use the hourly solar PV generation for a location in Metro Vancouver, British Columbia, based on simulated data from renewables.ninja[2]. The renewables.ninja converts solar irradiance from satellite reanalysis data into power output using the Global Solar Energy Estimator model [90]. The input variables to the LSTM and DWT-LSTM models are extracted from renewables.ninja simulation tool based on a solar PV and wind energy generation simulator considering weather data from global reanalysis models and satellite observations [90].

1) Photovoltaic solar energy generation

Solar PV is strongly dependent on climatic factors, especially sunny hours and temperature. Therefore, predicting these factors will help us to predict solar energy supply [89]. The hourly prediction of PV power outputs is considered a challenging problem due to the intermittency of solar energy resources and dynamic nature of meteorological data [20], [46]. The proposed DWT-LSTM and LSTM models are developed considering solar electricity output of the previous week, day and hour, hours of the day, air temperature, solar irradiance, air density, and cloud cover as external variables. The hourly solar electricity output is considered as the target variable. The hourly solar PV generation, solar irradiance, temperature, cloud cover and air density dataset of the considered location in Metro Vancouver, British Columbia, is based on simulated data from renewables.ninja online platform for renewable energy simulation. Forecasting solar power generation is strongly influenced by solar irradiance, temperature and solar generation weekly, daily, and hourly patterns. The input time series is divided into two groups. The first group is the training dataset from January first, 2019 to December first 2019, and the second group is the evaluating dataset from December 2^{cnd} 2019 until December 31^{st} 2019. Note that in our work we consider that the solar PV unit is a fixed top roof PV with a capacity of 10 kW, a 35-degree tilt, and a 135-degree azimuth.

2) Wind energy generation

Wind energy is a sustainable energy source with a high level of uncertainty. Wind power generation is among the fastest-increasing types of renewable energy generation. Due to the uncertainty and variable nature of wind, wind energy prediction requires an accurate model. Wind speed prediction has a significant role in wind energy generation as wind power prediction is not practicable without wind speed prediction [65]. In this study, wind energy supply is estimated based on

[1] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/N3HGRN

[2] https://www.renewables.ninja/

TABLE 4. Characteristics of the considered buildings.

House	Cover	House Type	Facing	Region	HVAC types
23	0.985	**Apartment** (High-rise or low-rise living units)	SE	YVR	BHE , NAC and FPG
24	0.998	**Modern** (Two/three-level houses build in and after the 1990s)	South	YVR	FAGF and FAC
25	0.994	**Character** (Multi-level houses build before 1940)	South	YVR	IFRHG and NAC
27	0.997	**Apartment**	NW	YVR	BHE, NAC
28	0.998	**Special** (Two-level houses built between 1965 to 1989)	North	YVR	FAGF, FPE, FPG and NAC

the wind speed prediction and the power output of the BWC 5kW Grid-Intertie wind turbine according to the wind energy production and wind speed data sheets Bergey Windpower Company (BWC). The considered wind turbine is a 6.2 diameter and 30-meter hub height small scale grid-connected wind turbine. The DWT-LSTM model is developed to forecast the wind speed based on temperature, air density, and the hourly relative air density changes as input variables. The considered variables are defined as follows [90]:

- **Wind speed**: the previous week, day and hour dataset of the wind speed are considered as inputs to represent the wind speed patterns.
- **Temperature**: temperature represents the influence of hourly air temperature fluctuation on wind speed deviations.
- **Air density**: Air is the mass per unit volume of the air. Air density fluctuates with variation in atmospheric pressure, temperature and humidity.
- **Hourly relative air density changes**: the relative air density represents the air pressure which is the main reason of blowing the wind.

Wind turbines have a lower limit for wind speed that the turbine is not spinning and an upper limit that the turbine's brakes are activated to prevent damages to the turbine. The lower speed of the BWC 5 kW turbine is 2 meters per second. The higher limit is 17 meters per second. Wind energy generation is mainly influenced by the technical characteristics of the wind turbine as the wind turbine manufacturing companies provide a table of wind energy generation based on wind speed. The provided wind energy based on the wind speed for a BWC 5kW, Grid-Intertie wind turbine is presented in Table 5.

