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

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ABSTRACT Buildings are responsible for 33% of final energy consumption, and 40% of direct and indirect CO_2 emissions globally. While energy consumption is steadily rising globally, managing building energy utilization by on-site renewable energy generation can help responding to 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 analyzes several factors including electricity price, uncertainty in climatic factors, availability of renewable energy sources (wind and solar), energy consumption patterns in buildings, and the non-linear relationships between these parameters 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 to minimize the reliance on the grid and electricity cost, especially during the peak hours. 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 combination of the deep learning forecasting, energy storage, and scheduling algorithm enables reducing annual energy import from the grid by 84%, which offers electricity cost savings by 87%. Finally, two smart active buildings configurations are financially analyzed for the next thirty years. Based on the results, the proposed smart building with solar Photo-Voltaic (PV), wind turbine, inverter, and 40.5 kWh energy storage has a financial breakeven point after 9 years with wind turbine and 8 years without it. This implies that implementing wind turbines in the proposed building is not financially beneficial.

INDEX TERMS Smart active buildings, AI-based energy model, deep learning, LSTM, energy system modeling, building energy management, discrete wavelet transformation, energy supply 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 improves 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 reduce the dependency on the grid and to mitigate GHG emission [3], [4]. Indeed, smart active building modelling has a significant role in improving energy efficiency,

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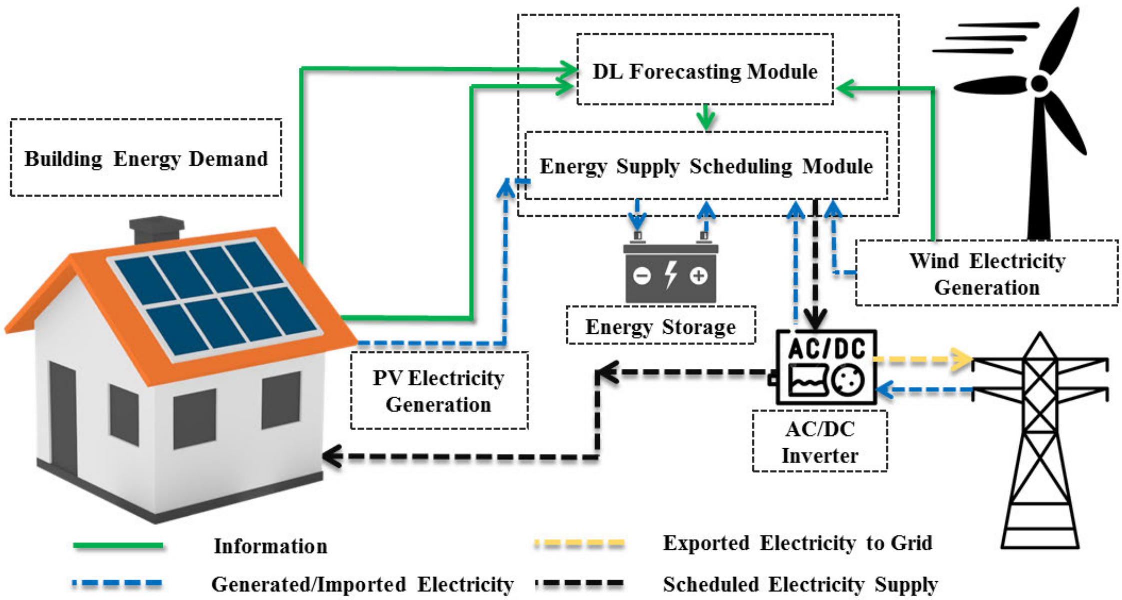


FIGURE 1. The schematic of an integrated smart active building with renewable energy sources.

Energy Storage (ES) measures and the development of renewable energy systems in buildings [5], [6]. An appropriate management and planning model for smart buildings enables using the renewable energy sources (RES) efficiently [7], [8].

To enable smart active buildings, however building energy modelling and forecasting are applied [9]. Smart building energy modelling systems include demand-side models, supply-side models, and hybridization of demand and supply models for building energy management [10]. As this is a multi-criterion problem, the building energy modelling requires considering both energy consumption and generation simultaneously [11]. The modelling depends on a wide range of variables, including consumption patterns, temperature, humidity, cloud cover, wind speed, air pressure, and ES capacity. In addition, the energy demand and supply in buildings are time-dependent and vary hourly, weekly, and seasonally [12].

For improving energy security, reducing the costs, and emissions, from the last decades the use of renewable energies have increased. For example, the capacity of Photo-Voltaic (PV) energy generation as a promising renewable energy (RE) technology has increased from 7 GW in 2017 to 17 GW in 2019 [13]. However, in practice implementing the renewable technologies are challenging [8]. For example, PV outputs fluctuate due to the variation of solar irradiance and temperature [14]. Wind energy is also another renewable energy source (RES) [15], in which the challenge pertains to the unpredictable wind speed and direction. Furthermore, there are hybrid RES that combine different energy generation sources such as wind-solar, solar-hydro, and wind-hydro hybrids [16] which offer benefits. For example, 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].

While, the main drivers for developing smart active buildings include energy efficiency, energy price, and environmental concerns; the main challenges are the efficient integration of RES and removal of energy conversion losses. To overcome the challenges, a smart integrated energy system (SIES) that considers both energy generation and consumption systems is required [18]. Figure 1 illustrates the concept of a smart integrated energy system. A SIES schedules various energy supply resources to optimize the energy supply package (i.e., renewable and non-renewable energy sources). 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 such as hourly or half-hourly datasets. Moreover, the energy modelling of the smart building equipped with RE sources involves a high level of complexity and non-linearity. Due to the reason that RE involves the intermittency of meteorological information and uncertainty in energy generation patterns during the day and across the seasons [20].

In this paper, we develop an artificial intelligence (AI)-based SIES to estimate the hourly, daily, and weekly building energy demand and supply. We model energy demand and energy supply using a hybridization of 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 province of British Columbia, Canada. Where, we use the average value of the five buildings' energy demand to eliminate the effects of accidental disturbances. Unlike Home Energy Management Systems (HEMS) scheduling methods which mostly focus 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-planned energy saving strategy. For forecasting and scheduling the energy supply and demand, we consider the buildings as a black-box unit. We also consider the user convenience, energy price, and energy sustainability; and we achieve the RE sources' maximum penetration.

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 policy-making as it enables policymakers to make critical decisions [22]. An efficient building energy management system needs accurate prediction of distributed energy sources such as wind or solar PV energy. On this basis, numerous methodologies have been developed comprising physical models, statistical and 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 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 CO_2 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 developments, 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, RES 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 sources 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 RES 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 RES supply in buildings; and second, it is crucial to decrease the energy exchange with the grid [32]. However, some studies report 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 calls for novel solutions [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 represent 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 were implemented to improve building energy management efficiency. This can be achieved by forecasting energy consumption/generation and scheduling energy demand.

Figure 2 presents the classification the forecasting methods. In this classification, the building energy forecasting methods are categorized into four groups: machine learning, deep learning, engineering methods, and hybrid methods. Due to the paramount role of deep learning methods 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 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

In literature, forecasting methods are divided into three groups, including statistical, engineering, and data-driven methods [34]. Data-driven forecasting methods refer to the

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
RES	Renewable Energy Sources	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-BM	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 Vehicle
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
RTE	Round Trip Efficiency	DOC	Depth of Charge

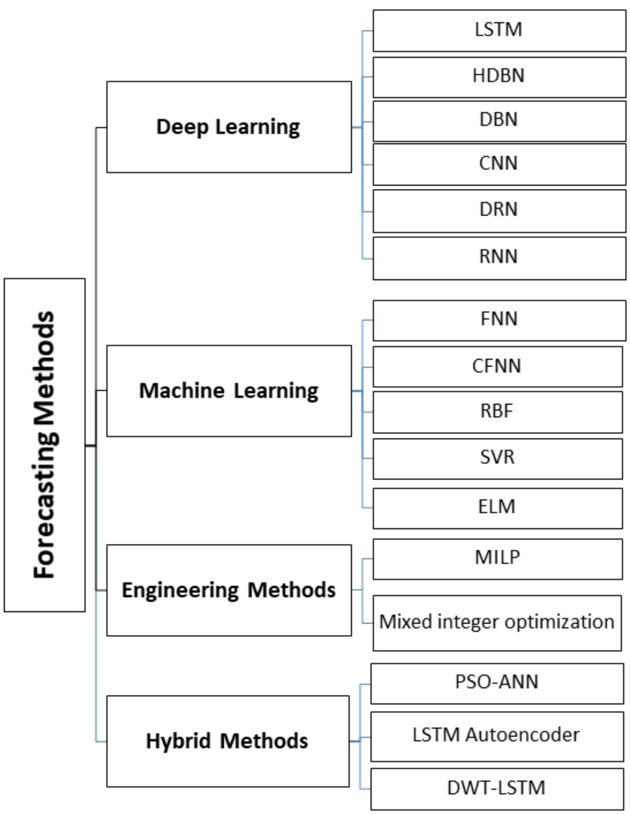


FIGURE 2. Classification of forecasting methods.

ensemble machine learning approaches and deep learning methods [35]. Therefore, in this paper, as presented in Figure 2, we divide the forecasting methods into Machine Learning (ML), Deep Learning (DL), engineering, and hybrid methods.

Engineering methods are among the most 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, engineering methods are effective and accurate in practice, they are complex to be modelled as these methods are based on physical principles. 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, ML methods are capable to 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),

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, and 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 feedforward, Elman feedforward, and RBF neural network	ENFF has a higher accuracy than BPNN and ARIMA
	H. Quan et al. [30]	Uncertainty estimation in forecasting energy load, wind and solar energy	Hybridization of lower-upper bound estimation, particle swarm optimization, and neural network	Hybridization of PSO and ANN has higher accuracy than ARIMA, ES and naive models
	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. Grid-GA searching is less time-consuming, and suitable for short-time forecasting of renewable generations and energy loads in smart community
	N. Ayoub et al. [42]	24 hour-ahead forecasting of energy demand solar and wind energy generation	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 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	LSTM is a strong architecture for both short and medium term forecasting
	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

and Radial Basis Function (RBF) neural network, showed the high performance of ML methods in energy demand and supply forecasting [39]. The work in [40] that evaluates the performance of support vector regression (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-genetic algorithm (GA) searching algorithm and 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 in 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 often 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 models [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 (CNN) 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 accuracy of the DL model. Furthermore, another study in [55] applies recurrent neural 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.

