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Short-term Forecasting of Electricity Consumption in Buildings for Efficient and Optimal Distributed Energy Management

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Abstract—**The electricity consumption profile of buildings are different from the typical load curves that represent the electricity consumption of large systems at the national or regional level. The electricity demand in buildings is many times lower than the region- or nation-wide demands. It is also much more volatile and stochastic, meaning that the conventional tools are not effective enough for straightforward application at a building demand level. In this paper, an integrated approach consisting of Hilbert-Huang Transform (HHT), Regrouping Particle Swarm Optimization (RegPSO) and Adaptive Neuro-Fuzzy Inference System (ANFIS) is devised for 24h-ahead prediction of electric power consumption in buildings. The forecasts are used as input information for smart decisions of distributed energy management systems that control the optimal bidding and scheduling of energy resources for building energy communities. The effectiveness of the proposed forecasting approach is demonstrated using actual electricity demand data from various buildings in the Otaniemi area of Espoo, Finland. The prediction performance of the proposed approach for various building types (energy customer clusters), has been examined and statistical comparisons are presented. The prediction results are presented for future days with a one-hour time interval. The validation results demonstrate that the approach is able to forecast the buildings' electricity demand with smaller error, outperforming five other approaches, and in reasonably short computation times.**

Keywords—**AI, ANFIS, building, electricity demand, energy management, feature extraction, forecasting, HHT, machine learning, parameter optimization, RegPSO.**

I. INTRODUCTION

In the traditional larger electric power system energy is produced by huge generation plants installed far away from load centers (consumers). This brings transmission power loss and obstructs the opportunity of localizing power production, causing a much reliance on huge power generation systems. Recently, a global conceptual energy shift has been devised to make the existing power generation system more reliable, cost-effective, eco-friendly, modern, and smart, in order to address the challenges the current power grid is facing [1], [2].

Electricity consumption relies on several facts, as the weather parameters (temperature, humidity, wind speed, cloud, rain, etc.), daylight durations, hours in days, days in weeks, months in years, seasons in years, workability (presence of work) condition, etc. This makes electricity demand prediction rather a complex task that looks beyond merely statistical tools. Recently, electric load prediction is being carried out employing many forecasting algorithms, and among them, ANFISs are one of the most prominent choices due to their capability to acquire knowledge from the environment and familiarize themselves [3].

Since the past few decades, it has become a common practice to consider various local energy generation resources (diesel, microturbine, PV, geothermal, etc.) as one of the construction items when new buildings are planned for construction. That means, in the recent decentralized power system paradigm, a building can be considered as a prosumer having its own local energy supply, with the assumption that balancing can possibly be achieved locally.

Moreover, it has been found that buildings consume a large quantity of energy. According to the Center for Clean Air Policy (CCAP), buildings account for almost 40% of the world energy consumption [4] and as Eurostat, buildings account for 38.1% of energy consumption in the EU, much greater than any other sector, including transport (33.3%) and industry/factory (25.9%) [5].

The load curves of buildings and other small-scale energy systems are different from typical electric power consumption curve, making the conventional techniques (developed for national or regional prediction) inappropriate for their straightforward application due to two bold reasons. In buildings, not only the total electricity demand level is many times less than the regional or national demand levels, but also the electricity demand profile manifests a more fluctuation and does not generally follow the same profile.

The integration of Information and Communications Technologies (ICTs) assisted intelligent operation, control, supervision and protection functions into buildings creates smart buildings of desired features. In this scenario, to properly manage the electricity generation of its energy production resources and reduce the building electricity bills, independent electricity demand forecasting is required for each particular building in question. Accurate forecast of electricity demand in buildings significantly helps the building energy suppliers or aggregators to have better decisions in the electricity market participation.

The existing electricity prediction approaches can be categorized based on the models they use as time-series and regression models. The time-series approaches describe future electricity demand based on its previous and present time series features [6]–[10]. The regression (causal) approaches characterize electricity demand based on external features that can possibly affect the electricity consumption [11] – [18].

Machine learning and artificial intelligence (AI) based approaches have been used for electricity demand predictions. For instance, expert systems in [19] and [20], fuzzy logic systems in [21] and neuro-fuzzy systems in [22] and [23]. It is observed that, the machine learning and AI based electricity demand forecasting methods have given better forecasting accuracy than the conventional methods (such as persistence, linear regression, nonlinear regression, ARIMA, etc.).

Artificial neural networks (ANNs), in different forms, among the famous AI methods have been widely utilized for electricity demand prediction. For instance, Multi-layer Perceptron (MLP) ANN in [24], RBF ANN in [25], SOM ANN in [26], and feedforward multi-layer (FFML) ANN in [27].

However, in the recent few years, fuzzy logic systems (FLSs) and ANFISs have become the most prominent techniques for electric load demand forecasting, with better performances than the ANNs do. The study in [3] developed an ANFIS based electric load prediction strategy for small region, high school campus area, with low consumption. Electricity consumption data and other parameters derived from the consumption, such as month and hour, were used as inputs to develop the forecasting strategy. The strategy was verified to be effective for electricity demand forecasting of small regions. Reference [6] provided an intelligent time series technique for electric load prediction of a complex energy system. The time series technique was modeled for medium- and long-term prediction horizons. It used electricity demand information of many previous years to develop the intelligent ANFIS model. The result obtained were estimates of electricity demand forecasts for several years ahead. The work in [9] devised an integrated fuzzy time-series and dynamic model to predict electric load demand a number of months ahead. Time series data of electric load was employed to develop the model. The devised integrated model was applied independently to single home, community, facility, and industrial cases. The outcomes found demonstrated that the devised model presented satisfactory forecasting accuracy over the tested months.

