II. Literature Survey

Studies related to the forecasting of air conditioning loads in the literature go back to the mid-1980s. In 1986, Carl and Gray from Pacific Gas and Electric Company investigated residential air conditioning load prediction on hourly basis [3]. Hull and Reddy recommended a procedure to group residential air conditioning load profiles during the hottest days in summer [4]. In 1993, Gustafson et al. presented an engineering model for estimating air conditioning load control effectiveness on three utility systems in the western United States [5]. In the same year, Yu and Wong researched on estimating residential air conditioner loads by using consumer survey information [6]. At the mid-2000s, Chen et al. performed short-term electricity forecasting of air conditioners of hospital by using backpropagation ANN [7]. In 2006, Yao et al. developed an innovative air conditioning load forecasting model based on radial basis function neural network (RBFNN) and combined residual error correction [8]. Mise et al. examined curtailment of air conditioning systems during peak load caused by the congestion of the grid power in Keio University Shonan Fujisawa Campus [9]. Xuemei et al. proposed a novel air conditioning load prediction based on autoregressive integrated moving average (ARIMA) and backpropagation neural network (BPNN) in 2009 [10]. At the beginning of 2010s, Chen et al. presented an algorithm based on differential evolution (DE) and SVM for air conditioning load prediction [11]. In 2012, Liao suggested a novel method combines wavelet neural network (WNN) and improvement differential evolution algorithm (IDEA) for air conditioning load forecasting [12]. McLorn et al. evaluated peak shifting techniques for residential air conditioning demand in Saudi Arabia [13]. Horowitz et al. forecasted residential air conditioning loads by using a doubly censored Tobit model [14]. Liao presented a hybrid differential evolution and WNN with a fuzzy expert system for the problem of air conditioning load forecasting [15]. In 2016, Su et al. researched on non-intrusive load monitoring of air conditioning using low-resolution smart meter data [16]. Hong et al. investigated optimal scheduling of energy consumptions for air conditioners in a smart community with renewables [17]. Ninagawa et al. predicted aggregated power curtailment of smart grid demand response of a large number of building air conditioners [18]. Yang et al. proposed a forecasting method of air conditioning energy consumption based on extreme learning machine (ELM) algorithm in 2017 [19]. Lork et al. presented an adaptive data driven approach for single unit residential air conditioning load forecasting using regression trees [20] and suggested a data driven framework for 15-minute ahead air conditioning load forecasting based on modern machine learning techniques such as SVM, ensemble trees, and ANN [21]. Finally, Mahdavi et al. employed model predictive control of distributed air conditioning loads in order to compensate fluctuations in solar power [22].

III. Material and Methods

A smart plug [23], is capable of measuring electrical parameters such as voltage, current, frequency, cos φ to calculate the consumed power and weather parameters including ambient temperature and indoor relative humidity, is used as a data acquisition terminal for air conditioning load forecasting in the server room of the hospital. Technical specifications of the air conditioner located in the server room are given in Table 1.

TABLE I. Technical Specifications of Air Conditioner [24]

Technical Specifications	Unit	
Operating Voltage	V	230
Frequency	Hz	50
Cooling Capacity	kW	6.8
Heating Capacity	kW	7.4
Power Consumption for both Cooling and Heating	kW	2.4
Running Current for Cooling	A	10.6
Running Current for Heating	A	10.5
Operating Temperature for Cooling	ºC	between 0 and 43
Operating Temperature for Heating	ºC	between -6 to 24
Refrigerant	N/A	R410A

Data set is constituted of values belonging to a period between December 5 and 12, 2017. Sampling period of the data acquisition terminal is 10-minute which is in the scope of very-short term horizon.

Input parameters of the forecasting process not only includes historical electric load of air conditioner, but also contains weather parameters such as outdoor temperature and outdoor relative humidity obtained from an external temperature-humidity transmitter mechanism operating with 4-20 mA analog output.

In order to treat missing values in the transmitter data, the data set is firstly imported into MATLAB, missing and erroneous values are examined, the cells having missing and erroneous values are converted into 'NaN', and then linear interpolation method is applied in the MATLAB environment to fill the estimated values instead of 'NaN' by using built-in 'linear' function.

The graphs illustrating temperature and humidity data with missing values of the transmitter are given in Fig. 2 and Fig. 3 respectively.

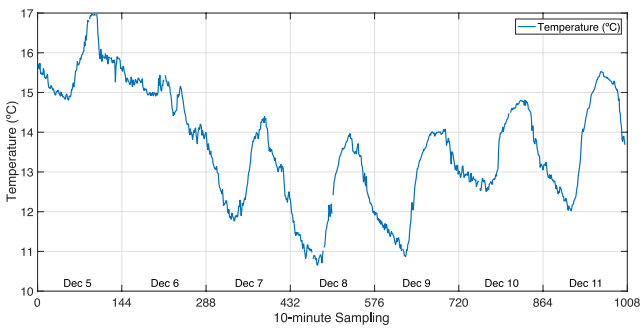

Fig. 2. Outdoor temperature between December 5 and 12, 2017.