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. [11]	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 PV 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]	PV power generation	LSTM-RNN	LSTM-RNN has a higher accuracy than BPNN SVM
	G. Li et al. [46]	PV 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 DWT	LSTM-DWT has a higher accuracy in comparison with RNN-DWT, LSTM, RNN, SVR and BP
	J. Ku et al. [15]	Wind speed forecasting	DWT, LSTM, and SVR	Equipping LSTM with DWT significantly increases the forecasting accuracy

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) is a sub-category of building energy management methods that aim 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 sources. 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].

The energy OS methods and renewable sources 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 OS 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. Indeed, the data-driven machine learning methods proved to be an efficient approach in tackling these types of challenges [67].

Another study in [68] integrates solar PV and an OS approach, 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 reduced over 90% emission compared with the study site's total emission. Indeed, 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 approach 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, while the IoT-based approach is used to collect the real-time data of energy consumption [70]; the data can then be analyzed to optimize the energy scheduling and to control the home energy consumption patterns in order to decrease the energy cost [11].

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) are 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 RES, 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.

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 lead 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 costs.

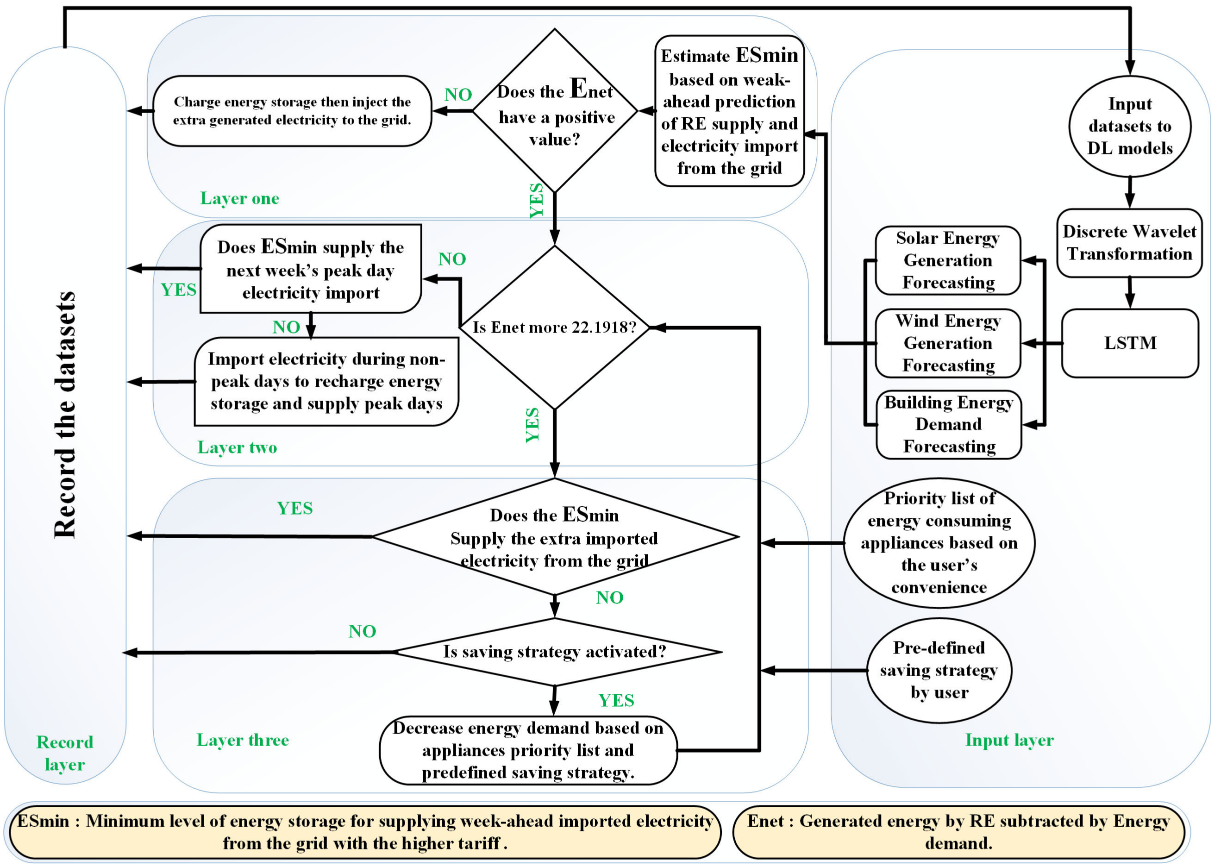


FIGURE 3. The schematic diagram of our proposed integrated energy system structure.

The studies mentioned in this subsection state that developing a smart building energy management framework is necessary to decrease reliance on energy grid and energy cost; as well as to increasing 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 considered 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 which are suitable for modelling complex and non-linear problems such as forecasting solar and wind energy generations as well as energy demands. Based on the forecasting results, we propose a scheduling algorithm which schedules energy demands to minimizes the electricity imported from the grid and consequently reduces energy costs during the peak days. Using the proposed algorithm, we thus achieve the lowest level of dependency on the energy grid and the highest level of RE penetration.

III. MATERIALS AND METHODS

In this section, first we 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 inputs 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, energy generation of the RE sources and their responses to the climatic patterns, time of the day, and day of the week. In addition, we have developed a novel framework 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 the schematic diagram of our proposed framework. In the figure, 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.

In general, the proposed method in our study includes integration of DWT and LSTM methods applied to forecast energy demand and energy supply and a scheduling framework to schedule 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 scheduling method is used for scheduling 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 is unable to supply the week ahead energy demand.

A. SCHEDULING FRAMEWORK

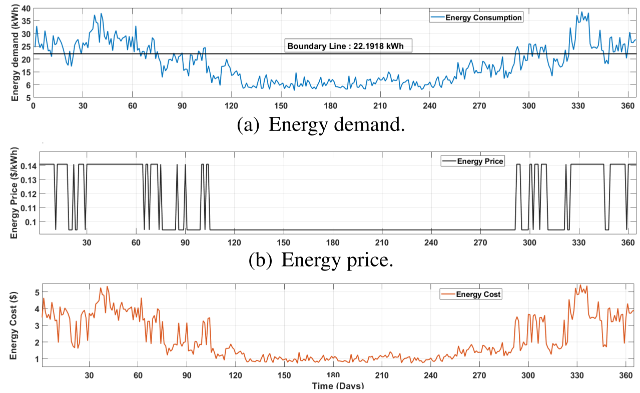
Scheduling energy supply in a smart active building plays an important role in saving RE for peak hours. The energy utilization in peak hours increase the buildings energy costs. In addition to the peak hours, the electricity price also has a significant role in building energy costs. Indeed, the electricity price per kWh increases by 50% for electricity consumption if electricity is consumed more than 22.1918 kWh per day. Hence, reducing reliance on the grid especially with the high tariff has a key role in decreasing building energy costs. The annual energy cost, energy demand, electricity price of the buildings for the year 2019 which is studied in this paper are demonstrated in Figure 4. These results show the average energy consumption of the buildings. As shown in Figure 4(a), energy demand during January, February, November, and December has increased; which results in increasing the energy costs in these months (as shown in Figure 4(c)). Buildings energy costs are also highly influenced by the electricity price. This is obviously depicted by the increase and decrease in energy price in Figure 4(b) and energy cost in Figure 4(c).

Therefore, to seek a solution for energy cost minimization, in this paper, we propose a scheduling framework to schedule RES supply and imported electricity from the grid. In the proposed framework, we define an index to represents the ratio of renewable energy supply to energy demand called Supply to Demand Index (SDI). The SDI is the measure of energy balance in the building which is estimated as follows:

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

where, the SDI represents supply to demand index, E_D and E_{RE} refers to energy demand and available RE energy supply, respectively. The SDI also shows the relationship between energy demand and the sum of RE supply and energy storage and should meet the following conditions:

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



(a) Energy demand.

(b) Energy price.

(c) Energy cost.

FIGURE 4. Annual energy demand and energy cost in 2019.

To define when the scheduling framework should use the inputs from 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. The index α is binary and defined as:

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

where, α returns zero for SDI value lower than 1 and one for SDI more than 1. Indeed, when SDI returns 1, the RE supply is greater or equal to building energy demand; otherwise the building demand should rely on energy storage (if available) and energy grid. In addition, the scheduling framework also estimates hour-ahead, day-ahead and week-ahead net energy generation/consumption. The net energy generation/consumption is the net energy supply subtracted by net energy demand as:

$$E_{Net} = E_{PV} + E_{Wind} - E_{Demand} \tag{4}$$

where, the E_{Net} is equal to subtraction of energy demand from the summation of renewable energy sources supply. The E_{Net} also 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.

In British Columbia, the electricity price has two tariffs based on daily electricity consumption; with 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. Whereas, the ratio of net electricity demand to the boundary value reflects that the imported electricity and calculated by:

$$EP = \frac{E_D - E_{RE}}{22.1918} \tag{5}$$

Where, EP is the index of imported electricity cost; E_D and E_{RE} indicate to the energy demand and the amount of the electricity load supplied by RE resources, respectively. Indeed, our scheduling framework relies on a binary approach to specify when the proposed building relies on the grid with the higher tariff. To this end, we define β for binary decisions as follows:

$$\beta = \begin{cases} 1, & \text{If } 1 \leqslant \text{EP} \\ 0, & \text{If } 0 \leqslant \text{EP} < 1 \end{cases} \tag{6}$$

As explained, 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. The β is 0 when the electricity demand is lower than the boundary load and 1 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. 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:

$$ES_{Min} = \sum (EP_i - 22.1918) \times \beta \tag{7}$$

Where, ES_{Min} is the minimum level of saved electricity in the energy storage to avoid reliance on the grid with higher electricity tariff; and EP_i is the electricity demand with the higher tariff in day i. The proposed framework applies the Equation 8 below and performs decisions for minimizing the reliance on the grid during the peak time.

$$E_{SG} = \sum (\alpha) \times ((E_{RE} - (E_{ES_{max}} - E_{ES}) - E_D)) \tag{8}$$

In the equation, 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. While applying this equation, the extra supplied electricity is used to recharge the energy storage and then the surplus electricity is sold to the electricity grid; then following decisions are also made by the scheduling framework:

- It specifies the week ahead energy demand and supply based on the predictions. Likewise, 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 *none-peak days*. Note that the term *none-peak days* refers to when extra RE supply is not able to supply the peak-days extra energy demand. In this way, the reliance on the grid is decreased during the peak days.
  In fact, the possibility of recharging the energy storage and maintaining its charge level at ES_{min} by E_{RE} is evaluated. During the next week, when the $\sum E_{RE}$ 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. During the next week, when the $\sum E_{RE}$ 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}.
- It stores 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 it exports the extra E_{RE} to the grid.
- It exports $(E_{Net} - 40.5)$ to the grid when $E_{RE} - E_D$ is positive and higher than the ES_{Max} (40.5 kWh).