F. ENERGY STORAGE

The annual energy demand and supply patterns have valuable information about the building energy system. As shown in Figure 10, the solar PV resources annually produce 2.2 times more than building energy demand. The energy demand reduces during the summer while solar PV energy generation increases significantly. Moreover, as it is noticeable in Figure 11, wind energy generation is significantly lower than solar energy generation, while wind energy generation has a higher level of stability during the day. Hence, developing a smart building energy system is necessary to increase the share of RER in the energy supply by implementing energy storage to save generated energy during the sunny and windy hours for peak shaving and returning the energy during the low energy

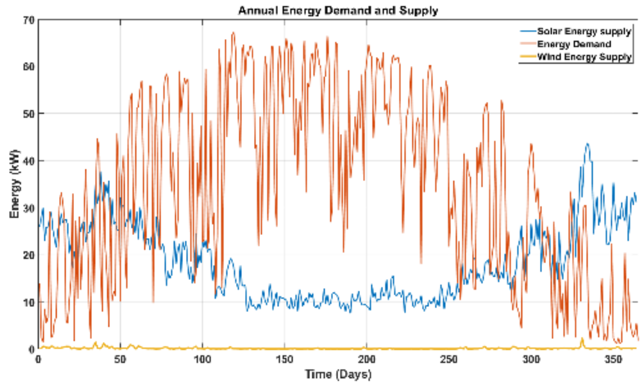


FIGURE 10. Annual Energy demand and supply.

generation hours. Energy storage can significantly decrease the energy cost, and reliance on the energy grid through peak shaving and energy scheduling [91]. The energy storage systems have been implemented for centuries and evolved to reach the current developments that many ES types are available for saving energy. ES systems are mainly developed for saving RERs such as wind and solar energy when they are in access to be used in the needed time. ES has several merits like increasing RE resources penetration, decreasing energy costs and increasing the energy system reliability. It also helps the electrical systems by Batteries are a type of electrochemical ES which are mature ES devices with high voltages, and high energy densities [91]. Lithium batteries have a significant role in electrical ES systems compared with other types of batteries due to their high specific energy density and energy density [92]).

The energy generation and consumption have an annual pattern which is illustrated in Figure 10. The net energy generation is equal to net RE energy generation subtracted by net energy demand in a daily interval. As it is noticeable in Figure 10, the solar PV energy generation has a significant role in moving toward a net-zero building while there are still challenges in supplying the energy demand during consecutive cloudy days such as the last month of the year. The annual energy demand and supply in Figure 10 depicts the importance of solar PV in a building supply system. The annual solar PV with a capacity of 10 kW generation is 12664 kWh, while a 5 kW wind turbine generates just 972 kWh, which is almost fifteen times less than solar PV generation. The main reason for this discrepancy is the low wind speed as a building size wind turbine has a low height, and the wind speed significantly decreases in low altitudes.

In this study, the daily mean energy demand, solar energy

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TABLE 5. Wind power generation of BWC 5kW, Grid-Intertie wind turbine based on wind speed.

Wind Speed (m/s)	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0	5.5	6.0	6.5	7.0	7.5
Power (kW)	0.0	0.0	0.03	0.09	0.2	0.32	0.49	0.71	0.9	1.24	1.59	1.97	2.35

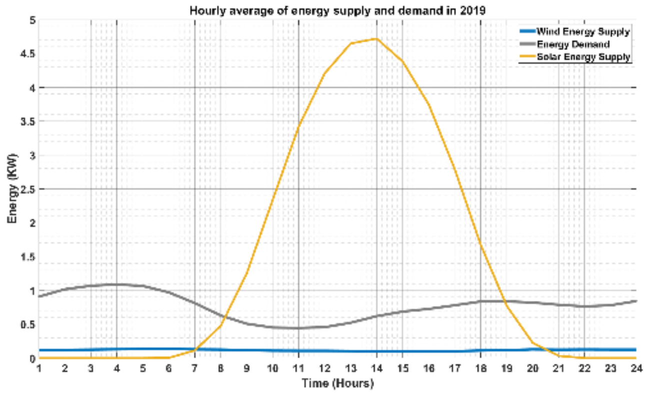

FIGURE 11. Hourly average energy demand and supply.

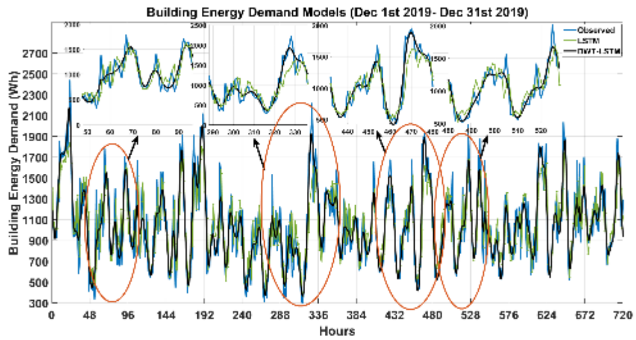

FIGURE 12. Energy demand models.