ANFIS and regression techniques were employed for predicting Iran's yearly electricity load in [11]. Socio-economic factors, energy-economic factors and national aggregated electricity consumption data have been utilized to construct the forecast model. The study summarizes that the ANFIS model gives an acceptable accuracy and outperforms the other evaluated conventional forecasting techniques. Reference [17] implemented fuzzy causal model for electric load demand prediction of summer and winter periods. It was implemented for 24h-ahead electricity consumption prediction in a utility company. The considered power system achieved a reliable operation using the developed fuzzy based electric load forecasting. The work in [18] has presented a short-term load forecasting (STLF) technique to use it in power system operational control strategy. It proposed a methodology to increase forecasting accuracy and reduce processing-time by employing FLS with one-hour intervals. The combination of ANFIS and wavelet transform in [14] and the hybridization of FLS with extreme learning machine (ELM) in [19] are also developed for electricity demand forecasting in different scenarios for improved prediction performance.

The literature survey in this study, as reported above, shows that most of the electricity demand forecasting models have been developed to forecast electric load demands at national or regional levels. However, the electricity demand forecasting at small-scale levels, such as microgrid/prosumer, residential entity, commercial area, industrial unit, single building or household still needs improvement and it is one of the hot research issues in the area of smart grids. Thus, this study can make a contribution to the field of electricity demand forecasting in buildings, small-scale level. Moreover, this study considers several relevant predictors to improve the prediction accuracy.

Furthermore, most of the previous ANFIS based load demand forecasting approaches have used a Back Propagation (BP) learning method to obtain the ANFIS membership function (MF) parameters. Although BP training technique needs less computation time, it may be stuck by suboptimal (local) solution and is therefore not capable to reach global (system-level) optimal solution. On the other hand, those previous forecasting researches that have used the combination of PSO and ANFIS employed the conventional PSO algorithm for searching the optimal values of the ANFIS MF parameters. Though the PSO has resulted in improved performance over the BP for the ANFIS training, it has shown premature convergence (stagnation or false convergence at local solutions) which does not guarantee reliable forecasting accuracy throughout the entire forecasting horizon and scenario.

To compensate the drawbacks of the BP and standard PSO algorithms for improved-performance ANFIS training, this study uses the RegPSO algorithm, which is capable to obtain global optimal solutions for almost all optimization problems [28], [29]. Hence, the optimization process of the RegPSO algorithm can obtain optimal parameter sets of the ANFIS MFs and thus accurate electricity demand forecasts.

Besides, unlike the previous researches on ANFIS based load demand forecasting, this study employs the HHT technique as a feature extraction technique to pick the most relevant features of the predictor variables for the RegPSO-ANFIS model.

In this paper, the Artificial Intelligence (AI) based integrated HHT-RegPSO-ANFIS approach is chosen to develop building electricity demand forecast model mainly because of its improved training mechanism, higher accuracy and smaller learning time.

The devised HHT-RegPSO-ANFIS based integrated electricity demand forecasting approach is compared with Persistence, ANN (back-propagation feedforward ANN), GA-ANN (GA combined with ANN), ANFIS (back-propagation ANFIS), and GA-ANFIS (GA combined with ANFIS), to demonstrate its robustness regarding prediction accuracy and other performance indexes.

The main targets and findings of this paper are outlined below.

(1) Present a new and effective AI based integrated approach for short-term (24h-ahead) electricity demand forecasting in buildings considering several predictor variables;
(2) Undertake performance assessment of the presented electricity demand forecasting approach over different building types (customer classes) such as residential, educational, offices, mixed-use type, and others.
(3) Improve forecasting accuracy, considering accuracy levels obtained by other five approaches.

The paper organization is given below. Section II presents the devised prediction approach and model framework. Section III describes the data sources and preparation techniques.
The HHT-RegPSO-ANFIS integrated framework and the theoretical concepts of HHT, RegPSO and ANFIS are given in Section IV. The various performance criteria used to estimate the prediction accuracy are given in Section V. The experimental findings and statistical analysis of the devised electricity demand forecasting strategy are given in Sections VI. The study is finally summarized in Section VII.

II. PROPOSED ELECTRICITY DEMAND FORECASTING APPROACH

This paper devises a novel building electricity demand prediction model using the hybridization of HHT, RegPSO and ANFIS. The HHT is utilized to extract relevant features of the electric load data series to obtain a cluster of enhanced-feature subseries for improved prediction accuracy. The past values of predictor variables and HHT extracted subseries of the electricity demand data are employed to train the ANFIS. The future series of predictor values are then employed to predict the next electricity demand subseries based on the trained ANFIS model. The RegPSO searches for the best parameter sets of the ANFIS MFs to attain improved prediction accuracy. Finally, the predicted or next (ahead) electricity demand time series is reassembled by employing an inverse HHT on the predicted subseries.

A two-year (2015 - 2016) window length information of building electricity demand history, meteorological variables, seasonal or calendar variations, building occupancy, and electricity price has been used to construct the proposed electricity demand forecasting model. The model is validated with actual electricity demand information of various buildings in the Otaniemi area of Espoo, Finland. The effectiveness of the devised electricity demand forecast model is tested with a one year (2017) testing window information. The forecast test results are presented for future days with a one-hour time interval. The forecast model of the devised integrated strategy has the ability to relearn any time when there is new learning dataset. The devised forecasting model is illustrated in Figure 1.

III. DATA DESCRIPTION AND PREPARATION

The predictor dataset employed to implement the proposed building electricity demand forecasting model, in this paper, are past values of electricity demand, meteorological variables (ambient air temperature, dew-point temperature and relative humidity), daily variations (hours in days), weekly variations (days in weeks), monthly variations (months in years), seasonal variations (seasons in years), building occupancy, electricity price, previous 24h average electricity demand, 24h lagged electricity demand, and 168h lagged electricity demand. Due to limitation of direct measurement of building occupancy data, we use indirect representation of the occupancy with two additional variables –

holiday/weekend indicator and period of the day (working mode, idle mode and cool-down period) variables. Electricity price is also one of the predictor variable for constructing the forecasting model in this paper. For customers with time-of-use electricity pricing agreements, it is obvious that their electricity consumption is lower during the low price periods and higher during the peak price periods. Hence, electricity price is considered as one of the predictor variables as it may affect the load prediction process.