In our paper, the scheduling framework tries to reduce the reliance on the electricity grid during the higher tariff. Moreover, we define a cost function 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 total cost C_t is estimated based on the two electricity tariffs and a hypothetical selling price to the grid. We take into account the injected electricity price to be equal to the lower electricity tariffs. Hence, we estimate the total electricity cost as follows:

$$\begin{aligned} C_t = & \sum (E_{SG} \times P_s) \\ & - \sum (E_{BG} \times (|\beta - 1|) \times P_{b_1}) + (E_{BG} \times (\beta) \times P_{b_2}) \end{aligned} \tag{9}$$

subject to:

$$\begin{cases} E_D(i) \leqslant E_{RE}(i) + E_S(i) + E_{BG}(i) \\ 0 \leqslant E_S(i) \leqslant 40.5 \\ E_{BG}(i) \leqslant 22.1918 \end{cases} \tag{10}$$

Where, 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 injected electricity to the grid, respectively. In addition, the constraints of the proposed scheduling framework are presented in Equation 10. In this equation, $E_D(i)$, $E_{RE}(i)$, $E_S(i)$, and $E_{BG}(i)$ refer to the energy demand, renewable energy supply, energy storage level, and imported electricity from the grid at moment i, respectively.

In our scheduling framework, the input variables are extracted from the forecasting results of the proposed deep learning models. The input variables include the energy demand, RE energy supply, imported energy from the grid, and injected energy to the grid. We have also developed a saving strategy in which the users choose a saving strategy based on the α and β factors (Equations 3 and 6) and their financial plans to reduce reliance on the grid on the one hand and decrease the energy costs on the other hand. Such that the users can modify the saving strategy to attain the best saving strategy with the highest convenience.

B. DISCRETE WAVELET DECOMPOSITION

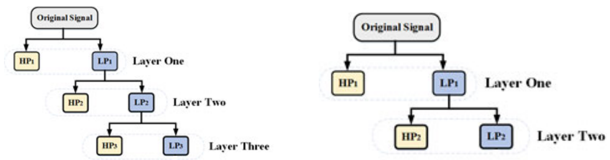
Discrete Wavelet Transform (DWT) methodology is a functional approach to derive valuable characteristics from the non-stationary time-series data analysis. DWT method decomposes a signal in a time-scaled way. The buildings energy demand, wind energy generation, and solar PV energy generation have a high 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. Therefore, the integration of DL models, such as LSTM models with DWT, has proven to be a powerful tool for modelling energy demands [74], PV energy [75], and wind energy generations [76]. Recently, hybridization of LSTM and DWT methods demonstrated to be effective in the forecasting of wind power generations [65], wind speed [15] and energy consumption [34].

The discrete version of Wavelet Transform (WT) is a common tool to reducing the load of continuous wavelet computation. It passes the signal through serial filters, including High Pass (HP) filters and Low Pass (LP) filters. Equation 11 and 12 represent the HP and LP. The DWT decomposition coefficients are computed through the passing process [77]:

$$x_1(n) = \sum_{k=0}^{L-1} c_k x(k-n) \tag{11}$$

$$x_2(n) = \sum_{k=0}^{L-1} d_k x(k-n) \tag{12}$$

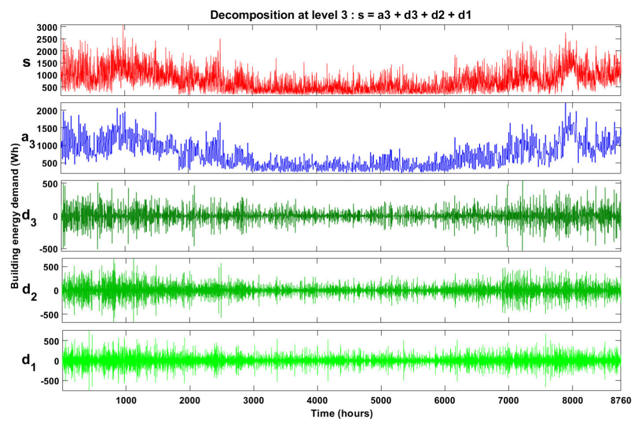
The LP and HP components are $x_1(n)$ and $x_2(n)$, respectively. The c_k and d_k are the coefficients of the LP and HP filters, respectively. The k also indicates the decomposition level, and n is the translating constant, which are integers. It is worth noting that DWT is a transformation function 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 depicted in Figure 5, the DWT 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. Therefore, using the DWT outputs improve the LSTM models' accuracy in forecasting the energy demand and the energy supply. Figure 5 presents the block diagram of our implemented DWT.



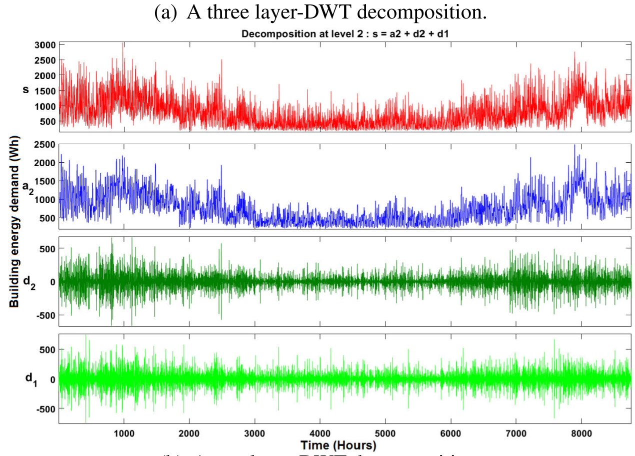
(a) A three layer-DWT structure. (b) A three layer-DWT structure.

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

The number of DWT layers plays a significant role in the level of denoising. When the number of layers increases, the short-term patterns vanish and the long-term patterns remain. Figure 6 demonstrates the building energy demand decomposition layers. While Figure 6(a) shows a three layer-DWT decomposition, Figure 6(b) depicts a two layer-DWT decomposition. Comparing the two layer and three layer decomposition of building energy explains that by increasing the number of layers in signal denoising, the short-term fluctuations are more likely removed and the long-term patterns become more visible. This is obvious from the plot in blue color in Figure 6(b), i.e., a_2 that is a denoised



(a) A three layer-DWT decomposition.

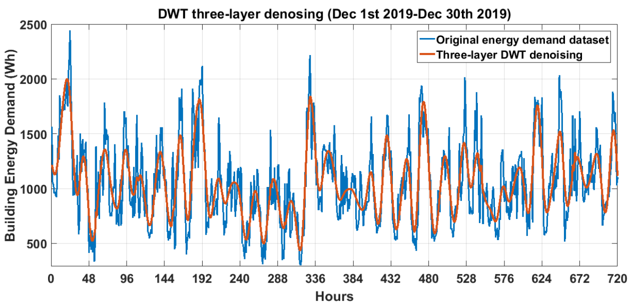


(b) A two layer-DWT decomposition.

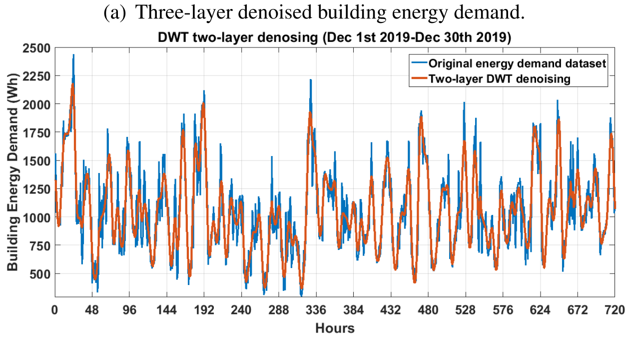
FIGURE 6. The denoising results of the proposed DWT denoising methods.

signal and has a higher level of short-term fluctuations when compared with the plot in blue color in Figure 6(a), i.e., a_3. In fact, increasing the number of decomposition layers helps extracting more clear long-term patterns, however this is at the price of increasing the risk of removing meaningful short-term patterns.

Figure 7 compares a two-layer and three-layer and DWT denoising process on building energy demands. It can be noticed in Figure 7(a), the daily patterns remains in the three-layer DWT while the hourly patterns are almost removed. In 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 would remove important short-term patterns, which decreases the model's reliability as it is not capable for short-term modelling.



(a) Three-layer denoised building energy demand.



(b) Two-layer denoised building energy demand.

FIGURE 7. DWT denoising of building energy demand.

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 (BP) learning algorithm, long-term dependencies face exploding and vanishing gradients. Deep learning methodology has attracted attention during the last 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]:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{13}$$
$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{14}$$
$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{15}$$
$$\hat{C}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{16}$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \hat{C}_t) \tag{17}$$
$$h_t = o_t \times \tanh(C_t)) \tag{18}$$

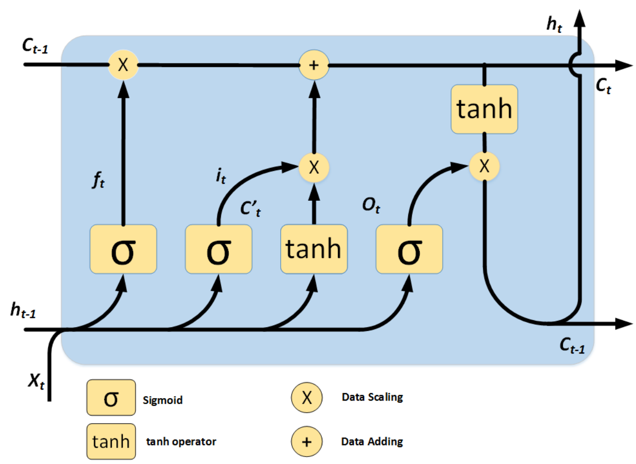


FIGURE 8. Structure of a LSTM cell.