supply, and wind energy supply are presented in Figure 11. The average daily solar electricity generation is 40.7 kWh, and the wind electricity generation is 2.83 kWh. The daily average energy demand of the considered buildings is 18.43 kWh. Solar energy is available between 7:00 a.m. to 6 p.m. The energy demand is 7.61 kWh in this period, while the total daily energy demand is 18.43 kWh. Hence, the ES should provide 10.8 kWh in the nighttime. However, there are anomalous days that have higher energy demand and lower energy supply. In Equation 18, the E_{Net} equals subtracted the energy demand from the summation of renewable energy resources supply. E_{Net} has a positive value as the energy generation is more than energy consumption. Conversely, the E_{Net} has a negative value when the energy generation is lower than the energy consumption. For this reason, we considered the lowest daily net energy $(-39.8kWh)$ in our estimation for the ES type selection.

$$E_{Net} = E_{PV} + E_{Wind} - E_{Demand} \tag{18}$$

Hence the PV and wind energy supply can securely supply the energy demand using an ES with a total capacity of more than 40 kWh. Considering the 100% round trip efficiency of the Lithium-ion batteries. There are multiple choices for ES due to the importance of financial and technical factors.

IV. RESULTS AND DISCUSSION

The proposed method in this study is composed of two main sections; the deep learning forecasting section and the decision-making framework. The forecasting section includes forecasting energy demand and energy supply. The decision-making framework is composed of three decision-making layers.

A. BUILDING ENERGY DEMAND FORECASTING

The LSTM and DWT-LSTM methods are employed to forecast building energy demand in this study. The developed methods are employed to forecast building energy demand, and the prediction of these models are compared with the observed energy demand of the buildings in Figure 12. These models forecast building energy demand from December second 2019 to December thirty-first 2019 (one month) with hourly intervals. The forecasting results are depicted in Figure 12. The RMSE, MSE, MAPE, and R Squared values of the proposed methods proved that these methods can accurately forecast building energy demand and RE supply. The building energy demand is highly fluctuating due to the intermittency and non-linearity of the buildings' energy consumption patterns. The DWT approach has efficiently decomposed the building energy demand without removing the main hourly, daily, and monthly patterns. The DWT approach effectively increased the accuracy of the DWT-equipped LSTM in comparison with the LSTM model. Moreover, Figure 12 compares the DWT-LSTM prediction results, LSTM prediction results and the observed building energy demand. Figure 12 clarifies that the DWT-LSTM outperforms the LSTM in forecasting the building energy demand. DWT-LSTM can forecast the building energy demand with a MAPE value of 8.57%, while the MAPE value of the LSTM is 18.2%.

B. WIND ENERGY GENERATION FORECASTING

According to the wind energy production and wind speed data sheets of Bergey Windpower Company, the wind energy generation is calculated based on the wind speed forecasting and the power output of the BWC 5kW Grid-Intertie wind turbine according to the wind energy production and wind speed data sheets of Bergey Windpower Company (BWC). In addition, the wind speed is forecasted using LSTM and DWT-LSTM methods, and the prediction results are depicted and compared with the observed value of the wind speed in Figure 13. The DWT-LSTM has significantly higher accuracy in comparison with the LSTM. Considering the MAPE value as the comparing index, the DWT-LSTM outperforms the LSTM in wind speed forecasting as it removes the noises

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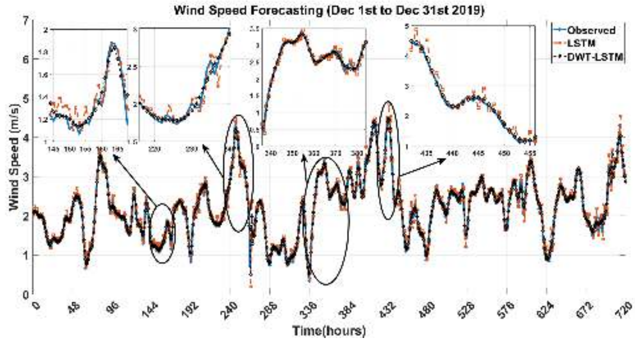

FIGURE 13. Wind speed prediction.

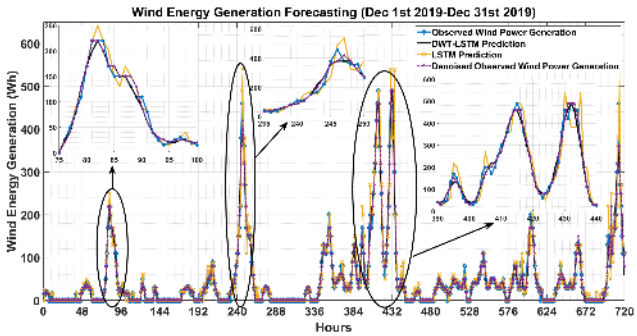

FIGURE 14. Wind energy supply prediction.

using a two-layer DWT approach. The two-layer DWT approach successfully removes the extra noises and accordingly increases the LSTM accuracy. The wind speed and the wind energy are forecasted from December second 2019 to December thirty first, 2019 (one month) with hourly intervals. The wind speed and the wind energy generation predictions are illustrated in Figure 13 and Figure 14, respectively.