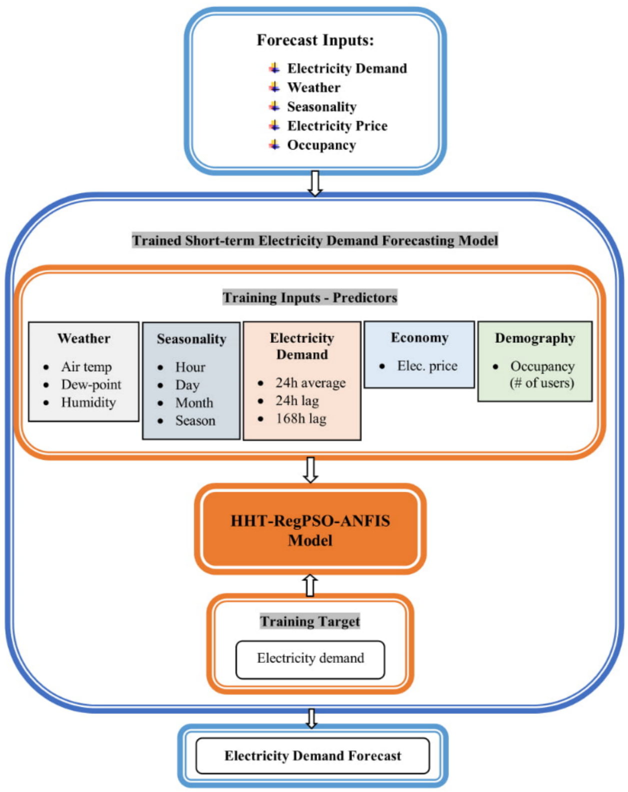

Figure 1. Proposed building electricity demand forecasting model.

The actual electricity demand data of various buildings in the Otaniemi area of Espoo, Finland has been used to develop the model. The electricity price data is obtained from the Nord pool [30]. The Finnish Meteorological Institute (FMI) [31] provides the weather observations. The calendar information is available in [32].

Some of the predictor variables should be processed to more simplified and matching representations ahead of the HHT decomposition and ANFIS learning. All the data values are converted into hourly (mean) values. The predictors and target data are finally arranged in one-hour resolution to fit the resolution differences of the different data sources. The weather forecast data record time zone (UTC) is converted to the local time to synchronize it with the time zone of the city where the buildings are located.

IV. Proposed HHT-RegPSO-ANFIS Integrated Model

A. Hilbert-Huang Transform (HHT)

The amplitudes of the electric load curves obtained from the buildings vary in each time instant. The HHT tool is employed to decompose the electricity demand data series into a cluster of data subseries. The resultant decomposed (subseries) data provides improved performance features than the original data. Thus, the decomposed data can be utilized to forecast the electricity demand with less prediction error.

By employing the HHT, the analogical time representation of the frequency presence in the initial electricity demand data is carried out to obtain the real-time frequency of data.

The real-time frequency is obtained employing the Hilbert transform (HT) [33]. HT for a monocomponent signal g(t) is described below.

$$h(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{g(\tau)}{t-\tau} d\tau \tag{1}$$

In (1), $g(t)$ and $h(t)$ designate the conjugate pair that describes time-series $f(t)$ given below.

$$f(t) = g(t) + jh(t) \tag{2}$$

The polar coordinate representation of (2) is expressed beneath.

$$f(t) = c(t)e^{j\emptyset(t)} \tag{3}$$

Here,

$$c(t) = \sqrt{g(t)^2 + h(t)^2} \tag{4}$$

$$\emptyset(t) = \arctan\left(\frac{h(t)}{g(t)}\right)$$

$c(t)$ and $\varphi(t)$ designate the real-time amplitude and phase of $f(t)$. $c(t)$ and $\varphi(t)$ represent the suboptimal (neighborhood) representation of an amplitude- and phase-angle-oscillating trigonometrical fit to $g(t)$. The real-time frequency $\omega(t)$ is obtained from the real-time phase expressed below:

$$\omega(t) = \frac{d\emptyset(t)}{dt} = \frac{\dot{h}(t)g(t) - h(t)\dot{g}(t)}{g^2(t) + h^2(t)} \tag{5}$$

$\omega(t)$ is essentially feasible merely if $\varphi(t)$ is a monocomponent signal. Since $\varphi(t)$ is derived from $g(t)$, $g(t)$ must be monocomponent signal as well. However, almost all practical signals, and particularly those found from weather forecasts and building electricity demand, are not mono-component. The work by Huang *et al*. [33] has described the Empirical Mode Decomposition (EMD) technique for decomposing multi-component signals into mono-component subseries signals. By using the HHT, the target, electricity demand, data is expressed by an aggregation of Intrinsic Mode Functions (IMFs). Each generated IMF is monocomponent quantity that must satisfy the requirements below:

(1) The quantity of zero touches and the quantity of extreme points should be same or vary, at extreme, by one
(2) The mean of the wraps found by local maximum points and minimum points must be zero at every instant.

The IMFs are derived from the initial data by employing a sifting technique. In the sifting technique, bottom and top wraps are formed by introducing an interpolating curve via the neighborhood minimum and maximum points. The wraps average q_1 is deducted from $g(t)$ to find the initial element d_1. To create the IMFs, the sifting process is successively carried out j times to d_i, till the IMFs are found:

$$d_{1k} = d_{1_{(j-1)}} - q_{1_j} \tag{6}$$

The sifting procedure ends if the standard-deviation of two serial outcomes is less than a specified threshold value. The initial IMF contains information about the peak frequency, is expressed as:

$$a_1 = d_{1_j} \tag{7}$$

Then, a_1 is deducted from the first signal, and the residue p_1, that holds information about the lesser frequency elements, is expressed as:

$$p_1 = g(t) - a_1 \tag{8}$$

In the process of the HHT EMD decomposition, p_1 is considered like the beginning signal. The procedure iterates, a_2 is calculated, etc., till either of the requirements below are satisfied:

(1) p_n or a_n has lower energy
(2) p_n is monotonic.

