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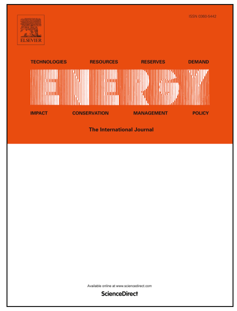

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Validation of a Community District Energy System Model Using Field Measured Data

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ABSTRACT

Load prediction is the first step in designing an efficient community district heating system (CDHS). Even though, several methods have been developed to predict the heating demand profile of buildings, there is a lack of method that can predict this profile for a large-scale community with a numerous user types in a timely manner and with an appropriate level of precision.

It, first briefly describes the 4-step procedure developed earlier, utilizing a Multiple Non-Linear Regression (MNLR) method, for predicting the heating demand profile of district, followed by description of the community structure, and its district system. It also reports the field measurement procedure for collecting the data required and the preliminary analysis data. Results obtained from a continuous monitoring of the CDHS over a two-year period is employed to validate the accuracy of the developed model in the predicting the CDHS's heating load profile. Finally, using the 4-step procedure, the district's energy demand profile is predicted, and compared with both the measured data and the initial prediction. The outcome shows a less than 11.2% in the mean square root error (MSRE) of the predicted and measured load profiles.

Keywords: Load Prediction, District heating System, Validation, Clustering

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1. Introduction

Providing secure and clean source of energy to respond the households' demand is one of the upmost fundamental challenges faced by the energy planners. In effect, households represent a significant share of the total energy demand; they are responsible for 40% and 26% of the total energy consumption in North America and Europe, respectively [1]. In the last few decades, using fossil fuels as the world's main energy source has resulted in their depletion and increased the level of CO_2 equivalent emissions. There are targets for reductions in CO_2 emissions worldwide. Specifically, the Energy Technology Perspective 2012 Roadmap (IEA) aims to reduce CO_2 emissions by 50% [2]. Given the expected rise in household energy consumption, the building sector is now required to adapt to the new ambitious demands of developing Net-Zero Energy Buildings/communities (NZEB) by 2050.

Numerous building energy conservation strategies have been tested using energy storage [3-5] and user-demand [6] methods. The Hybrid Community-District Heating System (H-CDHS) is a unique energy management alternative given its storage and renewable systems are integrated in the district's thermal energy system. Since the energy generated by renewable sources is not uniform throughout the day, a thermal energy storage unit allows the system to synchronize with the supply and demand. To implement this system effectively, it is essential to predict the H-CDHS' detailed energy demand profile[7].

Hence, several methods have been developed to model buildings' energy demand profile [8-10]. Given its restricted number of users, a small-scale Hybrid Community District Heating System (H-CDHS) energy demand profile can be predicted using a detailed model of users' consumption created with energy simulation models [8]. Conversely, in large district scale systems, due to the large volume of users, a comprehensive modeling is time-consuming, computationally expensive and sometimes impractical. Some researchers used comprehensive models to predict the heating demand profile of larger scale communities [11, 12]. To overcome this problem, variety of simplified models were developed to predict the heating demand profile or total energy demand of large communities. These simplified models could be divided into four major categories—black box models (e.g. ANN) [13]; gray box models [14, 15]; equivalent RC networks [16-18]; and regression models [19-24]. Regardless of the method chosen, previous demand estimates focused mainly on predicting the peak and total energy demand. Only few studies tried predicting the demand profile [11, 14, 23].

Though these simplified models could reduce the computational time to a fraction of that of comprehensive models, their simplicity would compromise the prediction accuracy due to limitation of the simplified models. Three major drawbacks could be assumed for most of these simplified modes. First, the low prediction accuracy emerging from assumptions made in modeling the individual buildings/units a) presentation of the occupants' behaviour and, b) the interaction of each building with surrounding buildings in an urban setting. One of the most challenging issues of heating demand prediction models is having to correct input parameters. Input parameters that are dependent on occupants' behaviour/activities, including heating set points and schedules; Internal heat gain due to occupants' activity and the building's heating system; natural ventilation flow rate; solar gains from using windows blinds or shades, etc. Second, scaling effects impair accuracy by oversimplifying scaling methods that extrapolate results from building level to the district level. And third, flexible methods that predict community load profile in diverse building types. More details regarding the limitation of previous projects can be found in previous works done by authors [8, 25]. Table 1 summarizes studies related to CDHS' heat demand prediction. A closer analysis of existing models reveals that the current scholarship requires further validation of models that predict heating demands using measured data.

This paper endorses a 4-step procedure developed to predict the energy demand profile for H-CDHS. It, first briefly describes the 4-step procedure [25] developed earlier for predicting the heating demand profile of district, followed by description of the community structure, and its district system. It also reports the field measurement procedure for collecting the data required for validating the model from the West Whitlawburn Housing Co-Operative (WWH) CDHS in Scotland. The measurement technique, and the preliminary analysis data are explained. Finally, using the 4-step procedure, the district's energy demand profile is predicted, and compared with both the measured data and the initial prediction.

Table 1: Load Prediction Summary

2. Methodology

2.1. The four-step demand profile procedure

Talebi et al [25] developed a simplified model to predict the heating demand profile and peak loads in complex district systems Figure 1 shows the procedure used in the development of the simplified models. The procedures are based on the Multiple Linear Regression (MLR) and Multiple Non-Linear Regression (MNLR) methods. In this four-step procedure, the entire district's heating demand profile is predicted by modeling each individual unit in the community using its physical and geometrical characteristics, the regions' meteorological information, and the occupants' general behavior.

1) In the first step, a sample building stock model (BSM) is segmented into different archetypes, and a reference building is defined for each archetype. The initial segmentation is completed by considering the building's construction method, physical and geometrical properties, and construction period [25]. Once the initial archetypes are determined, each archetype is further divided into sub-archetypes based on the occupancy schedule (e.g. residential user with high, medium and low usage, etc.) of the building within that archetype. Different methods are used for segmenting the BSM based on the occupancy schedule. While some researchers only segment the BSM based on major occupancy types (e.g. residential, commercial, or office types), others segment it following the user's energy profile. This study presents a more detailed approach for defining the number of archetypes as well as the reference building for each archetype. A hierarchical clustering method was adopted for this end. In this method, the data set is split into a prefixed number of clusters. The building closest to the centroid of that cluster is defined as a reference building for that cluster. To define the number of clusters required for a given data set, prefixed number of clusters, the optimal number of cluster is defined using the elbow method.

2) The second step involves building the model's input files. These files are constructed based on the physical properties of individual units, regional meteorological data, and occupants' behaviour. Four different input files were constructed for this study.

i) The first input file is the solar dependent variable. This variable is determined using the weather station closest to the district site and defines each unit's envelope assembly solar heat gain. The solar components obtained from the weather file are translated on each envelope assembly using the incident angle, orientation, and albedo of that assembly.

ii) The second input file is the thermal dependent file. The thermal dependent file defined based on the average heat transfer from the unit's exterior facade, considering its average thermal resistance of the exterior façade of the unit and the indoor-outdoor temperature difference.

iii) The third input file is the units' internal gain. Should specific data about units' internal heat generation be unavailable, the general households' average heat generation can be used.

iv) And finally, the fourth input file constructed based on the daily HVAC system on/off cycles.

3) In the third step, a ***reference building*'s** heating demand profile is initially defined using the data obtained from the measured data. An ANN model is then trained and tested using the ***reference building*'s** input file as well as the heating profile of them to obtain the regression coefficients. More detail information regarding the training of the model using the ANN method could be find in [25].

4) Finally, in the fourth step, once the MNLR model is trained separately for each archetype, using the ***reference building***, each individual unit's heating demand profile is predicted by adopting the input file of them [25].