C. PV SOLAR ENERGY GENERATION FORECASTING

The PV solar energy generation is forecasted using DWT-LSTM and LSTM considering the air temperature, solar irradiance on the ground surface, previous week, day and hour solar energy generation as inputs, and the hourly PV energy generation as the target variable. A two-layer DWT method is deployed to denoise the solar energy generation and the input variables to decrease the effects of noises while preserving the influential patterns in these variables.

Figure 15 clarifies the fact that equipping the LSTM method with the DWT denoising and decomposing method is not improving the accuracy of the solar energy forecasting model. The main reason is the high variation of the solar energy generation patterns, which misleads the DWT method to shave the energy generation peaks to decrease the wide range variation of the solar energy output. In other words, the DWT deciphers the solar energy generation fluctuations as noise and tries to remove them. Hence, implementing the DWT method in decomposing the solar energy generation dataset decreases solar energy generation forecasting accuracy.

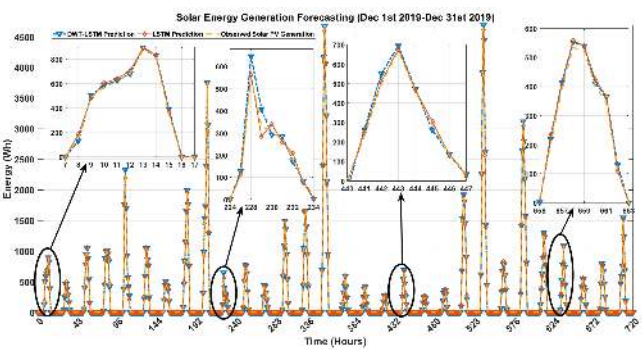

FIGURE 15. Solar Electricity supply prediction.

D. FORECASTING METHODS EVALUATION

In this study, we employed the Root Mean Square Error (RMSE), Mean Squared Error (MSE), Mean Average Percentile Error (MAPE), and R-Squared as indexes for model evaluation. The R-Squared is the proportion of variance of the observed dataset to the variance of the predicted dataset. The MSE, RMSE, MAPE, and R-Squared are estimated based on Equation 9, Equation 10, Equation 11, and Equation 12. The MSE, RMSE, MAPE, and R-Squared values of the DL models are estimated using [81]:

$$MSE = \sum_{t=1}^{n} \frac{1}{n}(Y_i - Y_i')^2 \tag{19}$$

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{1}{n}(Y_i - Y_i')^2} \tag{20}$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n} \frac{(Y_i - Y_i')}{Y_i} \tag{21}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{n}((Y_i - Y_i'))^2}{\sum_{t=1}^{n}((Y_i - \widehat{Y}_i))^2} \tag{22}$$

In Equations (19), (20), (21), and (22), the Y_i is the observed value, $\widehat{Y}_i$ is the average value of the observed value, and Y_i' is the DL models' forecasted value. The MAPE, RMSE, MSE, and R-Squared values of the energy demand forecasting model, solar energy generation forecasting model, and wind speed forecasting model are presented in Table 6. The MAPE, RMSE, MSE, and R-Squared values show that the DL models are considerably accurate in forecasting wind speed, solar energy generation, and energy demand. Unlike wind speed forecasting and energy demand forecasting models, the DWT-LSTM solar energy generation forecasting model has a lower accuracy than the LSTM method.

Table 7 presents the imported electricity from the grid, cost of imported electricity, and exported electricity to the grid considering the role of the rescheduling framework and the saving strategy. The imported electricity from the grid and electricity costs are estimated based on two-step electricity prices.

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TABLE 6. Deep learning modeling evaluation results.