Utilizing the aforementioned process, the decomposition of the initial multi-component signal $g(t)$ is expressed as follows.

$$g(t) = \sum_{i=1}^{n} a_i + p_n \tag{9}$$

Each IMF (a_i) is constrained to HT by (5) to determine the real-time frequencies. Since $g(t)$ is a multicomponent signal, it contains greater than one frequencies. Therefore, the HT based decomposition of $g(t)$ is given by following expression [33]:

$$g(t) = Re\{\sum_{i=1}^{n} c_i(t) exp(j \int \omega_i(t)dt)\} \tag{10}$$

Here, $c_i(t)$ and $\omega_i(t)$ are real-time quantities whose values change instantaneously. The Hilbert transform assisted Huang EMD preprocessor, expressed in (10), is also called the Hilbert-Huang transform (HHT).

HHT provides a comprehensive, adaptively flexible and almost orthogonal designation of the initial function compared to Fourier and Wavelet transforms [34], [35]. Therefore, in this paper, the HHT is selected for the devised day-ahead electricity demand forecasting model development because of its better performance for extracting important detail behaviors of the target variable. That is, in this study, the amplitudes of the IMFs resulted from the HHT decomposition (of the electricity demand) are used as target variable for the RegPSO-ANFIS based electricity demand forecasting model.

B. Regrouping Particle Swarm Optimization (RegPSO)

PSO is a non-deterministic, evolutionary and population-oriented global optimization technique motivated by social activities of animals like swarm of insects, flock of birds and school of fishes.

It does not require genetic manipulators like crossover or mutation as the other evolutionary type optimization algorithms, such as the GA optimization technique. It has very few describing parameters, only position and velocity, and hence it is easy for implementations.

PSO has been widely applied in power system studies for different application scenarios. Its general working principle and power system related applications are presented in [36].

The search space subset for the PSO positions (decision variables) can be defined as follows.

$$\Omega = \lfloor p_1^L, p_1^U \rfloor \times \lfloor p_2^L, p_2^U \rfloor \times ... \times \lfloor p_n^L, p_n^U \rfloor \subset R^n \tag{11}$$

where, the p is a vector of decision variables and $x \in R^n$, p_j^L and p_j^U are the smaller and higher boundaries of the search domain, respectively; j is the search space dimension index.

The kth particle position at the ith iteration is described as:

$$p_k(i) = p_k(i-1) + v_k(i);\ k = 1, 2, ..., M \tag{12}$$

where, M is swarm-size; $v_k(i)$ is kth particle velocity at the ith step.

The velocity exhibits the degree of change of the particle position and it is described below.

$$v_k(i) = \gamma(i)v_k(i-1) + l_1 rad_1\left(P_{best,k} - p_k(i-1)\right) + l_2 rad_2(G_{best} - p_k(i-1)) \tag{13}$$

where, $\gamma(i)$ is an iteration-dependent inertia coefficient. In this paper, value of $\gamma(i)$ is considered to reduce linearly following the iteration step to decay out the particle velocity in the subsequent iterations. This dynamic inertia coefficient for the particles' velocities enables the swarm of particles to converge more accurately, and expressed as follows.

$$\gamma(i) = \gamma_{max} - \left(\frac{\gamma_{max} - \gamma_{min}}{i_{max}}\right) i \tag{14}$$

where, γ_{max} is the initial inertia coefficient, γ_{min} is the final inertia coefficient, i_{max} is the highest number of iteration, l_1 is the cognitive learning speed, l_2 is the social learning speed, rad_1 and rad_2 are arbitrary numbers in (0,1) range, $P_{best,k}$ (pBest) is the optimal solution managed by particle k, and G_{best} (gBest) is the global optimum.

However, the standard PSO algorithm described above by (11) to (14) faces stagnation when the particles early converges to some particular area in the search domain [28]. Hence, there should an alternative mechanism that overcomes this early convergence problem of the standard PSO in order to utilize the computational simplicity, easy implementation and fast convergent advantages of the algorithm. In this study, the RegPSO algorithm is devised to avoid this stagnation (premature convergence) problem. RegPSO is an advanced version of the standard PSO algorithm equipped with anti-stagnation (anti-false-convergent) mechanism. It immediately reorganizes the swarm when stagnation is recognized or other stopping criteria (iteration number or function value) is satisfied [29]. This frees the particles in the swarm from possible stagnation problems, thus creating further explorations heading to the real global solution.

Different experimental tests have been conducted to measure the effectiveness of the RegPSO using common benchmark problems [28]. The RegPSO effectively estimates the global solution of the benchmark problems.

The swarm radius at iteration i is given by:

$$\delta(i) = Max\ of\ \|p_k(i) - G_{best}\|;\ k \epsilon \{1, 2, ..., N\} \tag{15}$$

As given by (15), the swarm radial range $\delta(i)$ is computed as the extreme Euclidean norm ($\|.\|$) between the particles' positions and global best solution.

The condition for the premature-convergence is given as follows.

$$\delta_{norm} = \frac{\delta(i)}{diam(\Omega)} < \varepsilon \tag{16}$$

where, δ_{norm} is the normalized swarm radius, $diam(\Omega)=\|range(\Omega)\|$ is the diameter of the search space and ε is the stagnation threshold.