Figure 1: Simplified procedure to predict the heating demand profile

3. **Description of the community district heating system design**

The selected Hybrid Community-District Heating System (H-CDHS) is a mid-size community district heating system in Whitlawburn, Cambuslang, Scotland. The WWH was established in 1989 to provide local community control and promote affordable quality housings for lower income families. The community consists of 640+ dwelling units with four types of buildings. Until 2007, all buildings used the conventional individual dwelling electrical heating systems for the space heating and domestic hot water (DHW) supply. In 2007, the administration board developed their own district heating system to give the community a more affordable energy and improve the quality of indoor environment by increasing energy efficiency and decreasing the energy cost. Thus, after performing a feasibility study, the community management decided to develop their own DHS using a central energy center[1], a network of insulated pipework connecting the boiler house to users, and individual direct heat interface units in each dwelling. Figure 2 shows the location of buildings connected to the H-CDHS with respect to the boiler house:

1- Newly renovated tower of 12 stories (6 towers)
2- Newly built duplex detached houses (50 buildings)
3- 4-story terrace buildings (10 buildings)
4- Community buildings (5 buildings)

Figure 2: Hybrid community-district heating system layout in Whitlawburn, Cambuslang, Scotland

Although most recent district systems prefer using medium to low temperature water to minimize heat loss, an operational temperature of 80°C was chosen in this case to satisfy the minimum temperature required for DHW usage. The proposed H-CDHS can be thus categorized somewhere between the second (high temperature) and third generation (energy storage) of the DHSs according to the district system's generation type (See Figure 3). In the first development phase, six high-rise towers and five terrace buildings were connected to the H-CDHS. To size the

[1] *A boiler house with a biomass boiler as its main heat generator, three backup gas boilers, and a 50 m^3 hot water thermal storage tank to cover potential winter peaks.*

boilers and the thermal storage tank, conservative industry standard sizing methods were used, following the Design Day method [ref old CIBSE Guide], which pre-dates the current guidance [new CIBSE Guide]. The district's energy demand was predicted based on the living space's total square meters and the Scottish building stock's annual energy consumption benchmarks [CIBSE TM46].

Figure 3: District heating systems generations [34]

4. Monitoring the district heating system's performance

Since 2014, the district heating system became operative and provides energy for more than 80% of the dwellings within the community. To better understand the system's heat flow, a monitoring Building Management System (BMS) interface was installed, enabling operators to monitor the system's energy generation, loss of the distribution network, and energy consumed by tenants at different measuring points (MP). The main advantage of having a BMS system with multiple MPs is that the data obtained from different MPs can be used to validate and calibrate other MPs and estimate heat loss in the H-CDHS. In other words, using the data collected from the district line and smart meters helps operators measure the energy purchased by tenants, compare it with the energy generated by the boiler house, and eventually determine the distribution networks' heat loss. Thus, the MPs potentially help verify the measurements' accuracy at different stages. There are five MPs types installed in the H-CDHS at different locations and data acquisition frequencies (see Figure 3):

1) Smart meters located in each dwelling monitor energy consumption of both space heating (SH) and domestic hot water (DHW) system every half hour.

2) Energy meters installed on the dual heat exchanger units for SH and DHW inside the dwelling heat interface units (HIUs) (See Figure 5) provide the supply and return hot water pipes' real-time mass flow rate and temperature, energy and volume pulse outputs, and accumulated energy consumed monthly.
3) Building block energy meters similar to those in the HIUs at the entrance of each building block were mainly used to measure the accumulated energy consumed.
4) District line meters measure the hot water flow rate, the H-CDHS main supply line's supply, and the boiler house's temperature every five minutes.
5) The boilers sensors measure the accumulated amount of fuel consumed and the energy generated by each boiler every fifteen minutes.

Figure 4: (A) Smart meter; (B) energy meter; (C) district and block meter; (D) boiler sensors

A dual pipe network transfers the heated water from the boiler house to the building units, where a dual heat exchanger ("sub-system") was installed to provide energy for space heating and domestic hot water purposes.

As previously mentioned, a wide range of users of different socio-economic levels and behavior demands are connected to the system. Since a large number of users are lower income families, their energy consumption, and consequently their annual energy demand, are highly dependent on their economical state and the financial support received. Thus, the management office developed a prepaid energy credit system allowing each tenant to buy a credit in advance. The prepaid system connects to a smart meter in each unit. Smart-meters function both as an MP and a user interface that records the costs associated with the energy consumed every half hour, which tenants could use to monitor their energy usage over time.

Figure 5: The dual heat exchanger sub-system

4.1. Limitations in demand profile prediction

After surveying the site and reviewing the plant sizing and load prediction procedures in the design stage, it was concluded that several initial simplifications were made to predict the district system's heating load. They are:

1) All users were treated identically, irrespective of their behaviour, socio-economical background, etc., leading to a potentially significant error in load prediction. For example, while some senior tenants heat their units at a higher temperature throughout the day, younger tenants try lowering their heating bill as much as possible by turning off the system at night, and by using it for a short time in the evening. Those for whom social welfare is the only income could potentially tolerate lower interior temperatures and use less hot water than more affluent tenants. These factors were not considered in detail in the early design stage.

2) All units were modeled following the same benchmark assumptions, while units' characteristics (e.g. layout, orientation, insulation level, and window-to-wall ratio) were ignored. For example, on top of developing the district heating system in 2007, the exterior facade of all high-rise towers was renovated by adding a new layer over it. Also, balconies were converted to solaria, primarily on the south and west sides, which could potentially compensate a large

amount of heat requirements during the day due to solar gains. This highlights the potential error in using standard benchmarks, which are commonly based only on floor area and building age.

3) System heat loss was estimated based on the operating temperature of the distribution network supply (85°C) and return (70°C), and the constant heat loss per degree temperature throughout the building envelope. This assumption could hold for newly renovated buildings, but not for partially renovated terrace buildings (the community's oldest buildings). In this case, the oversimplified assumption underestimates heat loss and thus overestimates the demand profile prediction. However, underestimating the buildings' heat loss could partly compensate for overestimating heating demands. But since the number of units in terrace buildings is less than 20% of the total units connected to the district system, this underestimation is not enough to compensate for an exaggerated heating load prediction for high-rise units.

Simplifications and conservative standard methods can greatly overestimate the overall energy and peak demands; cause oversized, inefficient systems with correspondingly increased capital costs provoked by short cycling and increasing inefficient combustion maintenance requirements; and potentially shorter lifetimes and replacement periods. Therefore, an alternative method that addresses these weaknesses was evaluated.

4.2. Data Validation

To ensure accuracy, all measured data were cross validated at three different levels: unit level, building level and district level. The methodology was applied to Arran tower (Tower #1) and Arian tower (Tower #2).

In the preliminarily validation of the data collected by smart metres in the Arran Tower units over four months of heating (November 2016 to February 2017), tenant occupancy was *verified and any changes in unit occupancy eliminated from results to avoid errors in the unit energy demand profile. After eliminating units with different tenants[2], the monthly energy demand of remaining units was calculated using the data collected from smart meters. The monthly energy demand in units with similar tenants is expected to correlate with the monthly outdoor temperature. Therefore, a unit's monthly usage in months with similar average outdoor temperatures should remain almost constant.*

To ensure building data accuracy, the cumulated monthly usage of all units in each building and the building's linearized heat loss were calculated and compared with the building meter. A similar procedure was chosen at the network level. The boiler house's total output was compared with the total accumulated energy demand of all buildings and network losses added.

5. Results and Conclusion

5.1. Primary analysis of the H-CDHS energy performance

In the first step, the CDHS' two-year long monitored data was analyzed. Results showed that CDHS' existing condition operates less efficiently with a higher heat loss than the expected design efficiency. Moreover, the predicted heating demand load for sizing the boiler house was 2-2.5 higher than the district's actual power demand load. This over estimating caused an oversizing of the boiler house. Given this, the boiler never worked at its optimal capacity and most of the time operated at a partial capacity, which decreased the system's efficiency.