Forecasting model	RMSE		MSE		MAPE		R-Squared	
	LSTM	DWT-LSTM	LSTM	DWT-LSTM	LSTM	DWT-LSTM	LSTM	DWT-LSTM
Wind speed (m/s)	0.147	0.06715	0.0218	0.01054	5.41%	3.63%	0.89	0.99
Solar supply (kWh)	0.033	0.0011	0.00169	0.0003	4.1%	4.9%	0.998	0.999
Energy demand (kWh)	0.176	0.111	0.0522	0.0123	18.2%	8.57%	0.63	0.91

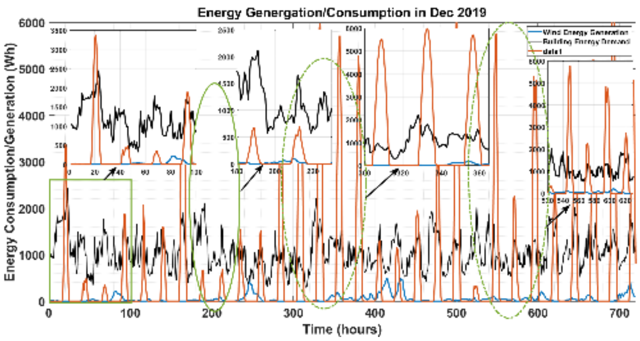
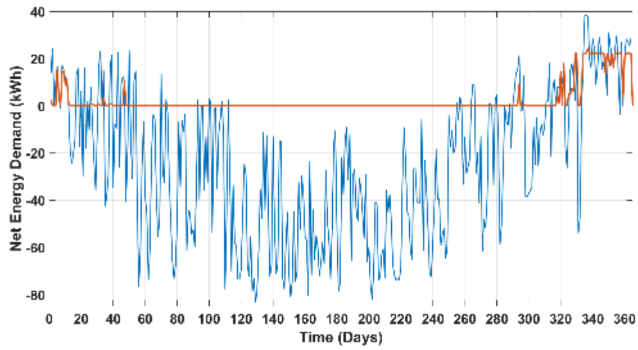


FIGURE 16. Net energy generation/consumption in December 2019.

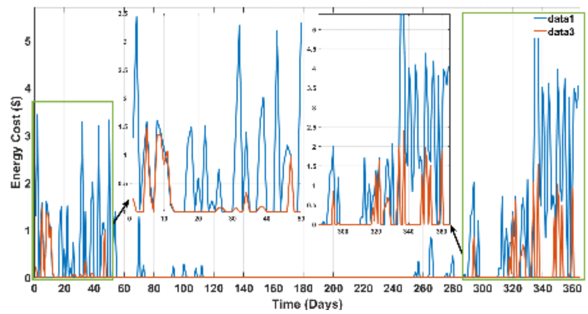
E. SCHEDULING FRAMEWORK

The proposed rescheduling framework is composed of a rescheduling algorithm and a saving strategy. The rescheduling algorithm tries to maximize the share of supplied energy demand by renewable energy resources and minimize the energy cost through decreasing electricity import during the peak days (days with higher than 22.1918 kWh energy demand). The framework reschedules the RE supply and electricity import weekly intervals based on the week-ahead forecasting results of RE supply and energy demand. Based on the SDI and EP values, the share of imported electricity from the grid and imported electricity from the grid during the peak days are estimated. The saving strategy is activated based on the user's predefined saving strategy. The saving strategy is defined to decrease the energy demand when the net energy demand exceeds the boundary layer. The saving strategy is activated to evaluate the rescheduled energy demand to identify the peak days that the rescheduling framework could not supply by energy storage. In this way, the saving strategy decreases the extra energy demand based on the user's predefined saving strategy and preference list.

Implementing the proposed framework in scheduling energy supply and energy demand of the buildings during 2019, reliance on the electricity grid, especially during the peak days, significantly decreased, and consequently, the cost of total imported electricity decreased. Figure 17(a) and Figure 17(b) demonstrates the role of the proposed scheduling method in decreasing reliance on the grid and electricity costs. In Figure 17(a), a comparison of the scheduled electricity demand (orange line) and the non-scheduled electricity demand (blue line) shows the role of the proposed method in decreasing reliance on the electricity grid. Considering a no saving strategy, the proposed rescheduling framework decreased the imported electricity from the grid from 1357 kWh to 845 kWh (37.7 %) and decreased the imported electricity



(a) Rescheduled net energy demand and non-rescheduled net energy demand/supply in 2019.



(b) Rescheduled energy cost and non-rescheduled energy cost in 2019.

FIGURE 17. Scheduled and non-scheduled energy demand and energy cost in 2019.

during the peak days by 85.6 % (from 118.7 kWh to 17.1 kWh). The rescheduling and saving strategies, including the no saving strategy and ten % saving strategy, decrease the annual electricity cost from 665 $ to 80.8 $ and 80.5 $.

As it is noticeable in Figure 18(a), during January, February, November, and December, energy demand increase on the one hand and RE supply decrease on the other hand. Accordingly, energy storage is vital in decreasing reliance on the grid during these months as the energy storage saves RE and low price electricity to consume in peak times. Using the proposed method not only decreases the energy import from the grid but also exports electricity to the grid during the peak RE supply. Figure 18(b) demonstrates the amount of exported electricity to the grid. The RE supply increases during the summers and decreases during the winters, as it is noticeable in Figure 18(b).