The RegPSO algorithm considers the particles in the swarm are very close to each other (premature convergence or stagnation occurs) and initiates the regrouping of the particles when (16) is satisfied. When the stagnation is detected by the condition specified in (16), regrouping of the particles in the swarm is initialized. The regrouping performs in the search space about the center of the global best position, G_{best}. The regrouping factor defined below is used [28]:

$$\rho < \frac{6}{5\varepsilon} \tag{17}$$

During the detection of the stagnation, the swarm regrouping range from the global best position is evaluated in each dimension as the smallest value of:

(a) The initial search space scope
(b) The multiplication of the regrouping ratio and highest norm from the global optimal position in the direction of dimension j as defined below:

$$range_j(\Omega^r) = min\left(range_j(\Omega^o), \rho \max\left|p_{k,j}^{r-1} - G_{best,j}^{r-1}\right|\right);\ k \epsilon \{1, 2, ..., N\} \tag{18}$$

Then, the swarm is regrouped by reinitializing the particles by the following new position update rule:

$$p_k = G_{best}^{r-1} + \vec{r}'.range(\Omega^r) - \frac{1}{2} range(\Omega^r) \tag{19}$$

where, $range(\Omega^r) = [range_1(\Omega^r), ..., range_n(\Omega^r)]$ which employs the arbitrary vector $\vec{r}' \epsilon (0,1)$ for making the swarm random.

The modified search domain for the RegPSO new positions is given by:

$$\Omega^r = \lfloor p_1^{L,r}, p_1^{U,r} \rfloor \times \lfloor p_2^{L,r}, p_2^{U,r} \rfloor \times ... \times \lfloor p_n^{L,r}, p_n^{U,r} \rfloor \tag{20}$$

Here, the associated lower and upper bounds are given by (21) and (22), respectively, as:

$$p_j^{L,r} = G_{best,j}^{r-1} - \frac{1}{2} range_j(\Omega^r) \tag{21}$$

$$p_j^{L,U} = G_{best,j}^{r-1} + \frac{1}{2} range_j(\Omega^r) \tag{22}$$

The regrouping index, r, is set to zero before the regrouping is triggered and increases by one successively as each regrouping takes place. G_{best}^{r-1} is the vector of true optimal positions at the final routine of the preceding group. $\vec{p}_k^{r-1}$ is the *k*th particle position at the final iteration of the prior grouping.

The initial search space Ω^o is associated with a regrouping catalogue of zero (r = 0). This indicates the regrouping task does not take place. The peak velocity for each regrouping is determined as follows.

$$v_j^{max,r} = \lambda . range_j(\Omega^r) \tag{23}$$

where, λ is the velocity clamping coefficient.

C. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS falls in the group of intelligent multi-layer artificial networks. It is a feedforward artificial network [37]. It is chosen for the electricity demand prediction model in the study mainly because of its improved training mechanism and small learning time. ANFIS has been used to nonlinear approximation and forecasting problems in which previous data or scenario is employed to forecast the future data or scenario. ANFISs integrate the self-taught capability of ANNs and the human linguistic expression to quantitative (or numeric) value conversion capability of fuzzy logic system (FLS) [38]. The ANFIS architectural configuration is depicted in Figure 2.

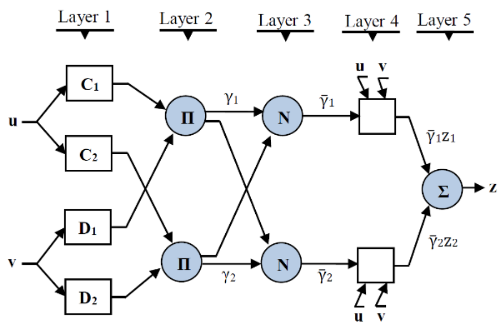

Figure 2. ANFIS architectural configuration.

In this study, the ANFIS model implemented is a Takagi-Sugeno FLS layered on an ANN network with five layers. The layers have plenty of nodes expressed with node functions (NFs). The NFs are presented below. Assume $Y_{j,i}$ designates the yield of node *i* of the *j*th layer.

In layer 1, each node is self-learning and its NF is expressed as:

$$Y_{1,i} = \mu C_i(u);\ i = 1, 2 \text{ or} \tag{24}$$

$$Y_{1,i} = \mu D_{i-2}(v);\ i = 3, 4 \tag{25}$$

Here, u or v is the *i*th node input. C_i (D_{i-2}) is the linguistic tag linked to the particular node. Consequently, $Y_{1,i}$ is the belongingness status of fuzzy-set C (C_1, C_2, D_1, or D_2). The membership status designates the grade by which the particular input u (or v) suits the linguistic label C. There are different types of membership functions (MFs) which have been used to evaluate the degree to which a given input belongs to a particular class or linguistic variable. For example, a general bell MF is expressed as follows.

$$\mu C_i(u) = \frac{1}{1+\left|\frac{u-r_i}{p_i}\right|^{2q_i}} \tag{26}$$

Here, $\{p_i, q_i, r_i\}$ is the ANFIS input layer MF parameter set. When these parameter set values change, the MF alters consequently, thus showing several types of MFs on linguistic label A_i. The other common and appropriate nominee MFs that can be utilized as a node function in layer 1 are the Gaussian MF, z-shaped MF, trapezoidal MF, triangular-shaped MF, s-shaped MF, and sigmoid MF [39]. This layer parameters are premise parameters.

In layer 2, the nodes π are described by yield denoting the rule firing power and this outcome is the multiplication of the entering raw-signals:

$$Y_{2,i} = \gamma_i = \prod_j \mu_j = \mu C_i(u).\mu D_i(u);\ i = 1, 2 \tag{27}$$

In layer 3, the nodes N evaluate the normalization of firing power of rule *i* by the overall combination of each rule's power:

$$Y_{3,1} = \bar{\gamma}_i = \frac{\gamma_i}{\sum_j \gamma_j} = \frac{\gamma_i}{\gamma_1+\gamma_2};\ i = 1, 2 \tag{28}$$

This layer outcomes are regularized firing powers due to the normalization process.