Tenants' behaviour is widely variable and possibly affected by individual characteristics, including economic status. The preliminary analysis of the data obtained from smart meters in each unit showed that units with almost identical physical characteristic have significantly

[2] *Between November 2016 and February 2017.*

different monthly energy demands. A field investigation and a recorded data reading revealed that only few units used a thermostat with a given set-point value to control the space heating. The majority did not use the heating system for most of a day. In most units, the heating system was off day and night, or only used briefly during the day. For tenants who turned on the heating more frequently, such unexpected behaviors were oversimplified in the CDHS' design stage, assuming that all tenants use thermostats to control space heating on a regular pattern day and night.

5.2. Clustering units

The first step in predicting the heating load, using the four-step procedure mentioned in the methodology section, is to define the number of clusters required. To do that, all the units were initially divided, based on their built form and construction type, into two archetypes—the newly renovated high-rise, and partially renovated old terrace buildings. The units within each archetype were further segmented based on their occupancy behavior. A sample population dataset was selected to define the optimal number of archetypes associated with the occupants' behavior in each construction type The total energy demand [kWh], the number of inter-unit heat exchanger on/off cycle per month, the peak monthly load [kW], the monthly heating degree day (HDD), and average monthly outdoor temperature were determined as effective parameters for defining the number of archetypes.

For large-scale communities with numerous users like WWH, using all monitored data from every individual unit to determine the parameters required for defining the optimal cluster number is computationally intensive. Instead of calculating the required parameters of all units, the parameters of a smaller sample data that could represent the same distribution as the whole community were considered (Arran tower, 72 units). The results were extrapolated to the entire data-set (Arian tower and the whole district).

Figure 6 shows Arran tower's average monthly energy demand (for all dwelling units) for both DHW and SH, between November 2016 and February 2017. This figure shows the range of energy demand fluctuation when outdoor temperatures and monthly HDD do not vary considerably. Variations between 5.17 [°C] and 5.98 [°C] for outdoor temperature and from 312 to 331 for monthly HDD (Figure 6) are not significant for most units. Results obtained for all individual units in the Arran tower show that the monthly energy demand remains almost constant, with unit-to-unit variation generally being much greater than that of a unit's monthly variation (except units 12, 37 and 39). Hence, most units' demand profile's monthly average is expected to remain almost constant (Figure 7).

Figure 6: Monthly consumption of individual units in ***Tower # 1, Arran Tower***

Figure 7: Outdoor temperature and HDD for the 2016-17 heating season (Nov 2016 - Feb 2017)

Using the five parameters, monthly consumption, number of inter-unit heat exchanger on/off cycle per month, monthly peak demand, monthly HDD and monthly outdoor average temperature, the K-means (number of clusters) varied between 1 and 20 to construct different numbers of clusters. Using an R software for each value of k, the square metric distance (m^2) of residual (R) from a reference point was determined in order to find the optimal number of archetypes (clusters) for simulation. This value was selected when the difference between the residual of two consecutive clusters became negligible. One should choose a number of clusters so that adding another cluster does not significantly increase the dataset presentation. The results are plotted in Figure 8, and it can be concluded that four to seven archetypes can be chosen as the optimal number. Here, k-means 4 was selected as the optimal number for demonstrating the method with adequate accuracy while maintaining computational costs low.

Given the hierarchical clustering approach, all units in the sample dataset (***Tower # 1***) were divided into four different archetypes: Non-Typical High Usage (**NTHU**) cluster 1, Non-Typical Low Usage (**NTLU**) cluster 2, Typical Thermostat Control Usage (**TTCU**) cluster 3, and Non-Typical Medium Usage (**NTMU**) cluster 4 (See Figure 9). The percentage ratio of units within each archetype is shown in Figure 9.

Figure 8: Optimal number of archetypes

Results obtained from the clustering in ***Tower # 1*** show that only 5% of units are of the TTCU archetype. This value was assumed to be 100% in the CDHS' design stage. The percentage of users in other archetypes are 16% (NTLU), 24% (NTMU), and 53% (NTHU).

Figure 9: Clustering results for Tower # 1

Figure 10 shows the typical daily demand profile of the *reference buildings* associated with each defined archetype obtained from the monitored data. It is important to note that in the training stage (step 3), the annual reference building's demand profile was used, while here only a typical daily demand was presented. The heating demand profile for different occupancy archetypes is similar to one reported by tenants in the field investigation. NTLU users' profile is largely dominated by a DHW usage in the morning and evening, and a slight use of space heating in the evening. NTMU users heat their space more frequently during the day, while NTHU and TTCU users generally use their thermostat to control space heating for defined periods. As a result, their heating profile is more continuous. NTHU users turn off their heating at night, while TTCU users keep it on the whole day, with variable night and day set points.

Figure 10: Demand Profile for Reference Buildings of Each Class
NTLU (1), NTMU (2), NTHU (3), TTCU (4)

5.3. Predictive models

After training the model using data from the reference buildings, and defining the input file for the remaining units, the heating demand profile of the district was predicted. The MNLR model was used here to predict WWH district's heating demand profile, trained by adopting the non-linear autoregressive model with an external Input (NARX). To account for the building's thermal mass effect on the unit's energy demand, the model used past target data, a demand profile, and other series of input parameters defined earlier in this paper. To predict the demand profile in future hours, previously predicted values and input files were used at the same time. To determine the number of past hours required in the training stage, the model was trained with different past hours ranging from 2 to 8 hours. The best fit was set as the number of past hours required for representing the thermal mass of the units. For this study, 4 hours was the best fit. Also in this study, the data for real H-CDHS was used to train and validate the MLNR model using the above-mentioned four-step procedure. To verify the models' flexibility to include different users' behavior, WWH's diverse community with a wider range of users' behavior was used.

Due to limitations in acquired data, the adapted methodology (Figure 5 and section 5) and associated Matlab code were slightly modified [25] to further improve the model's accuracy, as explained below:

- In addition to the *reference buildings*' demand profile and three sets of input files (i.e. solar dependent, internal gain dependent, and temperature dependent data files), a time-dependent factor related to the DHW was also considered.
- In the initial model [25], the indoor-outdoor temperature difference was used to generate the temperature dependent data file. In this study, only the outdoor temperature was considered since the units' indoor temperature was not monitored.
- Since the internal heat generation was not monitored in each unit, the electrical energy consumed by the reference building was used to indicate the unit's internal energy generation. The existing internal generation from the British Housing Model (BHM) was thus adopted and scaled down to match the energy consumption.
- The adjusted typical thermostat control profile with a thermostat set-point of 19°C was used for the common area. For the towers, the common area accounts for about 15.8% of the total area of which only 45% is assumed to be conditioned.

Using the latter modifications, the input file for all units was generated. Moreover, the reference buildings and their demand profiles were defined earlier in the clustering step. Having the reference building's input file and demand profile, the MNLR model was trained and the related coefficients were determined. To verify the model's accuracy, its prediction was compared with measured data at three different levels. At the first level, the Arran tower's

(Tower #1) heating demand profile[3] was predicted. At the second level, the model was applied to the Arian Tower (***Tower #2***) and its prediction was compared with the measured data. The entire district' total energy demand was then predicted and compared with the data acquired from the district's total energy demand.

Energy demand prediction for the Arran tower (Tower #1)

In first step, the energy demand profile of the Arran tower's *(Tower #1)* has been predicted. The predicted profile then compared with the one obtained from measured data. Figure 11 shows the energy demand profile for the first ten days of November 2016, where appears a generally good agreement between the model's prediction and the measured data. The MSRE calculated for the data predicted was around 12.6%. A discrepancy between the two curves is expected and can be attributed largely to the inevitable lack of information about occupants' inherently stochastic behaviour.