F. FINANCIAL ANALYSIS

In this study, we implemented Net Present Value (NPV) for the financial evaluation of the proposed investment in build-

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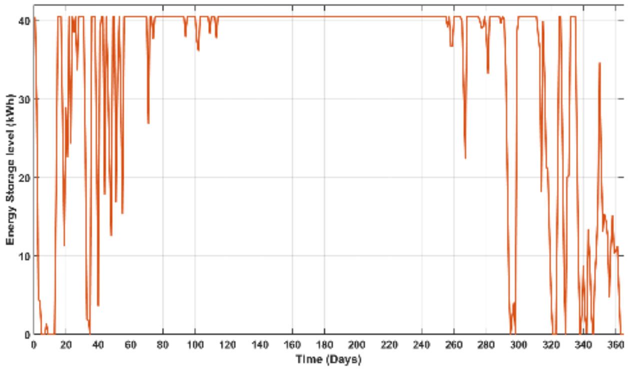
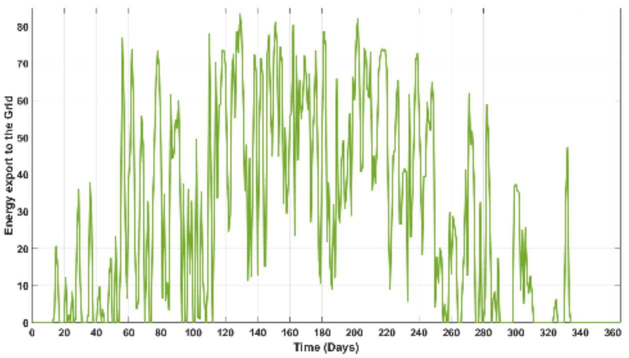
TABLE 7. Electricity costs and transactions with the grid during 2019.

Energy-saving Scenario	No Saving scenario		10% Saving scenario	
	Scheduled	Not scheduled	Scheduled	Not scheduled
Electricity import with Lower tariff	855.8	1222.55	855.5	1216.7
Electricity import with Higher tariff	2.17	109.4	0	59.9
Electricity Cost Higher tariff	0.3	15.42	0	8.44
Electricity Cost lower tariff	80.53	115.04	80.5	114.5
Electricity Export	7777	8250	7779.7	8310



(a) Energy Storage charge and discharge pattern



(b) Exported electricity to the grid.

FIGURE 18. Energy storage charge/discharge and exported electricity to the grid in 2019.

ing energy systems. NPV is a standard concept for modelling, representing and comparing represent economic preferences [93]. NPV is the sum of the present values of incoming and outgoing cash flows over a specific time. NPV can be described as the difference between the sums of discounted cash inflows and cash outflows NPV is estimated as follows [94]:

$$NPV = \sum_{t=0}^{n} (\frac{CI_t}{(1+r)^t} - CO_t) - CO_0 \tag{23}$$

Where n, r, CI_t, CO_t, and CO_O is the number of the periods, discount rate, cash inflow at moment t, cash outflow at moment t, and initial investment, respectively. The cash inflow, cash outflow, and maintenance costs are estimated

TABLE 8. The cash inflow and outflow patterns.

Cash Type	Source	Costs ($)	Time step (years)
Outflow	solar PV	2000	25
	Wind turbine	2105	15
	Inverter	890	10
	Energy storage	9600	25
Inflow	Exported electricity to the grid	748.75	1
	self-supplied electricity	843.4	1
O&M	solar PV	63.32 (0.005 $/kWh [95])	1
	Wind turbine	19.42 (0.02 $/kWh [95])	1
	Inverter	12.5 $/year [96]	1
	Energy storage	5 $/year [97]	1

based on the solar PV, wind turbine, inverter, and energy storage specification presented in Table 9. The estimated cash inflow, cash outflow, and maintenance costs are presented in 8. NPV is a valuable tool to determine whether a project will result in a net profit (NPV is positive; hence the investment would add value to the firm and the project may be accepted) or a loss (NPV is negative; hence the investment would subtract value from the firm and the project should be rejected) [94].

1) Financial analysis of the proposed smart energy management system

The cost of electricity generation from wind and PV has decreased significantly in the last few years. The electricity cost of wind power decreased from 113 to 62 USD per MWh during 2000–2017 in Germany. Furthermore, the electricity cost of PV decreased from 500 to 67 USD in the same period. Operation and maintenance costs are estimated at 20%–25% of RE generation costs in Europe [98].