In Equations (13)-(18), 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 Equations (13), (14), and (15) prepare 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 (17) and (18), respectively.

D. ENERGY DEMAND MODELING

Building energy systems are complex non-linear systems influenced by weather conditions, building operating modes, occupant schedules, and energy costs [86]. Energy demand forecasting models are mainly categorized into three groups: *i*) Engineering methods in which the thermodynamic and physical rules are implemented based on the building's complex parameters and the environment. *ii*) Statistical methods that are developed based on the energy-related factors correlations. Statistical models generally suffer from a lack of accuracy and flexibility. *iii*) AI-based methods which take energy consumption patterns as input and aim to find the non-linear relationship between the input datasets and the target datasets. AI-based approaches have higher accuracy and flexibility than engineering and statistical models [34]. In addition, AI-based building energy demand 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 AI-based forecasting methodologies from being widely implemented in the smart grid development process. Firstly, the reliability of AI-based 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) require 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]. In our case the input variables are as follows:

- **Building energy demand:** The data of previous week, day and hour average energy consumption of five residential buildings.
- **Holidays and weekends:** The impact of the weekends and holidays on the building energy demand are considered as a binary value (zero for holidays and weekends and 1 for non-holidays 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 our study, the implemented LSTM and DWT-LSTM model energy demand based on energy consumption, holidays, temperature, and the hour of the day historical datasets from January 1st 2019 to December 1st 2019 as training inputs. As shown in Figure 9, the energy demand is strongly influenced by air temperature, where the energy demand is decreased by the increase in the temperature. The energy demand in the buildings has a periodic pattern by having 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. The holidays 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 holidays and weekends are considered binary variables (one for holidays and weekends and zero for non-holidays and weekdays). It is worth noting that the hour of a day helps the LSTM model to extract hourly consumption patterns more accurately for a reliable prediction of building energy demand.

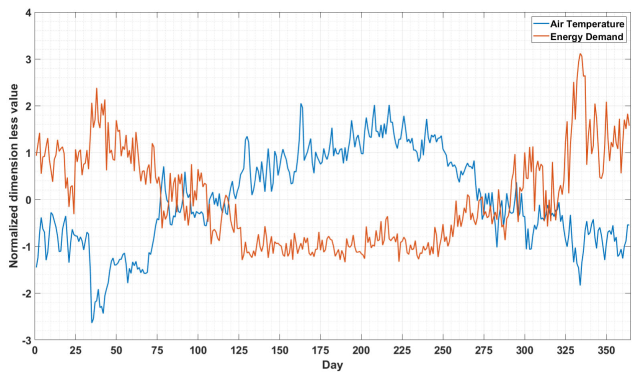


FIGURE 9. Air temperature and energy demand annual trends.

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 toward north, south, east or west. 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].

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

TABLE 4. Characteristics of the studied 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

E. ENERGY SUPPLY MODELING

The wind and solar energy supplies are highly affected by climatic factors (e.g., sunny hours, cloudiness, and wind speed). Consequently, 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] using the integration of DWT and LSTM [15], [64]. Utilizing these factors, we develop LSTM and DWT-LSTM models to predict wind and solar energy supplies 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[1]. 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 is required to forecast 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]. We developed our proposed DWT-LSTM and LSTM models using the 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 input variables[1]. 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 are 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 1st 2019 until December 30th 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 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[1]. The used 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.

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

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

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 sources 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 depicted 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 RES 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 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 many years and evolved to reach the current developments that many ES types are available for saving energy. ES systems are mainly developed for saving RES such as wind and solar energy and are used when needed. ES has several advantages like increasing RE resources penetration, decreasing energy costs and increasing the energy system reliability. ES also helps the electrical systems by batteries (i.e, electrochemical ES) which are mature ES devices with high voltages, and high energy densities [91]. Noting that the 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]).

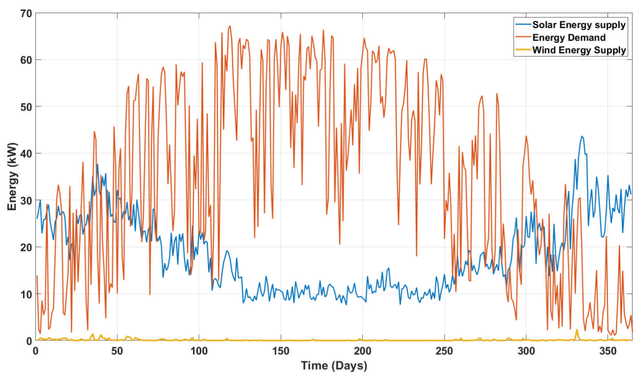


FIGURE 10. Annual energy demand and supply.

The energy generation and consumption have an annual pattern that 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 shown 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 964 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.

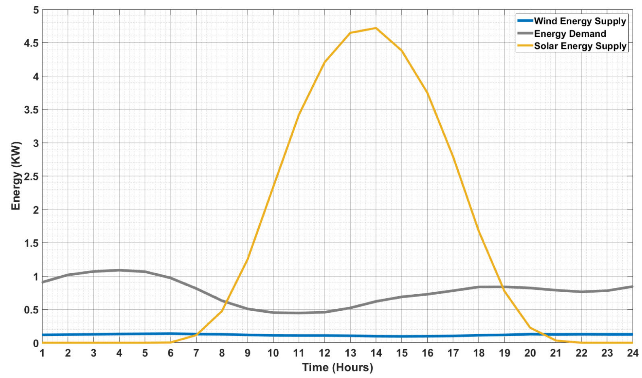


FIGURE 11. Hourly average energy demand and supply.

In our study, the daily mean energy demand, solar energy 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.

IV. RESULTS AND DISCUSSION

Our proposed method is composed of two main parts; the deep learning forecasting and the decision-making framework. The deep learning is used to perform forecasting energy demand and energy supply. The decision-making framework is composed of three decision-making layers. We utilized different performance metrics including Root Mean Square Error (RMSE), Mean Squared Error (MSE), Mean Average Percentile Error (MAPE), and R-Squared to evaluate the performance of the proposed methods. The R-Squared is the proportion of variance of the observed dataset to the variance of the predicted dataset. These metrics can be evaluated using

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

the following equations [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 these equations, Y_i is the observed value, $\widehat{Y}_i$ is average value of the observed value, and Y_i' is the DL models' forecasted value. Table 6 shows the results of used performance metrics for comparing LSTM and DWT-LSTM for three types of forecasting results, including wind speed, solar supply and energy demands. They will be described in details in the following subsections.

A. BUILDING ENERGY DEMAND FORECASTING

In our study, we develop the LSTM and DWT-LSTM methods to forecast building energy demand. Figure 12 shows the forecasting results of these models and shows the comparison of the forecasting results with the observed energy demand of the buildings. These models forecast building energy demand from 1^{st} to 30^{th} December 2019 (one month) with hourly intervals. Figure 12 demonstrates that DWT-LSTM and LSTM methods have good performance in forecasting the building energy demand when comparing with observed real data of energy demand. However, the results show 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%. In addition, DWT-LSTM and LSTM methods are potential for forecasting the peak energy demands. As shown in Figure 12, the building energy demand has sudden increases between hour 0-24, 144-192, and 312-360 which are the weekends. This states that despite the high intermittency of building energy demand fluctuations; DWT-LSTM and LSTM methods have a high level of accuracy in forecasting building energy demand.

Moreover, the results of RMSE, MSE, MAPE, and R-Squared values of the methods prove that the 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. Therefore, the DWT approach effectively increases the accuracy of the DWT-equipped LSTM in comparison with the LSTM model.

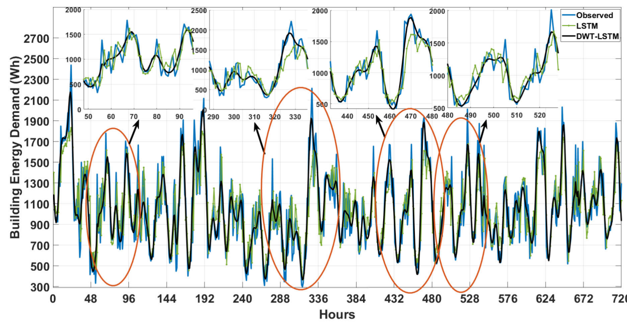


FIGURE 12. Energy demand models (Dec 1^{st} 2019-Dec 30^{th} 2019).

B. RENEWABLE ENERGY GENERATION FORECASTING

1) WIND SPEED AND WIND ENERGY

We forecast the wind speed using the DWT-LSTM and LSTM methods in order to estimate wind energy generation. The wind speed and the wind energy generation predictions are illustrated in Figure 13 and Figure 14, respectively. The wind speed and the wind energy are forecasted from 1^{st} to 30^{th} December 2019 (one month) with hourly intervals.

According to the wind energy generation and wind speed data sheets of Bergey Windpower Company, the wind energy generation is calculated using the wind speed forecasting and the power output of the BWC 5kW Grid-Intertie wind turbine. The results of the wind speed forecasting using LSTM and DWT-LSTM methods are depicted and compared with the observed values of the wind speed in Figure 13. Based on these results, the DWT-LSTM has higher accuracy in comparison with the LSTM method. In addition, considering the MAPE value, the DWT-LSTM outperforms the LSTM in wind speed forecasting as it removes the noises using a two-layer DWT approach. It is worth noting that the two-layer DWT approach successfully removes the extra noises and accordingly increases the LSTM accuracy.

Using the data sheet from the Bergey Windpower Company, future wind energy generation can be estimated from the results of wind speed forecasting as illustrated in Figure 14. The results demonstrate that the estimated wind energy supply prediction follows the pattern of observed wind energy supply. Furthermore, due to the noise

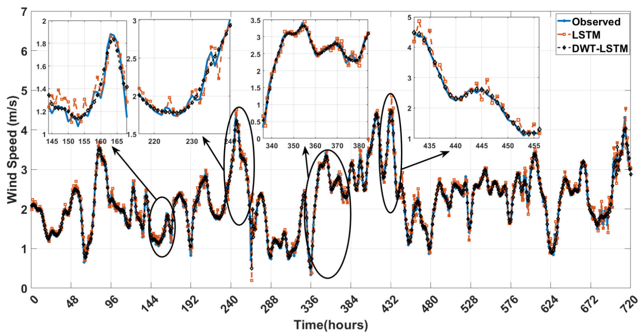


FIGURE 13. Wind speed prediction (Dec 1st 2019-Dec 30th 2019).