Figure 11: Model prediction (Orange) vs. measured energy demand (Blue) for Tower #1

Energy demand prediction for the Arian tower (Tower #2)

At the second level of model validation, the model's prediction is validated with the measured data for the Arian tower *(Tower #2)*. No data collected from this tower was previously used to generate the model associated with the units' energy demand profile. The Arian tower holds 72 units and is approximately 300 meters away from the boiler house. Figure 12 compares the model's prediction and the measured data for the first 10 days of the November 2016. A good agreement can be observed. The MSRE calculated for the predicted data is around 11.2% for the

[3] *This tower was used earlier to define the number of archetypes and the profile associated with each archetype.*

whole year and 8.2% for the heating season. The predicted demand's general trend matches the measured demand. Considering the data used to generate the demand profile model was based on that of occupants in a different tower, the result is remarkably good.

Figure 12: Model prediction (Orange) vs. measured energy demand (Blue) for Tower # 2

District energy demand prediction

The WWH district consists of six 12-story towers and five 4-story terrace buildings connected to the boiler house through an underground piping distribution network. To predict the entire WWH district system' total energy demand, predicting the lost and delivered energies is required and calculated in this section. To predict the entire WWH H-CDHS' demand, the demand of each block has to be calculated. The losses associated with the distribution system itself must then be factored in.

The underground piping network has been used in in this project is an insulated dual pipe network transferring hot water at a flow temperature of 85 ℃ and a return temperature of 70 ℃ with a total length of 2.4 km (1.2 km supply and 1.2 km return). Figure 13 shows the underground piping network' operational temperature.

Figure 13: *Underground network's operational temperature*

Instead of changing the room operational temperature, the underground network's operational temperature remains relatively constant during the year to control the amount of heat transfer from the boiler house to the consumers. This causes the system's mass flow rate to continuously vary during a day. Figure 14 shows the fluctuating water flow rate in the first 10 days of November 2016.

Figure 14: Water flow rate vs. outdoor temperature in the distribution network

Having the underground network's total length alongside its operational temperature, the supply and return pipes' water mass flow rate, the outdoor temperature, the thermal properties of the soil and pipe insulations, and the distribution network's total heat loss can be determined. To simplify the prediction process, a linear relation for the temperature difference between the operational temperature and surrounding environment temperatures is pre-assumed. Figure 15 shows the underground distribution network's predicted heat loss for the entire system.

Figure 15: Distribution network's monthly heat loss projection

Since for many units the demand profiles are not available (see section 4), the energy demand predicted for the entire system is compared with the total energy generated by the boiler house. As stated earlier, the boiler house's sensor measures only the accumulated amount of fuel consumed and the energy generated by each boiler every fifteen minutes. Figure 16 and Table 2 show the district's predicted accumulated energy demand against the energy generated by the boiler house.

Figure 16: Accumulated predicted energy delivered vs actual generated energy in the boiler house

Table 2: Accumulated predicted energy delivered vs actual generated energy in the boiler house and error

Results show a higher agreement between the predicted and actual energy demand with a monthly discrepancy between -4% to 6%, except in January 2017, when the error was approximately 30%. This error is due to a relatively high heat loss in the distribution network. In January 2017, given two faulty bypass valves in two different towers, the system's mass flow rate increased. Percent and results in increasing the higher heat loss of the system compared with normal condition. Over a year, the accumulated energy demand predicted (3,288,340 kWh) shows a discrepancy of about 5% compared with the actual energy generated by the boiler house (3,138,431 kWh). The underestimation of the total energy demand of the district is mainly due to the buildings' heat loss, especially the older 4-stories terrace building with higher envelope deterioration. However, in the training process (Step 3), the reference profile obtained from the Arran tower, which is better renovated comparing with the terrace buildings, was used with a relatively lower heat loss. It is important to note that in the training stage, the MNLR model was trained once using the reference building obtained from the Arran tower. These trained models were later used to predict the heating demand profile of remaining units, only by adopting their input file. Moreover, the ratio of the occupants' behavior considered in TTCU in terrace buildings was slightly higher.

6. Conclusion

The existing simplified models used for predicting the CDHSs demand lack the flexibility to predict loads for diverse user types. To predict the heating demand, this study used a mid-size community district energy system with diverse user types was investigated using a newly proposed procedure. The main conclusion of this study can be summarized as follows:

- At an early design stage, the community's heating demand profile was predicted following a simplified model with an average national energy benchmark for Scotland. The only adjustment made to the benchmark was a 20% reduction in the overall energy consumption and peak demand to compensate for the occupants' economic status. The results of this oversimplification was overestimating the peak energy demand by a factor of 2.
- The prediction shows high correlations between the predicted and actual profile even though the heating demand profile consist of both SH and DHW usage. The suggested procedure captured the profile with an acceptable accuracy level—11.2% in the annual RMSE, and 8.2% in the seasonal RMSE.
- Results shows that the prediction accuracy remains close both at the building and community levels due to the models' flexibility in capturing the demand profile of every individual unit. Unlike most existing models, the suggested procedure, which extrapolates the data based on the number of the users or total floor area, this model predicts the community load by envisaging that of every single user.

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Table 1: Load Prediction Summary

Author	Ref	Year	Prediction period	Prediction Type/Resolution	Method
Fonsenca et al.	[26]	2015	Annual	Total Energy Demand	Simplified Modeling/ Adjusted HDD
Powell et al.	[13]	2014	Daily	One day forecasting	NARX**; ANN
Tuominen et al.	[19]	2014	Annual	Total Energy Demand	Linear Development Using REMA
Filogamo et al.	[16]	2014	Annual	Total Energy Demand	Simplified Equivalent RC
Koene et al.	[17]	2014	Annual	Total Energy Demand	Simplified Equivalent RC
Gadd et al.	[27]	2013	Daily	Average Daily and Hourly Variation	Time Series
Caputo et al.	[28]	2013	Annual	Total Energy Demand	Comprehensive Modeling
Nouvel et al.	[29]	2013	Annual	Total Energy Demand	Quasi State Monthly Energy Balance
Galante et al.	[20]	2012	Annual	Total Energy Consumption	Linear Regression Analysis
Ali et al.	[30]	2011	Annual	Peak Load and Total Demand	Multivariant Regression
Lee et al.	[15]	2011	Annual	Total Energy Demand	Gray Box Model
Theodoridou et al.	[12]	2011	Annual	Annual Peak Demand	Comprehensive Modeling
Goia et al.	[31]	2010	Monthly	Peak Load Forecasting	Linear Regression & Clustering
Mavrogianni	[21, 24]	2009	Annual	Annual Heating Degree Day	Linear Regression
Linda Pedersen et al.	[22]	2008	Annual	Linearized peak Day Profile*	Linear Regression
Ihara et al.		2008	Annual	Total Energy Demand	Gray Box
Heiple et al.	[11]	2008	Annual	Hourly / Total Energy Demand	Software Modeling, "eQUEST"
Nielsen et al.	[14]	2006	Annual	Profile	Gray Box
Tanimoto et al.	[32]	2008	Annual	Peak Demand	Stochastic method
Koroneos		2005	Annual	Total Energy Demand	Gray Box
Ratti et al.		2004	Annual	Total Energy Demand	Multivariant Regression
Shimoda et al.	[33]	2004	Annual	Total EUI / Total Energy Demand	Software Modeling, "SCHEDULE"
Eicker	[18]	2004	Annual	Total Energy Demand	Simplified Equivalent RC
Dotzauer	[23]	2002	Annual	Profile	Linear Regression