In layer 4, each node is self-learning and the nodes calculate their associated rule to the entire yield as follows.

$$Y_{4,i} = \bar{\gamma}_i z_i = \bar{\gamma}_i(a_i u + b_i u + c_i) \tag{29}$$

where, $\{a_i, b_i, c_i\}$ is the ANFIS output layer MF parameter set; $\bar{\gamma}_i$ is the result from layer 3. The constant MF and linear MF are the most appropriate and commonly used MFs in the output layer. This layer parameters are resultant parameters.

In layer 5, the ending node Σ computes the end-result by adding all the entering inputs as:

$$Y_{5,i} = \sum_i \bar{\gamma}_i z_i = \frac{\sum_i \gamma_i z_i}{\sum_i \gamma_i} \tag{30}$$

Therefore, a self-learning (adapting) AI model corresponds to *Sugeno* FLS in the context of functional performance.

In this study, the ANFIS network utilizes the RegPSO algorithm to optimally search the ANFIS MF parameters. These MF parameters are augmented to parameters of the RegPSO. The MSE is employed as fitness function in the RegPSO. The target of the devised integrated model is to realize a possible smallest value for the objective cost function. This ANFIS MF parameter optimization search procedure run until the electricity demand prediction error arrives at a present minimum value or zero. The RegPSO algorithm has the benefit of computational easiness for a pre-specified dimension of ANFIS network topology. That is why it is chosen for this paper as a best tool for the ANFIS based electricity demand forecast model parameter optimization.

The ANFIS model in this study is implemented using Matlab Software. Various set of parameters such as MF types, number of MFs, learning algorithms, etc. have been investigated experimentally to obtain the ANFIS optimal configuration having the lowest error.

D. Operation of the Proposed HHT-RegPSO-ANFIS Model

Here, the detail operation and calibration of the integrated approach employed to implement the devised electric load prediction approach are described systematically, as illustrated in Figure 3.

As it is clearly depicted in Figure 3, the HHT tools are used in the first and final steps of the forecasting process, for the electricity demand variable decomposition and reconstruction purposes, respectively.

The target variable, electricity demand, series is first decomposed into several subseries (IMFs) by the HHT. The decomposed historical subseries are then used to train the ANFIS Network using the RegPSO optimization method. The trained ANFIS model maps the nonlinear relationship between the predictor variables and electricity demand subseries. Then, the future (next day) predictors are fed to the developed (trained) RegPSO-ANFIS network to predict the future electricity demand subseries of the buildings. Lastly, the future electricity demand subseries are reassembled to give the desired electricity demand forecast.

V. Forecasting Accuracy Assessment

To assess the accuracy of the devised integrated HHT-RegPSO-ANFIS electricity demand forecasting strategy, the MAPE (mean absolute percent error), RMSE (root mean squared error) and NMAE (normalized mean absolute error) and FS (forecast skill) criteria are utilized.

The accuracy assessment criteria are calculated in terms of the actual electricity demand, and given hereafter.

The MAPE is given as:

$$MAPE = \frac{100}{N}\sum_{h=1}^{N}\left|\frac{P_h^a - P_h^f}{P_h^a}\right| \tag{31}$$

where, P_h^a and P_h^f are the real and prediction values of the electricity demand at hour h, respectively, and *N* is the forecasting horizon and its value is 24 for day-ahead forecast.

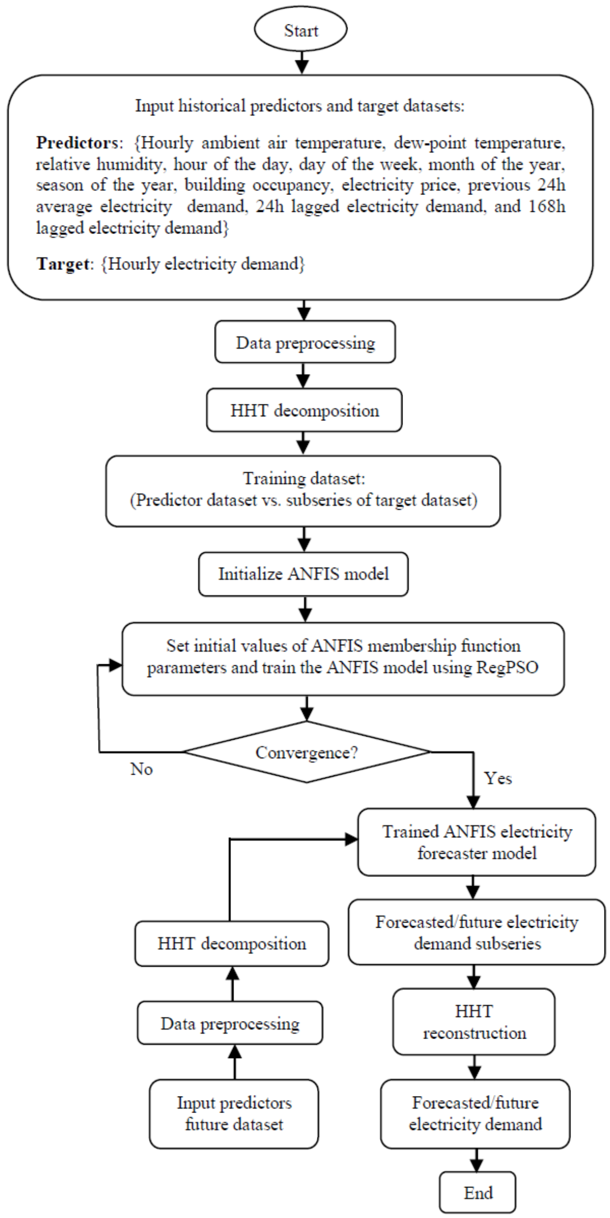

Figure 3. Proposed electricity demand forecasting algorithm

The RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{h=1}^{N}\left(P_h^a - P_h^f\right)^2} \tag{32}$$

The NMAE is expressed as:

$$NMAE = \frac{1}{N}\sum_{h=1}^{N}\frac{\left|P_h^a - P_h^f\right|}{P_{peak}} \tag{33}$$

where, P_{peak} is the peak aggregate electricity demand of the building.