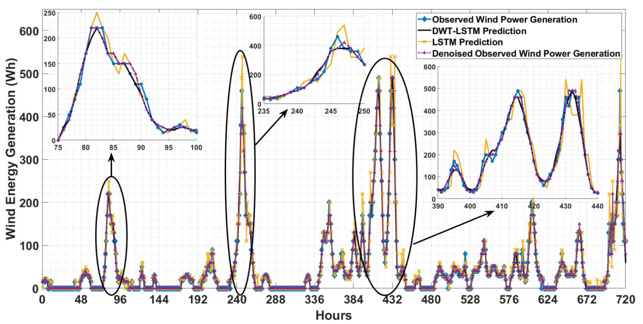


FIGURE 14. Wind energy supply prediction (Dec 1st 2019-Dec 30th 2019).

removal effect, Figure 14 also depicts that DWT-LSTM method is more accurate than LSTM method in forecasting wind energy supply.

2) SOLAR PV ENERGY

We forecast the solar PV energy generation by DWT-LSTM and LSTM using the air temperature, solar irradiance on the ground surface, previous week, previous day and previous hour solar energy generation data 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. As a result, the effects of noises decrease while preserving the influential patterns in these variables. However, in the method development phase some important features may be missed to be captured due to the DWT implementation

Figure 15 shows the performance of DWT-LSTM and LSTM methods for solar electricity supply prediction. This comparison of results clarifies the fact that equipping the LSTM method with the DWT denoising and decomposing method does not improve 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 important patterns in solar energy generation dataset. The DWT method considers the energy generation peaks as noises and tries to remove them. This results in decreasing the wide range variation of the solar energy output. In other words, the DWT decomposes the solar energy generation fluctuations as noise and tries to remove them. Therefore, implementing the DWT method in

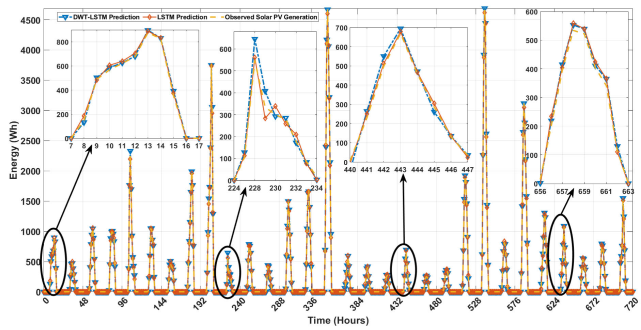


FIGURE 15. Solar electricity supply prediction (Dec 1st 2019-Dec 30th 2019).

decomposing the solar energy generation dataset decreases the accuracy of solar energy generation forecasting. In conclusion, by looking at the Table 6, the results of both methods are acceptable for forecasting the solar PV energy supply.

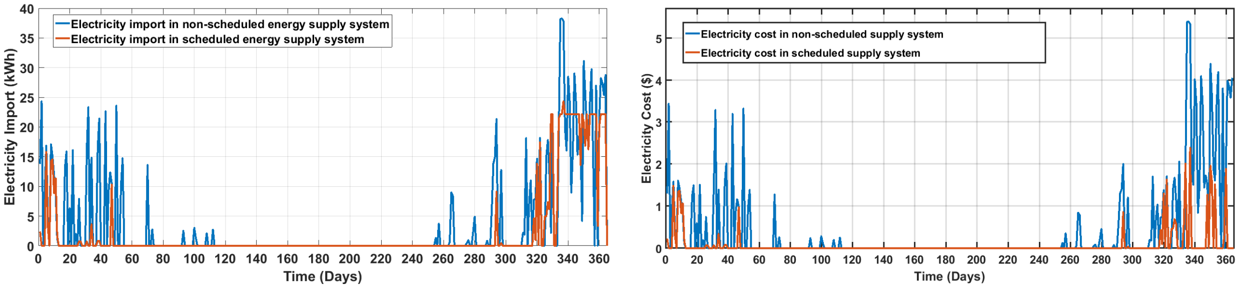
C. SCHEDULING FRAMEWORK

Our proposed scheduling framework is composed of a scheduling algorithm and a saving strategy. The scheduling algorithm aims to maximize the share of supplied energy demand by renewable energy sources; and minimize the energy cost through decreasing electricity import during the peak days (i.e., days with higher than 22.1918 kWh energy demand). The framework schedules the RE supply and electricity import in weekly intervals based on the week-ahead forecasting results of RE supply and energy demand. Based on the SDI (Equation 1) and EP (Equation 5) outputs, the share of imported electricity from the grid and also imported electricity amount during the peak days are estimated. In addition, saving strategy is activated based on the user's predefined strategy. Saving strategy decreases the extra energy demand based on the user's preference to reduce the reliance on the grid during the peak days. Saving strategy is defined to decrease the energy demand when the net demand exceeds the boundary layer. Indeed, saving strategy is activated to evaluate the scheduled energy demand to identify the peak days which the scheduling framework cannot supply by energy storage.

Table 7 presents the results of scheduling framework when saving strategy is applied. Table 7 shows the results of the imported electricity from the grid, cost of imported electricity, and exported electricity to the grid in 2019. The results of the imported electricity from the grid and electricity costs in the table are estimated based on two-step electricity prices. Let's recall that the first-step price and second-step price are considered for lower than 22.1918 kW per day and more than 22.1918 kW per day, respectively. According to the results in table, implementing the scheduling framework alone decreases the annual electricity cost from 130.46$ to 80.8$; and integration of the scheduling framework with the saving strategy reduces the annual electricity cost to 80.5$. Furthermore, in the second-step price (more than 22.1918 kWh per day), the scheduling framework decreases

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

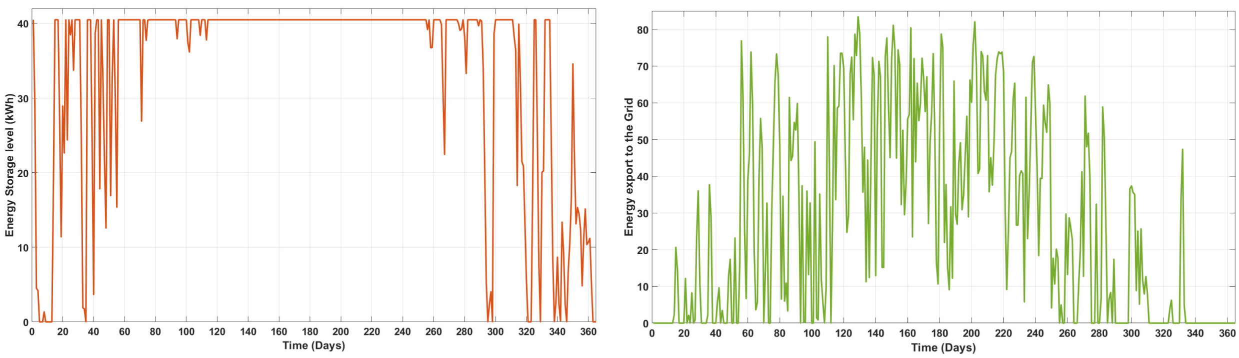
Energy-saving strategy	No saving strategy		10% saving strategy	
	Scheduled	Not scheduled	Scheduled	Not scheduled
Electricity import with lower tariff	855.8	1222.55	855.5	1216.7
Electricity import with higher tariff	2.17	109.4	0	59.9
Electricity cost higher tariff	0.3	15.42	0	8.44
Electricity cost lower tariff	80.53	115.04	80.5	114.5
Electricity export	7777	8250	7779.7	8310



(a) Scheduled electricity import and non-scheduled electricity import.

(b) Scheduled energy cost and non-scheduled energy cost.

FIGURE 16. Scheduled and non-scheduled electricity import and electricity cost in 2019.



(a) Energy storage charge and discharge pattern

(b) Exported electricity to the grid.

FIGURE 17. Energy storage charge/discharge and exported electricity to the grid in 2019.

the imported electricity from the grid from 15.42 kWh to 0.3 kWh. Using both scheduling framework and saving strategy also reduce the imported electricity from the grid from 15.42 to 0 kWh. Moreover, as shown in Table 7, considering a no saving strategy the proposed scheduling framework decreases the imported electricity from the grid from 1332 (1222.55 + 109.4) kWh to 858 (855.8 + 2.17) kWh, which is equal to 35.5% reduction.

Figure 16 demonstrates the impact of the proposed scheduling method in decreasing reliance on the grid and reduction of electricity costs. Figure 16(a) and 16(b) illustrate the electricity import from the grid and energy costs in both scheduled energy supply and non-scheduled energy supply systems. In these figures, the orange line represents the scheduled electricity import; and the blue line presents the non-scheduled electricity import from the grid.

Figure 16(a) shows the scheduled electricity import and non-scheduled electricity import in 2019. This figure explains that during January, February, November, and December, the electricity import increases. This is obvious in the start and in the end of the plot (between day 1 to day 60; and day 300 to 365). In this figure, comparing the orange and blue lines shows that the electricity import is considerably reduced from the grid after applying the scheduling framework. In addition, the amount of electricity import always has been below 22.1918 kWh per day (i.e., the boundary that specifies the cost of the electricity.), except only in day 337. Note that exceeding this boundary increases the electricity price by 50%.

Figure 17 shows the energy storage charge/discharge and exported electricity to the grid in 2019. While, Figure 17(a) illustrates the energy storage charging and discharging patterns; Figure 17(b) demonstrates the amount of exported electricity to the grid. As it is illustrated in Figure 17(a), the energy storage has a significant role during January, February, November, and December as the RE supply is lower during this periods of the year. Based on this figure, RE supply increases during the summer time and decreases during the winter. Moreover, as shown in Figure 17(b) the exported electricity to the grid is at its lowest level during this period as the RE supply is saved in the energy storage; that was for minimizing the reliance on the grid. The conclusion is that utilizing the our proposed method not only decreases the energy import from the grid but also exports electricity to the grid during the peak RE supply.