	Predicted		Actual		Error
	Monthly	Accumulated	Monthly	Accumulated	
Apr-16	265000	265000	282000	282000	6%
May-16	301003	566003	293610	575610	-3%
Jun-16	424837	990840	409140	984750	-4%
Jul-16	175360	1166200	168770	1153520	-4%
Aug-16	189030	1355230	185340	1338860	-2%
Sep-16	173552	1528782	177190	1516050	2%
Oct-16	259411	1788193	266710	1782760	3%
Nov-16	356885	2145078	368310	2151070	3%
Dec-16	388553	2533631	429580	2580650	10%
Jan-17	245779	2779410	349300	2929950	30%
Feb-17	359021	3138431	358390	3288340	0%

Table 2: Accumulated predicted energy delivered vs actual generated energy in the boiler house

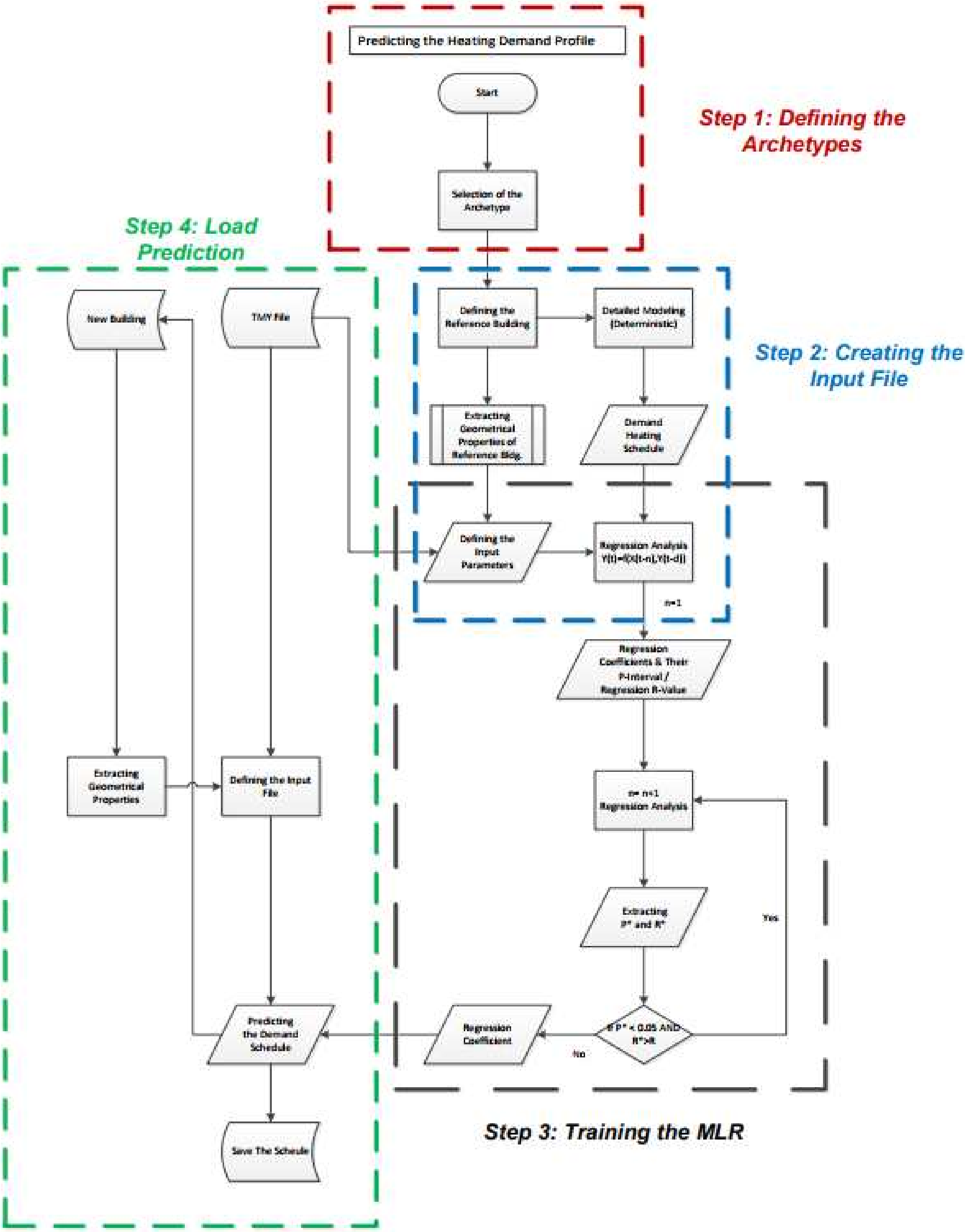