In this section, we used NPV value to evaluate the proposed building energy management system financially. We evaluate the whole system considering the role of solar electricity generation, wind turbine electricity generation, building energy demand, capital investment, and maintenance costs. Financial analysis of the proposed method should include the solar PV panels and wind turbine role according to the importance of electricity generation in returning the

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investment.

Solar PV systems convert the energy of the solar light into electricity using PV cells. The electricity output of the PV panels culminates when the sun's light beams are perpendicular to the surface of the PV panel. Due to the earth's elliptical movement around the sun and spinning itself, the solar reception angle changes daily and seasonally. However, a sun tracking system tackles seasonal and diurnal reception angles disparities through constantly controlling PV panel positioning toward the sun's rays in order to achieve a perpendicular condition and the increase of the electricity output of the PV panels [99].

Although the dual-axis solar tracking systems have higher energy generation in comparison with fixed solar systems and single-axis solar tracking systems, the high investment and maintenance costs outweigh the extra generated energy [99], [100].

Accordingly, we implemented a fixed solar PV system to decrease both the investment and maintenance cost of solar PV system so that the smart building energy system has the lowest financial break-point.

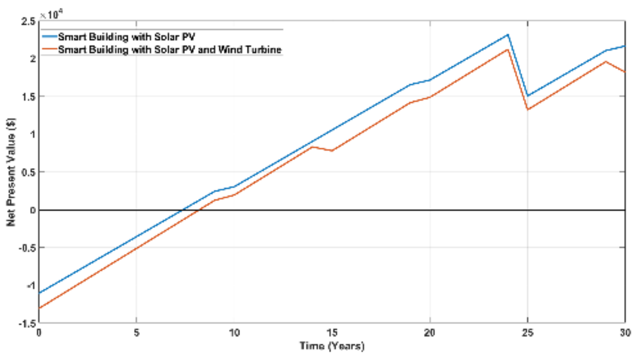

FIGURE 19. Net Present value of the proposed energy management systems.

TABLE 9. The specification of proposed wind turbines, inverters, energy storage, and solar PV panels.

Wind Turbine	**BWC**	**RX OEM ODM**	**FLTXNY**
Model	BWC-GI 5kW	RX-5000H3	FH-5000
Diameter	9 (m)	6 (m)	2.4 (m)
Max power	5000W	5000W	5000W
Height	30 (m)	9 (m)	5 (m)
Startup speed	2.5m/s	3m/s	3m/s
Max speed	20 (m/s)	35 (m/s)	45 (m/s)
Lifespan	20 year	15 year	15 year
Axis	Horizontal	Horizontal	Vertical
Price	$21,995	$2,105	$2,754
Inverter	**Growatt/Deye**	**Bluesun**	**Growatt**
Model	10000TL3-S	BSM5000 8K-B2	M3-15KTL3-X
Input voltage	160-1000	550	580
Output voltage	220-415	220-400	220-400
Efficiency	99.5%	98.55%	98.5%
Warranty	5 (years)	5 (years)	5 (years)
Life Span	10 (years)	10 (years)	10 (years)
Max power	10kW	10kW	10 kW
Price	$890	$850	$950
Energy Storage	**Tesla PW 2**	**Lithtech**	**Sunpal**
Capacity	13.5 kWh	10.24 kWh	9.6 kWh
Depth of charge	100%	100%	100 %
Round trip efficiency	90%	90%	90 %
Cycles	5000	6000	6000
Lifespan	25 year	25-year	25 year
Warranty	10 years	7 years	10 years
Price	7600$/pc	2400$/pc	2562$/pc
Solar PV	**Rosen Poly**	**Teejoin**	**Sunkean**
Model	RS360P-72	TJ-TD320	SKE350M-72
Dimension (cm)	195.6*99.2*4	164*99.2*3.5	195.6*99.2*4
Panel efficiency	18.6%	20%	19-22%
Warranty (years)	30	25	5
Cell type	EVA/POE	mono c-Si	mono c-Si
Max Power	370	370	350
Price	0.20 $/W	0.23 $/W	0.21 $/W