The FS criterion estimates the merit of prediction approaches by referring the prediction accuracy obtained by evaluated approaches to persistence predictions, which assume time lag electricity demand correlations (similarities). For 24h-ahead predictions, the persistence forecast is given by:

$$P_h^f(t) = P_h^a(t-24) \tag{34}$$

The FS criterion is calculated based on the relation of the RMSEs of forecasting models with reference to persistence method [35], [40], it is given as follows.

$$FS = 1 - \frac{RMSE_{Model}}{RMSE_{Persistence}} \tag{35}$$

A forecast-skill value of 1 indicates a perfect model, and 0 indicates the prediction approach's RMSE is the same as the reference's RMSE (no improvement from the persistence). A negative FS tells lower effectiveness of the prediction approach than the reference. Based on the above expression of the FS criterion, the persistence approach should have FS value of zero.

VI. Experimental Results and Discussions

In this study, the integrated HHT-RegPSO-ANFIS model is developed for short-term (24h-ahead) building electricity demand forecasting. Electricity demand data of four building types (pilot customer classes) in the Otaniemi area of Espoo, Finland have been used to construct and validate the forecasting model. The buildings are Building A (residential building type), Building B (educational building type, contains classrooms and laboratories), Building C (office building type), and Building D (mixed use building, contains computer laboratories and health care center). The buildings have a peak (in the three years period: 2015 - 2017) aggregate electricity demand of 236 kW, 626 kW, 29 kW, and 86 kW, respectively.

The prediction performance of the devised forecast model is verified with a one-year (2017) window length testing data. However, to illustrate the testing results here, the model testing result is given for randomly chosen four weekdays and four weekends/holidays representing the weekdays and weekends of the four seasons of the year: summer weekday (Wednesday - July 26, 2017), summer weekend (Sunday - July 16, 2017), fall weekday (Thursday - Oct 12, 2017), fall weekend (Saturday - Oct 28, 2017), winter weekday (Monday - January 9, 2017), winter holiday (Sunday - January 1, 2017), spring weekday (Tuesday – April 18, 2017), and spring weekend (Saturday – April 8, 2017). Hence, particular days with better electricity demand profiles are not chosen deliberately. This demonstrates an irregular forecast accuracy distribution in the testing year that reveals the actual electricity consumption in the buildings.

The forecast results are presented for the random testing days with one-hour time resolution. The electricity demand forecasts by the proposed integrated HHT-RegPSO-ANFIS method are depicted in Figures 4 to 5 for weekdays and weekends/holidays, respectively.

The plots for the forecast results are presented for some of the pilot buildings, due to limitation of space.

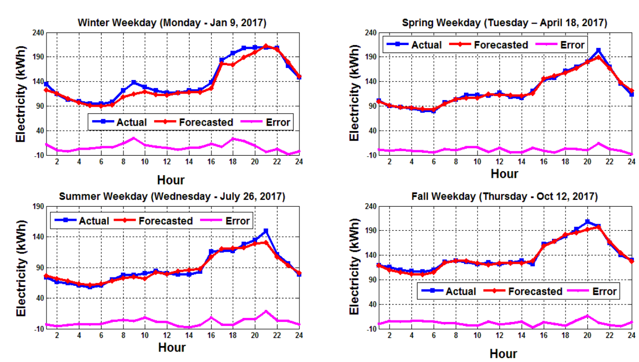

Figure 4. Real vs. forecasted electricity demand in weekdays for Building A – residential building

As it can be observed in Figures 4 to 5, the forecasts by the devised integrated HHT-RegPSO-ANFIS approach follow the actual electricity demand trends with smaller gaps (errors).

Table I provides the values of the criteria employed to estimate the error of the proposed integrated HHT-RegPSO-ANFIS approach for 24h-ahead forecasting of building electricity demand.

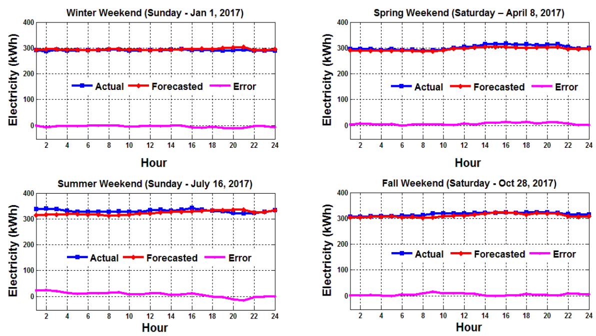

Figure 5. Real vs. forecasted electricity demand in weekends for Building B – educational building

TABLE I
ACCURACY OF THE PROPOSED MODEL FOR BUILDING C – OFFICE BUILDING

Day Type		MAPE (%)	RMSE (kW)	NMAE (%)	Forecast Skill (%)
Winter	Weekday	5.07	0.82	3.05	76.19
	Holiday	6.65	0.69	2.65	71.28
Spring	Weekday	9.21	1.61	6.28	63.01
	Weekend	12.75	1.42	6.09	84.34
Summer	Weekday	6.45	0.85	3.17	32.23
	Weekend	7.81	0.78	3.24	11.42
Fall	Weekday	7.10	0.87	3.61	46.66
	Weekend	9.49	0.98	3.63	73.03
Average	Weekday	6.96	1.04	4.03	54.52
	Weekend	9.176	0.97	3.91	60.01
Total Average		**8.06**	**1.01**	**3.97**	**57.26**

The values, in Table I, are shown for one of the pilot buildings, due to limitation of space. As clearly presented in Table I, the proposed approach has effectively achieved very acceptable (accurate) values in all the evaluated accuracy criteria. As we compare the performance of the devised approach between the weekdays and weekends, it is seen that the prediction accuracy is lower during the weekdays except for the residential building type. Furthermore, regarding the building types, the proposed model has resulted in very accurate and acceptable forecasting accuracy for all building types. Specifically, the model has achieved an excellent performance (MAPE of 1.91%) for the educational building type and relatively lowest accuracy (MAPE of 10.23%) for the mixed-use building type.