Figure 1: Simplified procedure to predict the heating demand profile

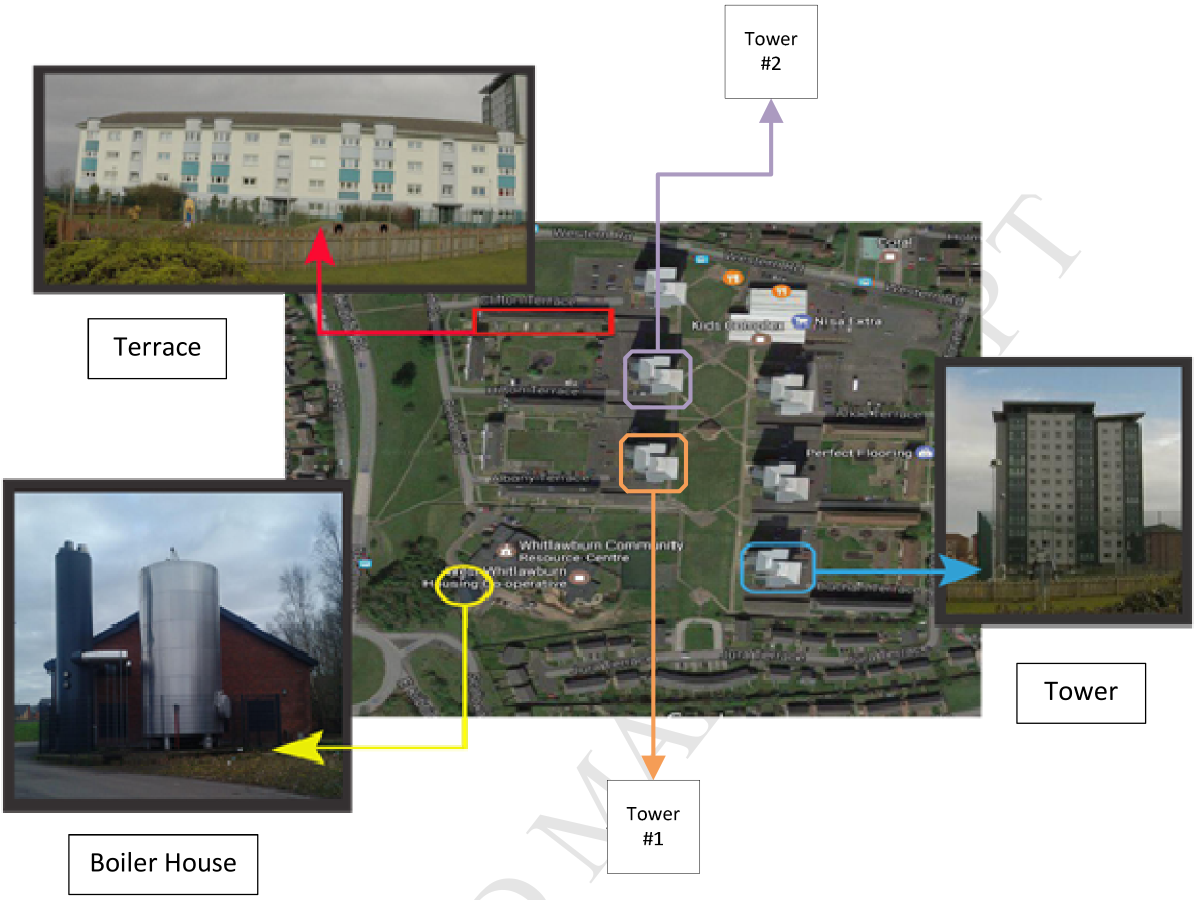
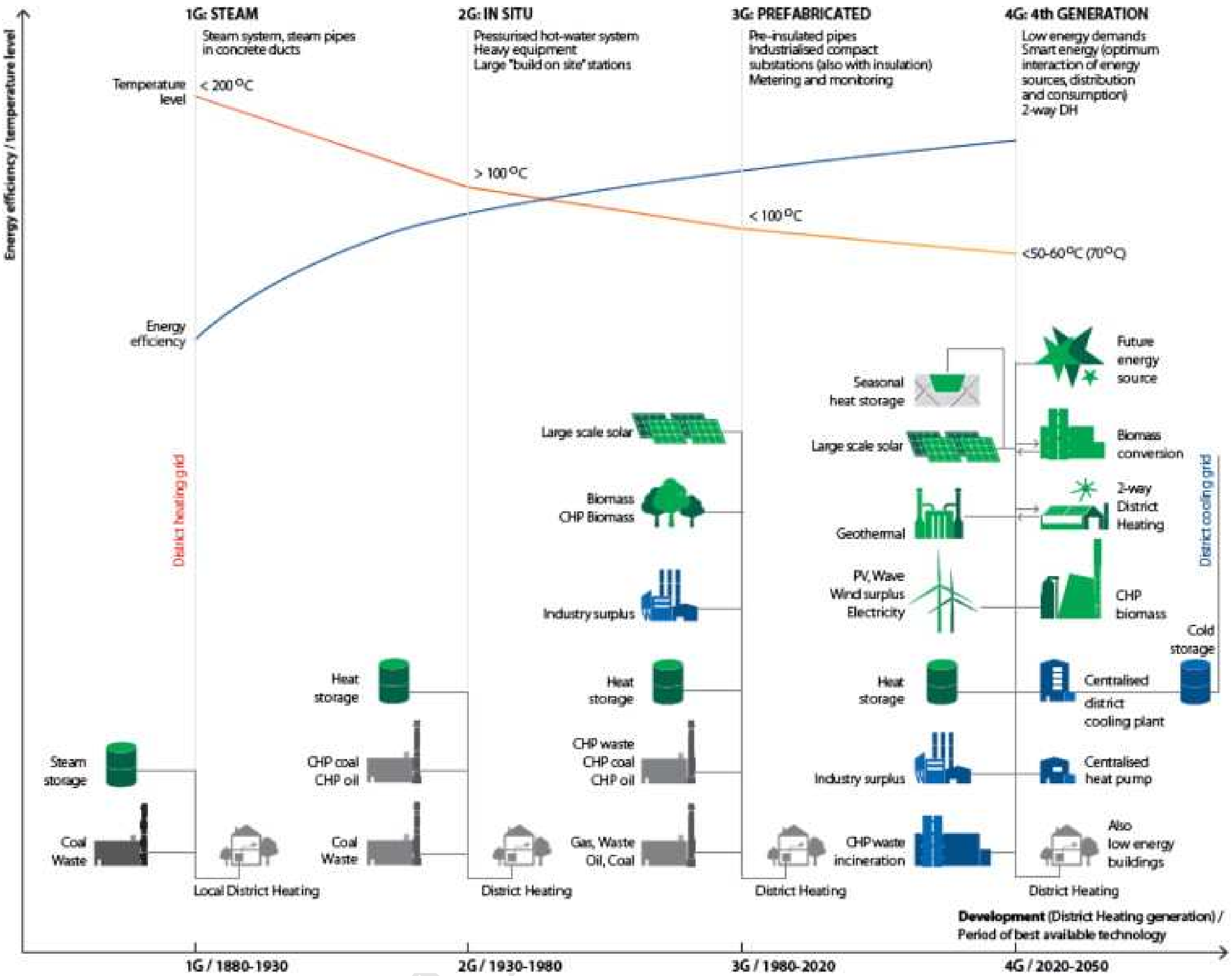


Figure 2: Hybrid community-district heating system layout in Whitlawburn, Cambuslang, Scotland



1) Figure 3: District heating systems generations [34]

Figure 4: (A) Smart meter; (B) energy meter; (C) district and block meter; (D) boiler sensors

Figure 5: The dual heat exchanger sub-system

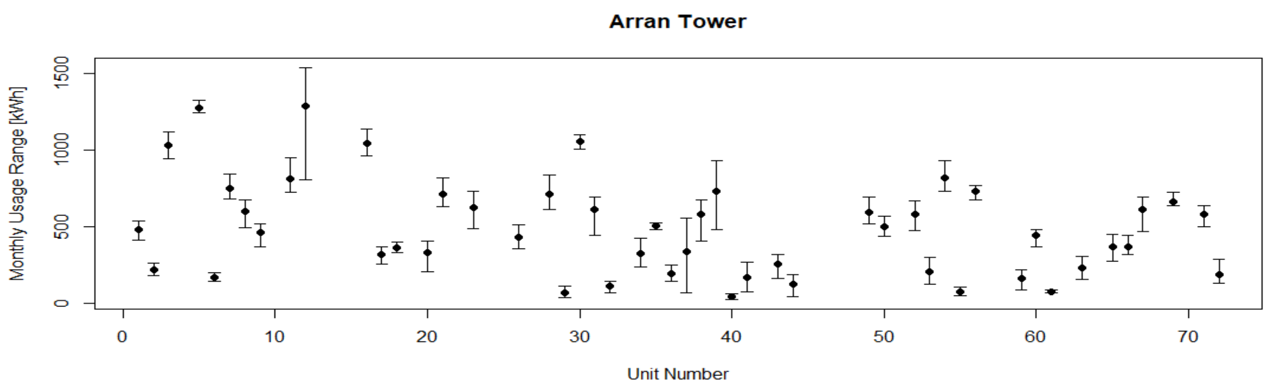


*Figure 6: Monthly consumption of individual units in **Tower # 1, Arran Tower***

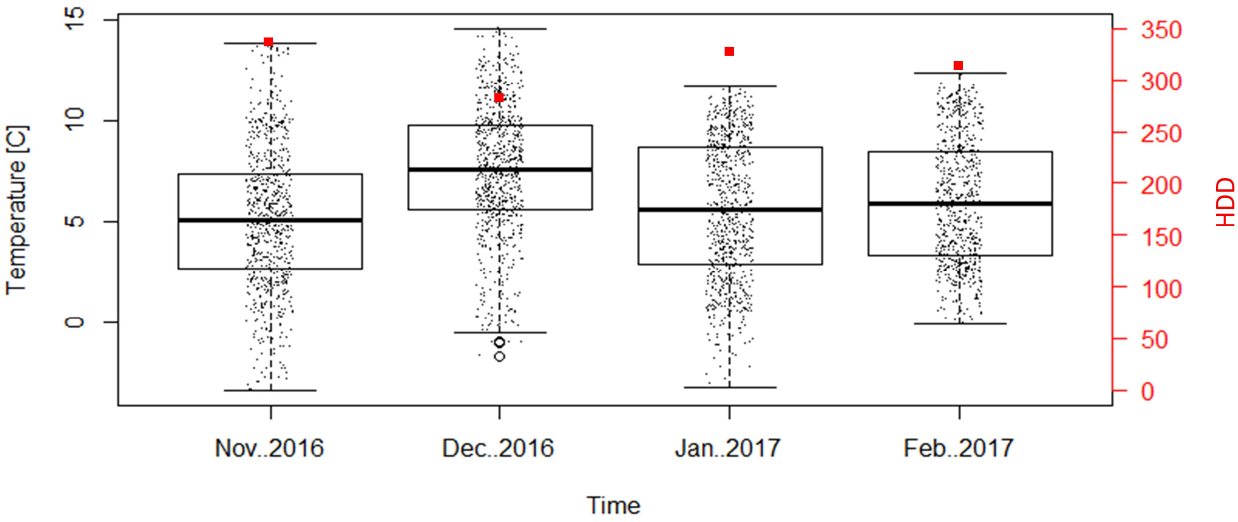


Figure 7: Outdoor temperature and HDD for the 2016-17 heating season (Nov 2016 - Feb 2017)