In conclusion, implementing our proposed framework for scheduling energy supply of the buildings (as shown in Figure 16) notably decreases the reliance on the electricity grid especially during the peak days, and consequently reduces the total cost of imported electricity from the grid.

D. FINANCIAL ANALYSIS

In our study, we implemented Net Present Value (NPV) for the financial evaluation of the investment in building energy systems. NPV is a standard concept for modelling, representing and comparing economic preferences [93]. NPV is the sum of the present values of incoming and outgoing cash flows over a specific time. NPV is described as the difference between the sum of discounted cash inflows and outflows and calculated 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 indicate to the number of time steps, discount rate, cash inflow at moment t, cash outflow at time t, and initial investment, respectively. The cash outflow is composed of operational and maintenance (O&M) costs, and capital costs. While, capital costs are the initial investment for installation of the energy system; O&M costs are the annual costs for maintenance and servicing of the system. The cash inflow, cash outflow, and maintenance costs are estimated based on the solar PV, wind turbine, inverter, and energy storage specifications. The specifications of the solar PV, wind turbine, inverter, and energy storage is presented in Table 8. The estimated cash inflow, cash outflow, and O&M costs are presented in Table 9. NPV is a valuable tool to determine whether a project will result in a net profit or a loss. Net profit is when the NPV is positive and the investment adds value to the energy system. A loss is when NPV is negative and the investment subtracts value from the energy system [94].

1) FINANCIAL ANALYSIS OF THE PROPOSED SMART ENERGY MANAGEMENT SYSTEM

In our study, we use 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 includes the impact of solar PV panels and wind turbines in returning the 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. This is to achieve a perpendicular condition and the increase of the electricity output of the PV panels [95].

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 of dual-axis solar tracking systems

TABLE 8. 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 (years)	20	15	15
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 (years)	5	5	5
Life Span (years)	10	10	10
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
DOC	100%	100%	100%
RTE	90%	90%	90%
Cycles	5000	6000	6000
Lifespan (years)	25	25	25
Warranty (years)	10	7	10
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

TABLE 9. The cash inflow and outflow patterns.

Cash Type	**Source**	**Costs ($)**	**Time frame (years)**
Outflow	solar PV	2000	25
	Wind turbine	2105	15
	Inverter	890	10
	Energy storage	9600	25
Inflow	Electricity export	748.75	1
	self-supplied electricity	843.4	1
O&M	solar PV	63.3 (0.005 $/kWh [97])	1
	Wind turbine	19.4 (0.02 $/kWh [97])	1
	Inverter	12.5 $/year [98]	1
	Energy storage	5 $/year [99]	1

outweigh the extra generated energy [95], [96]. Due to this reason, in our implementation we utilized a fixed solar PV system in order to decrease both the investment and maintenance costs so that the smart building energy system has the lowest financial breakeven point. In this paper, the implemented solar PV units and the wind turbine annually generate 12664.03 kWh 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 in 2019.

TABLE 10. Annual energy demand and supply. The G/C indicates to generation/consumption in 2019.

Variables	G/C	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

Using the information provided in Table 10, thus, we can calculate the cash inflow based on the G/C energy and electricity tariffs utilizing the definitions of the BC-Hydro company. This company defines a pricing policy for decreasing energy consumption. This company introduces energy in two tariffs; low energy consumption price and high energy consumption price. These two prices are specified based on the daily and two-month energy consumption boundary 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 [100].

Accordingly, by implementing the proposed method, the building annual energy cost decreases from 665$ (6709 kWh) to 80.8$ (858 kWh), which equals to 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 presented in Table 7, the scheduling algorithm solely decreases the reliance on the grid from 1333 kWh/year to 858.9 kWh/year. This translates to 35.5% reliance on the grid. In addition, the algorithm decreases the reliance on the grid during the peak days from 109.4 kWh/year to 2.17 kWh/year (98%) when without saving strategy; and to 0 (100%) kWh/year with a 10% saving strategy. Based on the calculations presented in Table 9, implementing a smart building integrated with a 10 kW PV system and 5 kW wind turbine provides 1591$ cash inflow annually, while the same system without the wind turbine provides 1500$ cash inflow annually. Considering the wind turbine cash inflows and outflows, the conclusion is that utilizing wind turbine is not economically beneficial in our proposed building energy system. This is demonstrated in Figure 18.

The figure shows the NPV of both building energy systems. The smart building that is integrated with a solar PV system

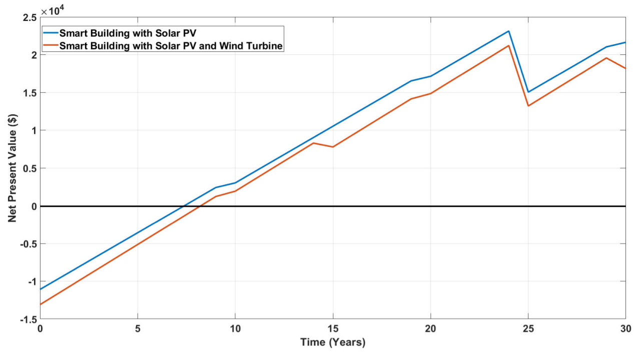


FIGURE 18. Net present value of the proposed energy management systems.

is more economical than the building integrated with both solar PV and wind turbine. The figure shows the break even points are nine years for the building with solar PV, wind turbine, inverter, and energy storage; and eight years for a building with solar PV, inverter, and energy storage. The break even points are the intersections of the two plots with the straight black line.

V. CONCLUSION

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. The complexity increases as renewable energy is variable, unpredictable, and weather dependent. In our paper, using weather and energy consumption/generation patterns, we developed deep learning models to forecast energy demands and supplies for five buildings in Vancouver in British Columbia. Our method uses the combination of discrete wavelet transformation and long short-term methods (DWT-LSTM). The results showed that the method can model building energy demands and renewable energy supplies with a high level of accuracy in terms of mean average percentile error (MAPE) ranging from 1.24% to 2.89%.

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 scheduling 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, our integrated smart energy framework can help the building owner to meet their 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. In addition, implementing the proposed framework can cover up to 83.2% of electricity load by renewable energy sources. 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.

Our scheduling framework further increases the renewable energy sources 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 breakeven point after 9 years. With the same specifications except for the wind turbine, the proposed smart building framework has a financial break even point after 8 years. To this end, 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 compared to the case without wind turbines.

As our future work, we plan to focus on net-zero smart buildings 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. We also plan to consider load scheduling problems and use additional factors such as user satisfactions.

REFERENCES

[1] V. Pérez-Andreu, C. Aparicio-Fernández, A. Martínez-Ibernón, and J.-L. Vivancos, "Impact of climate change on heating and cooling energy demand in a residential building in a Mediterranean climate," *Energy*, vol. 165, pp. 63–74, Dec. 2018.

[2] S.-H. Kim, S. Lee, S.-Y. Han, and J.-H. Kim, "Scenario analysis for GHG emission reduction potential of the building sector for new city in South Korea," *Energies*, vol. 13, no. 20, p. 5514, Oct. 2020.

[3] D. Dominković, V. Dobravec, Y. Jiang, P. Nielsen, and G. Krajačić, "Modelling smart energy systems in tropical regions," *Energy*, vol. 155, pp. 592–609, Jul. 2018.

[4] V. Vahidinasab, C. Ardalan, B. Mohammadi-Ivatloo, D. Giaouris, and S. L. Walker, "Active building as an energy system: Concept, challenges, and outlook," *IEEE Access*, vol. 9, pp. 58009–58024, 2021.

[5] G. C. Gissey, B. Zakeri, P. E. Dodds, and D. Subkhankulova, "Evaluating consumer investments in distributed energy technologies," *Energy Policy*, vol. 149, Feb. 2021, Art. no. 112008.

[6] N. H. Motlagh, A. Khatibi, and A. Aslani, "Toward sustainable energy-independent buildings using Internet of Things," *Energies*, vol. 13, no. 22, p. 5954, Nov. 2020.

[7] M. H. Dadashi-Rad, A. Ghasemi-Marzbali, and R. A. Ahangar, "Modeling and planning of smart buildings energy in power system considering demand response," *Energy*, vol. 213, Dec. 2020, Art. no. 118770.

[8] S.-V. Oprea, A. Bâra, Ş. Preda, and O. B. Tor, "A smart adaptive switching module architecture using fuzzy logic for an efficient integration of renewable energy sources. A case study of a RES system located in Hulubeşti, Romania," *Sustainability*, vol. 12, no. 15, p. 6084, Jul. 2020.

[9] M. Bourdeau, X. Q. Zhai, E. Nefzaoui, X. Guo, and P. Chatellier, "Modeling and forecasting building energy consumption: A review of data-driven techniques," *Sustain. Cities Soc.*, vol. 48, Jul. 2019, Art. no. 101533.

[10] W. Li, T. Logenthiran, V.-T. Phan, and W. L. Woo, "Implemented IoT-based self-learning home management system (SHMS) for Singapore," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 2212–2219, Jun. 2018.

[11] J. Han, C.-S. Choi, W.-K. Park, I. Lee, and S.-H. Kim, "Smart home energy management system including renewable energy based on ZigBee and PLC," *IEEE Trans. Consum. Electron.*, vol. 60, no. 2, pp. 198–202, May 2014.

[12] X. Xu and P. X. W. Zou, "Analysis of factors and their hierarchical relationships influencing building energy performance using interpretive structural modelling (ISM) approach," *J. Cleaner Prod.*, vol. 272, Nov. 2020, Art. no. 122650.

[13] *Europe Annual PV Capacity Additions 2017–2022 and Average Annual Additions for 2023–2025 by Country*, Int. Energy Agency, Paris, France, Nov. 2020.

[14] F. Wang, Z. Xuan, Z. Zhen, K. Li, T. Wang, and M. Shi, "A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework," *Energy Convers. Manage.*, vol. 212, May 2020, Art. no. 112766.

[15] J. Ku and B. C. Kovoor, "A wavelet-based hybrid multi-step wind speed forecasting model using LSTM and SVR," *Wind Eng.*, pp. 1–22, Oct. 2020, doi: 10.1177/0309524X20964762.

[16] J. Mirez, L. Hernandez-Callejo, M. Horn, and L.-M. Bonilla, "Simulation of direct current microgrid and study of power and battery charge/discharge management," *Dyna*, vol. 92, pp. 673–679, Nov. 2017.