Besides, as we compare the performance of the devised integrated approach among the seasons, it is observed that the forecast errors are higher during winter and summer seasons for some of the buildings. This is because there are higher consumptions of electricity and much uncertainty in winter and summer seasons due to environmental (weather) impacts.

Table II presents an effectiveness comparison between the devised integrated HHT-RegPSO-ANFIS based building electricity demand forecasting strategy and other five strategies (Persistence, ANN, GA-ANN, ANFIS, and GA-ANFIS), based on the MAPE criteria. The comparison is shown for one of the pilot buildings, due to limitation of space.

TABLE II
COMPARATIVE MAPE (%) FOR BUILDING D – MIXED-USE BUILDING

Day Type		Persistence	ANN	GA-ANN	ANFIS	GA-ANFIS	HHT-RegPSO-ANFIS
Winter	Wd[1]	27.63	6.67	5.91	5.51	5.44	5.34
	Hd[2]	8.97	7.46	6.23	6.12	6.04	5.89
Spring	Wd	18.60	14.51	12.92	12.04	11.75	11.46
	We[3]	44.41	20.87	18.72	18.30	17.88	17.46
Summer	Wd	36.11	25.80	22.70	21.16	20.64	20.12
	We	15.70	14.27	13.00	12.71	12.42	12.00
Fall	Wd	8.30	8.09	7.17	6.68	6.60	6.47
	We	23.52	3.74	3.31	3.24	3.20	3.05
Average	Wd	22.66	13.77	12.17	11.35	11.11	10.85
	We	23.15	11.58	10.31	10.09	9.89	9.60
Total Average		**22.90**	**12.68**	**11.24**	**10.72**	**10.50**	**10.23**

[1]Wd = Weekday, [2]Hd = Holiday, [3]We = Weekend

The devised integrated strategy provides the lowest forecast error; the total mean MAPE obtained, respectively for the residential type, educational type, office type and mixed-use type buildings, is 4.16%, 1.91%, 8.06%, and 10.23%. The devised strategy's total mean MAPE increment compared to the other five strategies is 42.38%, 19.38%, 8.37%, 4.59% and 3.03%, respectively, for the residential building type, 81.76%, 19.07%, 9.05%, 4.5% and 2.55%, respectively, for the educational building type, 62.75%, 19.07%, 8.62%, 4.61% and 2.89%, respectively, for the office building type, and 55.33%, 19.32%, 8.98%, 4.57% and 2.57%, respectively, for the mixed-use building type. The same training dataset is used for each of the presented approaches and each approach is implemented with its optimal parameters and setups.

For further extensive comparison of the various forecasting models evaluated in this study, demonstrative experimental results for the complete one-year (2017) testing data are provided next, in Table III.

TABLE III
COMPARATIVE MAPE (%) FOR ONE-YEAR (2017) TEST DATA FOR BUILDING B – EDUCATIONAL BUILDING

Month	Persistence	ANN	GA-ANN	ANFIS	GA-ANFIS	HHT-RegPSO-ANFIS
January	13.76	1.53	1.35	1.26	1.24	1.22
February	14.59	1.62	1.44	1.34	1.32	1.29
March	7.71	1.68	1.49	1.39	1.35	1.32
April	9.46	2.06	1.83	1.71	1.66	1.62
May	10.71	2.33	2.07	1.93	1.88	1.83
June	2.14	2.13	1.87	1.74	1.70	1.65
July	2.30	2.28	2.01	1.87	1.82	1.77
August	1.64	1.62	1.43	1.33	1.29	1.26
September	2.21	1.88	1.67	1.56	1.53	1.50
October	2.25	1.92	1.71	1.59	1.56	1.53
November	2.67	2.28	2.02	1.88	1.86	1.82
December	23.56	2.62	2.32	2.16	2.13	2.09
Average	**7.75**	**2.00**	**1.77**	**1.65**	**1.61**	**1.58**

As verified by the demonstrative experimental results in Table III, the proposed forecasting model annual MAPEs for all the buildings have almost similar values as that of the randomly chosen testing days. This verifies the consistency of the proposed model performance throughout the year. In addition, the devised integrated HHT-RegPSO-ANFIS model still outperforms all the other evaluated models.

VII. CONCLUSIONS

The devised integrated electricity demand strategy is based on the hybridization of the HHT, RegPSO and ANFIS. A two-year (2015 - 2016) historical data of predictors is utilized to develop the forecast model of the devised strategy. The prediction accuracy of the devised strategy is tested with a one-year (2017) window length testing data. The modeling approach has the ability to learn any time when there is a new training dataset. The application of the devised strategy for 24h-ahead building electricity demand forecasting is new and effectively successful. The total mean values of MAPE, NMAE and FS, obtained for the whole testing year, are 4.17%, 2.10% and 39.92%, respectively, for the residential type building, 1.58%, 1.05% and 62.44%, respectively, for the educational type building, 7.12%, 2.64% and 59.03%, respectively, for the office type building, and 9.25%, 4.17% and 54.46%, respectively, for the mixed-use type building. The devised model outperforms other five evaluated electricity demand forecasting models, regarding forecasting accuracy measures. The model has given very accurate forecast results for all the building types. The mean execution time for 24h-ahead forecast (excluding training time) is lower than 10 sec using MATLAB simulation environment on a research workstation with Intel Core i7-6820HQ Processor, 2.70 GHz CPU, 16 GB RAM. Therefore, the presented numerical results and performance comparisons with other approaches verify the capability and suitability of the devised integrated approach for a short-term electricity demand prediction in building energy systems.

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