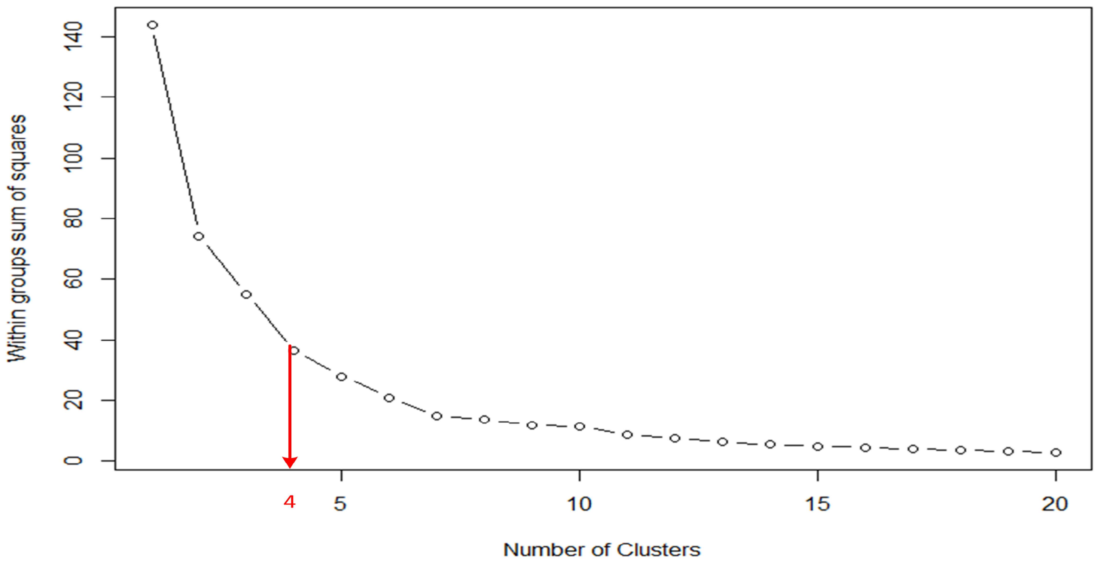


Figure 8: Optimal number of archetypes

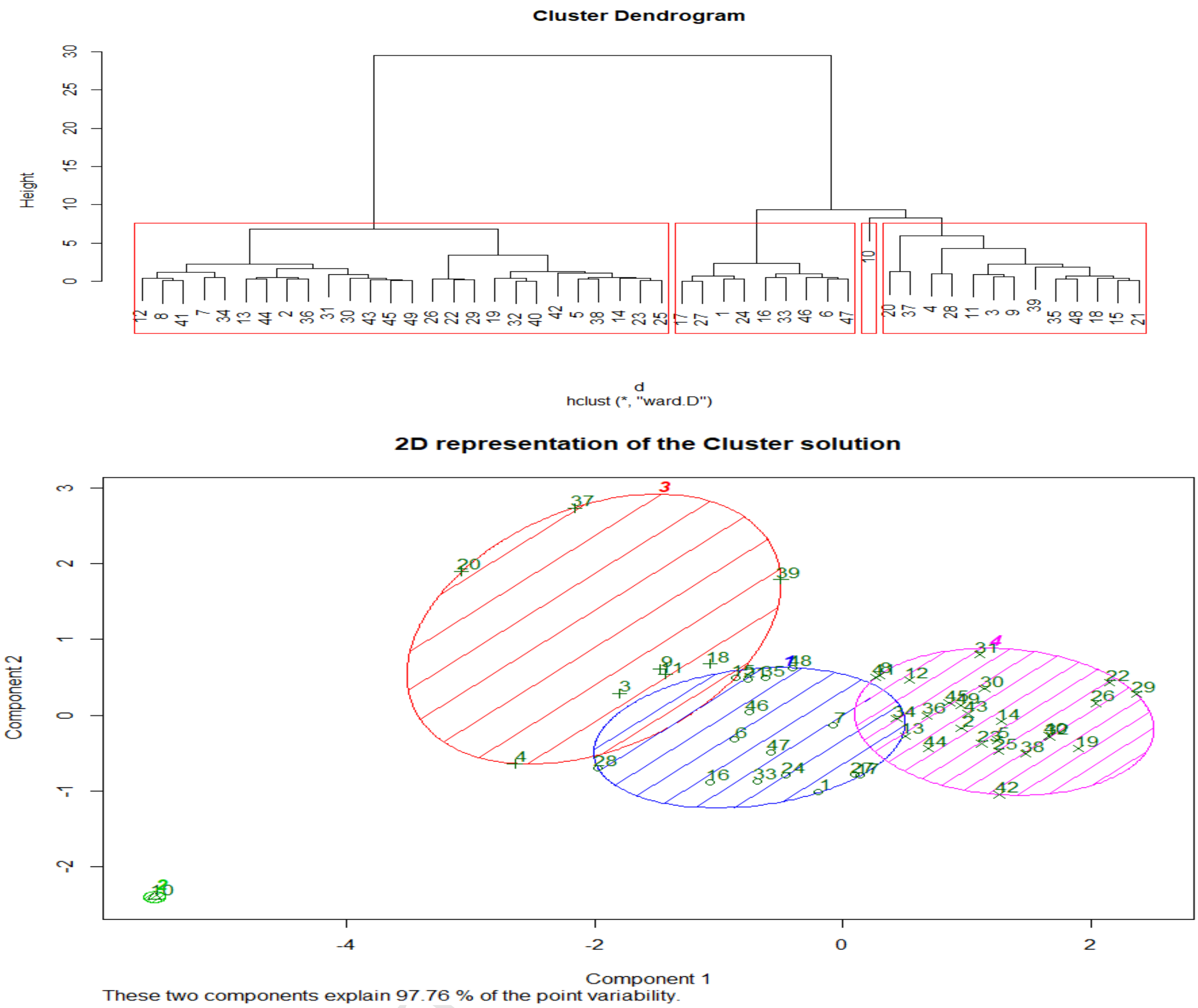
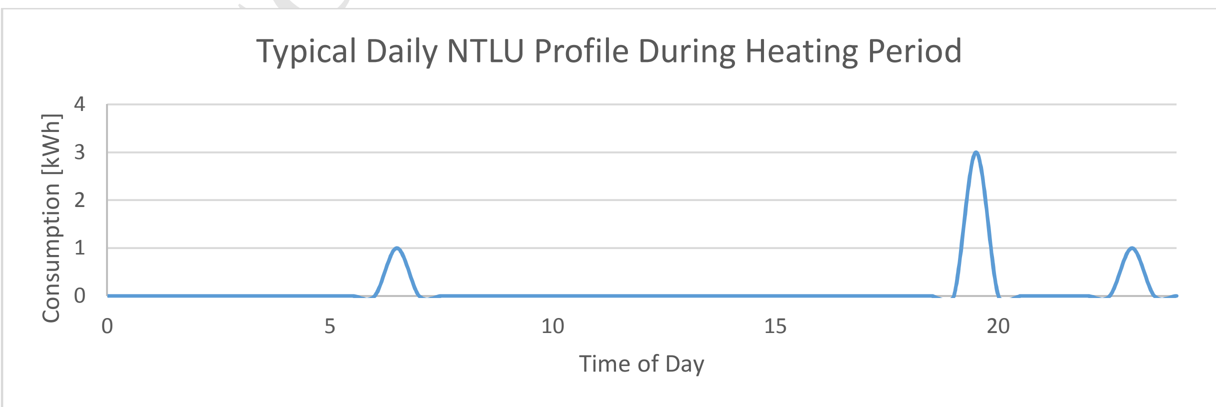
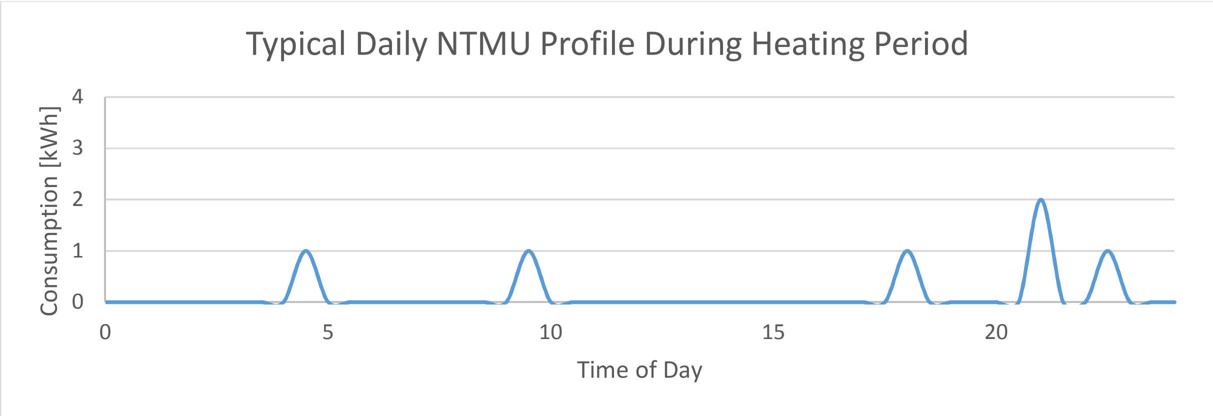
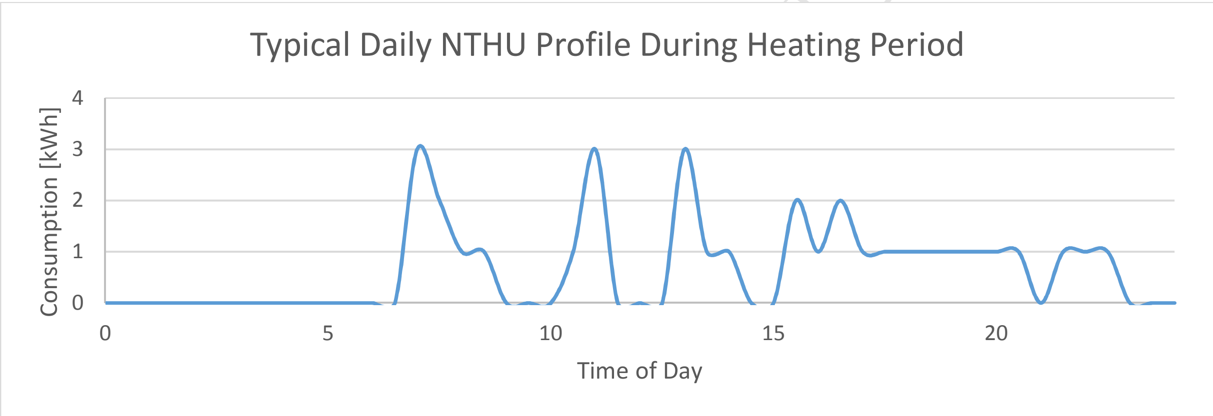