[17] M. L. Guen, L. Mosca, A. T. D. Perera, S. Coccolo, N. Mohajeri, and J.-L. Scartezzini, "Improving the energy sustainability of a Swiss village through building renovation and renewable energy integration," *Energy Buildings*, vol. 158, pp. 906–923, Jan. 2018.

[18] H. Golpîra and S. A. R. Khan, "A multi-objective risk-based robust optimization approach to energy management in smart residential buildings under combined demand and supply uncertainty," *Energy*, vol. 170, pp. 1113–1129, Mar. 2019.

[19] A. Gellert, A. Florea, U. Fiore, F. Palmieri, and P. Zanetti, "A study on forecasting electricity production and consumption in smart cities and factories," *Int. J. Inf. Manage.*, vol. 49, pp. 546–556, Dec. 2019.

[20] D. Lee and K. Kim, "Recurrent neural network-based hourly prediction of photovoltaic power output using meteorological information," *Energies*, vol. 12, no. 2, p. 215, Jan. 2019.

[21] J. Leitao, P. Gil, B. Ribeiro, and A. Cardoso, "A survey on home energy management," *IEEE Access*, vol. 8, pp. 5699–5722, 2020.

[22] S. Ruzic, A. Vuckovic, and N. Nikolic, "Weather sensitive method for short term load forecasting in electric power utility of Serbia," *IEEE Trans. Power Syst.*, vol. 18, no. 4, pp. 1581–1586, Nov. 2003.

[23] B. Dong, C. Cao, and S. E. Lee, "Applying support vector machines to predict building energy consumption in tropical region," *Energy Buildings*, vol. 37, no. 5, pp. 545–553, May 2005.

[24] L. Bartolucci, S. Cordiner, V. Mulone, V. Rocco, and J. L. Rossi, "Hybrid renewable energy systems for renewable integration in microgrids: Influence of sizing on performance," *Energy*, vol. 152, pp. 744–758, Jun. 2018.

[25] X. Guan, Z. Xu, and Q.-S. Jia, "Energy-efficient buildings facilitated by microgrid," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 243–252, Dec. 2010.

[26] N. H. Motlagh, S. H. Khajavi, A. Jaribion, and J. Holmstrom, "An IoT-based automation system for older homes: A use case for lighting system," in *Proc. IEEE 11th Conf. Service-Oriented Comput. Appl. (SOCA)*, Nov. 2018, pp. 1–6.

[27] K. Amasyali and N. M. El-Gohary, "A review of data-driven building energy consumption prediction studies," *Renew. Sustain. Energy Rev.*, vol. 81, pp. 1192–1205, Jan. 2018.

[28] M. Asif and T. Muneer, "Energy supply, its demand and security issues for developed and emerging economies," *Renew. Sustain. Energy Rev.*, vol. 11, no. 7, pp. 1388–1413, Sep. 2007.

[29] M. Hasanuzzaman and L. Kumar, "Energy supply," in *Energy for Sustainable Development*. Amsterdam, The Netherlands: Elsevier, 2020, pp. 89–104.

[30] H. Quan, D. Srinivasan, and A. Khosravi, "Short-term load and wind power forecasting using neural network-based prediction intervals," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 25, no. 2, pp. 303–315, Feb. 2014.

[31] J. Jurasz, A. Beluco, and F. A. Canales, "The impact of complementarity on power supply reliability of small scale hybrid energy systems," *Energy*, vol. 161, pp. 737–743, Oct. 2018.

[32] D. Arcos-Aviles, J. Pascual, F. Guinjoan, L. Marroyo, P. Sanchis, and P. M. Marietta, "Low complexity energy management strategy for grid profile smoothing of a residential grid-connected microgrid using generation and demand forecasting," *Appl. Energy*, vol. 205, pp. 69–84, Nov. 2017.

[33] M. Molina-Solana, M. Ros, M. D. Ruiz, J. Gómez-Romero, and M. J. Martín-Bautista, "Data science for building energy management: A review," *Renew. Sustain. Energy Rev.*, vol. 70, pp. 598–609, Apr. 2017.

[34] N. Somu, G. Raman M R, and K. Ramamritham, "A deep learning framework for building energy consumption forecast," *Renew. Sustain. Energy Rev.*, vol. 137, Mar. 2021, Art. no. 110591.

[35] T. Ahmad, H. Zhang, and B. Yan, "A review on renewable energy and electricity requirement forecasting models for smart grid and buildings," *Sustain. Cities Soc.*, vol. 55, Apr. 2020, Art. no. 102052.
[36] O. Elma, A. Taşcıkaraoğlu, A. T. İnce, and U. S. Selamoğulları, "Implementation of a dynamic energy management system using real time pricing and local renewable energy generation forecasts," *Energy*, vol. 134, pp. 206–220, Sep. 2017.
[37] J. K. Gruber, M. Prodanovic, and R. Alonso, "Estimation and analysis of building energy demand and supply costs," *Proc. Energy*, vol. 83, pp. 216–225, Dec. 2015.
[38] H.-X. Zhao and F. Magoulès, "A review on the prediction of building energy consumption," *Renew. Sustain. Energy Rev.*, vol. 16, no. 6, pp. 3586–3592, 2012.
[39] M. Q. Raza, N. Mithulananthan, J. Li, and K. Y. Lee, "Multivariate ensemble forecast framework for demand prediction of anomalous days," *IEEE Trans. Sustain. Energy*, vol. 11, no. 1, pp. 27–36, Jan. 2020.
[40] A. Moradzadeh, A. Mansour-Saatloo, B. Mohammadi-Ivatloo, and A. Anvari-Moghaddam, "Performance evaluation of two machine learning techniques in heating and cooling loads forecasting of residential buildings," *Appl. Sci.*, vol. 10, no. 11, p. 3829, May 2020.
[41] Y. Li, Z. Wen, Y. Cao, Y. Tan, D. Sidorov, and D. Panasetsky, "A combined forecasting approach with model self-adjustment for renewable generations and energy loads in smart community," *Energy*, vol. 129, pp. 216–227, Jun. 2017.
[42] N. Ayoub, F. Musharavati, S. Pokharel, and H. A. Gabbar, "ANN model for energy demand and supply forecasting in a hybrid energy supply system," in *Proc. IEEE Int. Conf. Smart Energy Grid Eng. (SEGE)*, Aug. 2018, pp. 25–30.
[43] S. A. Adewuyi, S. Aina, and A. I. Oluwaranti, "A deep learning model for electricity demand forecasting based on a tropical data," *Appl. Comput. Sci.*, vol. 16, no. 1, pp. 1–13, 2020.
[44] M. Cai, M. Pipattanasomporn, and S. Rahman, "Day-ahead building-level load forecasts using deep learning vs. traditional time-series techniques," *Appl. Energy*, vol. 236, pp. 1078–1088, Feb. 2019.
[45] C. Correa-Jullian, J. M. Cardemil, E. L. Droguett, and M. Behzad, "Assessment of deep learning techniques for prognosis of solar thermal systems," *Renew. Energy*, vol. 145, pp. 2178–2191, Jan. 2020.
[46] G. Li, H. Wang, S. Zhang, J. Xin, and H. Liu, "Recurrent neural networks based photovoltaic power forecasting approach," *Energies*, vol. 12, no. 13, p. 2538, 2019.
[47] J. Zhang, R. Verschae, S. Nobuhara, and J.-F. Lalonde, "Deep photovoltaic nowcasting," *Sol. Energy*, vol. 176, pp. 267–276, Dec. 2018.
[48] S. Bouktif, A. Fiaz, A. Ouni, and M. A. Serhani, "Optimal deep learning LSTM model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches," *Energies* vol. 11, no. 7, p. 1636, Jun. 2018.
[49] M. Miljanovic, "Comparative analysis of recurrent and finite impulse response neural networks in time series prediction," *Indian J. Comput. Sci. Eng.*, vol. 3, no. 1, pp. 180–191, 2012.
[50] N. Wei, C. Li, X. Peng, Y. Li, and F. Zeng, "Daily natural gas consumption forecasting via the application of a novel hybrid model," *Appl. Energy*, vol. 250, pp. 358–368, Sep. 2019.
[51] F. Azeem, G. B. Narejo, and U. A. Shah, "Integration of renewable distributed generation with storage and demand side load management in rural islanded microgrid," *Energy Efficiency*, vol. 13, no. 8, pp. 217–235, 2020.
[52] M. Sechilariu, F. Locment, and L. T. D. Santos, "A conceptual framework for full optimal operation of a grid-connected DC microgrid," in *Proc. IEEE Int. Conf. Ind. Electron. Sustain. Energy Syst. (IESES)*, Jan. 2018, pp. 296–301.
[53] L. Du, L. Zhang, and X. Tian, "Deep power forecasting model for building attached photovoltaic system," *IEEE Access*, vol. 6, pp. 52639–52651, 2018.
[54] X. Kong, C. Li, F. Zheng, and C. Wang, "Improved deep belief network for short-term load forecasting considering demand-side management," *IEEE Trans. Power Syst.*, vol. 35, no. 2, pp. 1531–1538, Mar. 2020.
[55] B. Kermanshahi, "Recurrent neural network for forecasting next 10 years loads of nine Japanese utilities," *Neurocomputing*, vol. 23, nos. 1–3, pp. 125–133, 1998.
[56] L. Wen, K. Zhou, S. Yang, and X. Lu, "Optimal load dispatch of community microgrid with deep learning based solar power and load forecasting," *Energy*, vol. 171, pp. 1053–1065, Mar. 2019.
[57] N. Al Khafaf, M. Jalili, and P. Sokolowski, "Application of deep learning long short-term memory in energy demand forecasting," in *Proc. Int. Conf. Eng. Appl. Neural Netw.* Cham, Switzerland: Springer, 2019, pp. 31–42.
[58] H. Karunathilake, K. Hewage, J. Brinkerhoff, and R. Sadiq, "Optimal renewable energy supply choices for net-zero ready buildings: A life cycle thinking approach under uncertainty," *Energy Buildings*, vol. 201, pp. 70–89, Oct. 2019.
[59] Y. Ma and B. Li, "Hybridized intelligent home renewable energy management system for smart grids," *Sustainability*, vol. 12, no. 5, p. 2117, Mar. 2020.
[60] X. Jin, T. Jiang, Y. Mu, C. Long, X. Li, H. Jia, and Z. Li, "Scheduling distributed energy resources and smart buildings of a microgrid via multi-time scale and model predictive control method," *IET Renew. Power Gener.*, vol. 13, no. 6, pp. 816–833, Apr. 2019.
[61] D. Zhang, N. Shah, and L. G. Papageorgiou, "Efficient energy consumption and operation management in a smart building with microgrid," *Energy Convers. Manage.*, vol. 74, pp. 209–222, Oct. 2013.
[62] S. Aslam, A. Khalid, and N. Javaid, "Towards efficient energy management in smart grids considering microgrids with day-ahead energy forecasting," *Electr. Power Syst. Res.*, vol. 182, May 2020, Art. no. 106232.
[63] T. Hossen, A. S. Nair, S. Noghanian, and P. Ranganathan, "Optimal operation of smart home appliances using deep learning," in *Proc. North Amer. Power Symp. (NAPS)*, Sep. 2018, pp. 1–6.
[64] J. Yang, S. Zhang, Y. Xiang, J. Liu, J. Liu, X. Han, and F. Teng, "LSTM auto-encoder based representative scenario generation method for hybrid hydro-PV power system," *IET Gener., Transmiss. Distrib.*, vol. 14, no. 24, pp. 5935–5943, Dec. 2020.
[65] Y. Liu, L. Guan, C. Hou, H. Han, Z. Liu, Y. Sun, and M. Zheng, "Wind power short-term prediction based on LSTM and discrete wavelet transform," *Appl. Sci.*, vol. 9, no. 2, p. 1108, 2019.
[66] M. Sadat-Mohammadi, M. Nazari-Heris, E. Nazerfard, M. Abedi, S. Asadi, and H. Jebelli, "Intelligent approach for residential load scheduling," *IET Gener., Transmiss. Distrib.*, vol. 14, no. 21, pp. 4738–4745, 2020.
[67] S. Kim, R. Mowakeaa, S.-J. Kim, and H. Lim, "Building energy management for demand response using kernel lifelong learning," *IEEE Access*, vol. 8, pp. 82131–82141, 2020.
[68] M. S. Islam, "A techno-economic feasibility analysis of hybrid renewable energy supply options for a grid-connected large office building in southeastern part of France," *Sustain. Cities Soc.*, vol. 38, pp. 492–508, Apr. 2018.
[69] J. Liu, M. Wang, J. Peng, X. Chen, S. Cao, and H. Yang, "Techno-economic design optimization of hybrid renewable energy applications for high-rise residential buildings," *Energy Convers. Manage.*, vol. 213, Jun. 2020, Art. no. 112868.
[70] N. H. Motlagh, M. Mohammadrezaei, J. Hunt, and B. Zakeri, "Internet of Things (IoT) and the energy sector," *Energies*, vol. 13, no. 2, p. 494, Jan. 2020.
[71] S. Lee and D.-H. Choi, "Energy management of smart home with home appliances, energy storage system and electric vehicle: A hierarchical deep reinforcement learning approach," *Sensors*, vol. 20, no. 7, p. 2157, Apr. 2020.
[72] A. Tascikaraoglu, A. R. Boynuegri, and M. Uzunoglu, "A demand side management strategy based on forecasting of residential renewable sources: A smart home system in Turkey," *Energy Buildings*, vol. 80, pp. 309–320, Sep. 2014.
[73] K. Yan, W. Li, Z. Ji, M. Qi, and Y. Du, "A hybrid LSTM neural network for energy consumption forecasting of individual households," *IEEE Access*, vol. 7, pp. 157633–157642, 2019.
[74] Y. Gao, C. Fang, and Y. Ruan, "A novel model for the prediction of long-term building energy demand: LSTM with attention layer," *IOP Conf. Ser., Earth Environ. Sci.*, vol. 294, Aug. 2019, Art. no. 012033.
[75] S. F. Stefenon, C. Kasburg, A. Nied, A. C. R. Klaar, F. C. S. Ferreira, and N. W. Branco, "Hybrid deep learning for power generation forecasting in active solar trackers," *IET Gener., Transmiss. Distrib.*, vol. 14, no. 23, pp. 5667–5674, Dec. 2020.
[76] Y. Li, H. Wu, and H. Liu, "Multi-step wind speed forecasting using EWT decomposition, LSTM principal computing, RELM subordinate computing and IEWT reconstruction," *Energy Convers. Manage.*, vol. 167, pp. 203–219, Jul. 2018.
[77] Ö. Yildirim, "A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification," *Comput. Biol. Med.*, vol. 96, pp. 189–202, May 2018.