In this paper, the solar PV units and the wind turbine annually generate 12664.03 and 964 kWh, respectively. The building's annual energy demand is 6597.7 kWh, the net electricity import from the grid is 1332 kWh, and the net electricity export to the grid is 7777 kWh. Table 10 presents the total energy demand and energy production in the building through a year. The net energy generation/consumption diagram is presented in Figure 11, which shows the difference in the energy supply and energy demand in Dec 2019. When the RE sources' energy production is higher than the energy demand, the building generates energy; hence, this diagram shows the energy generation while it depicts energy consumption when the energy demand is higher than energy production. In other words, the zero lines are when the energy demand is equal to the energy supply. Above the zero lines is when the RE energy supply is more than the energy demand. Conversely, below the zero line shows how much the energy demand is higher than the grid's RE energy supply. The BC-Hydro company developed a pricing policy for decreasing energy consumption. In this regard, this company presents energy in two tariffs; low energy consumption price and high energy consumption price. These two energy consumption prices are specified based on the daily and two-month energy consumption boundary between 22.1918 kWh and 1350 kWh, respectively. Based on the energy consumption boundary value, the energy price is considered 0.0941 $/kWh for low energy consumption and 0.141 $/kWh for high energy consumption [101]. Accordingly, by implementing the proposed method, the building annual energy cost decreases from 665 $ (6709 kWh) to 80.8 $ (858 kWh), an 87.5 % decrease in energy cost. Besides, the building can return 731.8 $ (7777 kWh) annually by selling the extra generated RE to the grid. As it is noticeable in Table 7, the rescheduling algorithm solely decreased the reliance on the grid from 1333 kWh/year to 858.9 kWh/year, which is 35.5 % in reliance on the grid. Also, the proposed algorithm decreases the reliance on the grid during the peak days from 109.4 kWh/year to 2.17 kWh/year (98 %) and 0 (100 %) kWh /year without saving strategy and with a ten % saving strategy, respectively.

Implementing a smart building integrated with a 10 kW PV

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TABLE 10. Annual energy demand and supply. The G/E indicates to generation/consumption.

Variables	G/E	Price($)
Solar energy generation (kWh)	12664	1191.7
Wind energy generation (kWh)	964	90.7
Energy Demand (kWh)	6709	930
Net Electricity import from the grid (kWh)	859	80.8
Net Electricity export to the grid (kWh)	7777	731.8

system and 5Kw wind turbine provides 1591 $ cash inflow annually, while the same system without the wind turbine provides 1500 $ cash inflow annually. Figure 19 demonstrates the NPV of both proposed building energy systems. As it is noticeable in Figure 19, the smart building integrated with a solar PV system is more economical than the smart building integrated with both solar PV and wind turbine as the breaking point is eight years for a smart building with solar PV, wind turbine, inverter, and energy storage and nine years for a smart building with solar PV, inverter, and energy storage. Table 10 presents the annual energy generation and price of the produced energy according to the BCHydro tariffs. Besides, the capital cost and specifications of the possible choices for accumulative 10 kW rooftop PV panels, 5 kW wind turbine, and 40 kWh energy storage are presented in Table 9.

V. CONCLUSIONS

Building energy management with renewable energy sources is a complex and non-linear problem that conventional methods are unable to cope with such a problem. In this paper, using weather and energy consumption/generation patterns, we developed deep learning models to forecast energy demand and supply for five buildings in Vancouver in British Columbia. The method uses the combining discrete wavelet transformation and long short-term methods (DWT-LSTM). The results showed that the method can model building energy demand and renewable energy supply with a high level of accuracy in terms of mean average percentile error ranging from 1.24% to 2.89%. In addition, the integrated smart energy system can supply energy demand for 304 days in a year without reliance on grids and can export more than 57% of generated solar and wind energy to the grid. We also developed a monitoring and scheduling framework that uses the forecasted energy demand, renewable energy supply, the state of charge of energy storage, energy cost, and availability of the energy grid to schedule the energy demand. The framework implements a rescheduling algorithm based on week-ahead prediction of energy demand, energy supply, energy storage level of charge, and energy costs to minimize the reliance on the grid and energy cost, especially during peak days. As a result, implementing the proposed framework can cover up to 83.2% of energy load by renewable energy resources. Implementing the proposed framework also decreases energy import from the grid by 98% during the higher electricity tariff (peak days) and 87.2 % of total imported electricity from the grid. It further increases the renewable energy resources utilization by 57%. Moreover, based on financial analysis of two smart building systems, the proposed smart building with solar PV, wind turbine, inverter, and 40.5 kWh energy storage has a financial breakpoint of 9 years. With the same specifications except for the wind turbine, the proposed smart building has a financial breakpoint of 8 years. Thus, the framework is expected to return the capital investment in 8 years. That is by considering the warranty and the lifespan of the implemented technologies, replacement costs, power exportation income, and operational and maintenance costs. Finally, based on the financial analysis, implementing wind turbines in the proposed building has a negative NPV growth which is not economically beneficial. As our future work, we plan to focus on net-zero smart building with renewable energies, where we aim to investigate the combination of deep learning methods and optimization algorithms such as the Sine Cosine Algorithm, Genetic Algorithm, and Wolf Pack Algorithm. In addition, in our future load scheduling problems, we also plan to consider additional factors, such as user satisfactions.

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