[78] M. Hosseinzadeh, "Robust control applications in biomedical engineering: Control of depth of hypnosis," in *Control Applications for Biomedical Engineering Systems*. Amsterdam, The Netherlands: Elsevier, 2020, pp. 89–125.

[79] M. A. Zaidan, N. H. Motlagh, P. L. Fung, D. Lu, H. Timonen, J. Kuula, J. V. Niemi, S. Tarkoma, T. Petäjä, M. Kulmala, and T. Hussein, "Intelligent calibration and virtual sensing for integrated low-cost air quality sensors," *IEEE Sensors J.*, vol. 20, no. 22, pp. 13638–13652, Nov. 2020.

[80] Y.-S. Park and S. Lek, "Artificial neural networks: Multilayer perceptron for ecological modeling," in *Developments in Environmental Modelling*, vol. 28. Amsterdam, The Netherlands: Elsevier, 2016, pp. 123–140.

[81] S. A. Nabavi, A. Aslani, M. A. Zaidan, M. Zandi, S. Mohammadi, and N. H. Motlagh, "Machine learning modeling for energy consumption of residential and commercial sectors," *Energies*, vol. 13, no. 19, p. 5171, Oct. 2020.

[82] X. Qing and Y. Niu, "Hourly day-ahead solar irradiance prediction using weather forecasts by LSTM," *Energy*, vol. 148, pp. 461–468, Apr. 2018.

[83] S. Hochreiter and J. Schmidhuber, "LSTM can solve hard long time lag problems," in *Proc. Adv. Neural Inf. Process. Syst.*, 1997, pp. 473–479.

[84] Z. Khan, T. Hussain, A. Ullah, S. Rho, M. Lee, and S. Baik, "Towards efficient electricity forecasting in residential and commercial buildings: A novel hybrid CNN with a LSTM-AE based framework," *Sensors*, vol. 20, no. 5, p. 1399, Mar. 2020.

[85] C. Tian, "A deep neural network model for short-term load forecast based on long short-term memory network and convolutional neural network," *Energies*, vol. 11, no. 12, p. 3493, 2018.

[86] X. Li and J. Wen, "Review of building energy modeling for control and operation," *Renew. Sustain. Energy Rev.*, vol. 37, pp. 517–537, Sep. 2014.

[87] V. Verma and K. Murugesan, "Optimization of solar assisted ground source heat pump system for space heating application by Taguchi method and utility concept," *Energy Buildings*, vol. 82, pp. 296–309, Oct. 2014.

[88] S. Makonin, "Hue: The hourly usage of energy dataset for buildingsin British Columbia," *Data Brief*, vol. 23, 2019, Art. no. 103744.

[89] B. Zakeri and S. Syri, "Electrical energy storage systems: A comparative life cycle cost analysis," *Renew. Sustain. Energy Rev.*, vol. 42, pp. 569–596, Feb. 2015.

[90] S. Pfenninger and I. Staffell, "Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data," *Energy*, vol. 114, pp. 1251–1265, Nov. 2016.

[91] S. Koohi-Fayegh and M. A. Rosen, "A review of energy storage types, applications and recent developments," *J. Energy Storage*, vol. 27, Feb. 2020, Art. no. 101047.

[92] N. Nitta, F. Wu, J. T. Lee, and G. Yushin, "Li-ion battery materials: Present and future," *Mater. Today*, vol. 18, no. 5, pp. 252–264, 2015.

[93] V. Lidia, "The net present value and the optimal solution of linear programming in investment decisions," *Ann. Univ. Oradea, Econ. Sci. Ser.*, vol. 29, no. 2, pp. 135–145, 2020.

[94] H. Gaspars-Wieloch, "Project net present value estimation under uncertainty," *Central Eur. J. Oper. Res.*, vol. 27, no. 1, pp. 179–197, Mar. 2019.

[95] B. Asiabanpour, Z. Almusaied, S. Aslan, M. Mitchell, E. Leake, H. Lee, J. Fuentes, K. Rainosek, N. Hawkes, and A. Bland, "Fixed versus sun tracking solar panels: An economic analysis," *Clean Technol. Environ. Policy*, vol. 19, no. 4, pp. 1195–1203, May 2017.

[96] M. Sadat-Mohammadi, M. Nazari-Heris, H. Nafisi, and M. Abedi, "A comprehensive financial analysis for dual-axis sun tracking system in Iran photovoltaic panels," in *Proc. Smart Grid Conf. (SGC)*, Nov. 2018, pp. 1–6.

[97] M. E. Nejad, E. Ghezi, and M. R. T. Sabzevar, "Technical and economic design of solar/wind hybrid systems with the goal of minimizing the annual cost of energy using the improved teaching-learning algorithm," *Int. J. Acad. Eng. Res.*, vol. 2, no. 10, pp. 1–7, 2018.

[98] A. Ihsan, M. J. Brear, and M. Jeppesen, "Impact of operating uncertainty on the performance of distributed, hybrid, renewable power plants," *Appl. Energy*, vol. 282, Jan. 2021, Art. no. 116256.

[99] M. Said and A. Yassin, "Operation study of a combined system of diesel engine generators and wind turbine with battery storage system," in *Proc. 6th Int. Conf. Adv. Control Circuits Syst. (ACCS), 5th Int. Conf. New Paradigms Electron. Inf. Technol. (PEIT)*, Nov. 2019, pp. 1–5.

[100] B. C. Hydro. (2021). *British Columbia Residential Electricity Rate*. [Online]. Available: https://app.bchydro.com/accounts-billing/rates-energy-use/electricity-rates/residential-rates

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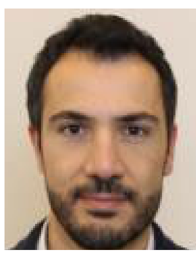

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