Figure 9: Clustering results for Tower # 1




Typical Daily NTMU Profile During Heating Period
Consumption [kWh]
0
1
2
3
4
0
5
10
15
20
Time of Day


Typical Daily NTHU Profile During Heating Period
Consumption [kWh]
0
1
2
3
4
0
5
10
15
20
Time of Day

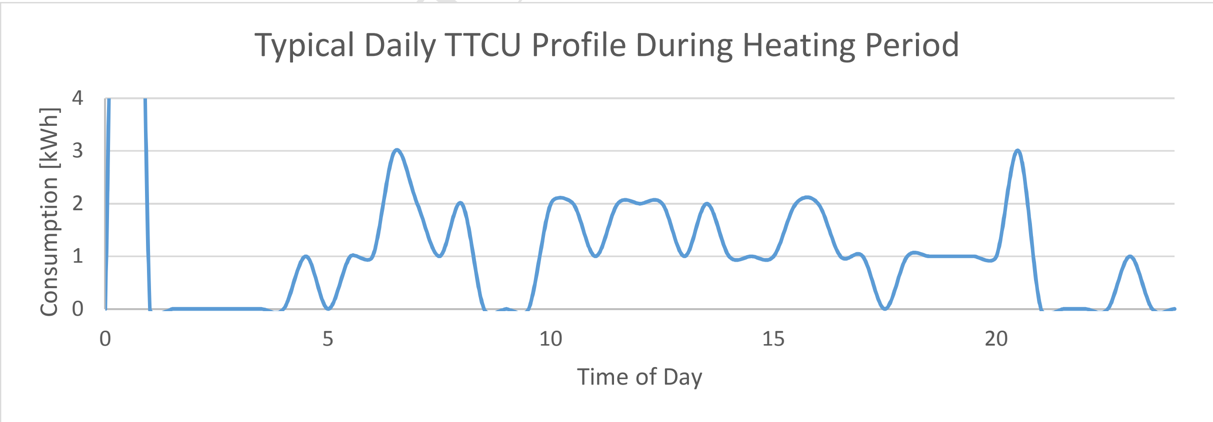

Typical Daily TTCU Profile During Heating Period
Consumption [kWh]
0
1
2
3
4
0
5
10
15
20
Time of Day

Figure 10: Demand Profile for Reference Buildings of Each Class
NTLU (1), NTMU (2), NTHU (3), TTCU (4)

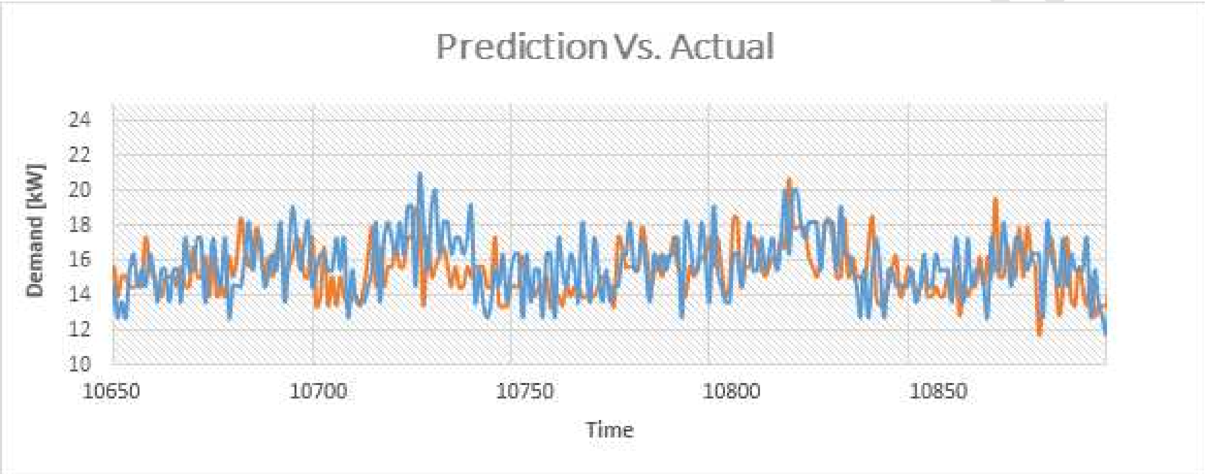


Figure 11: Model prediction (Orange) vs. measured energy demand (Blue) for Tower #1

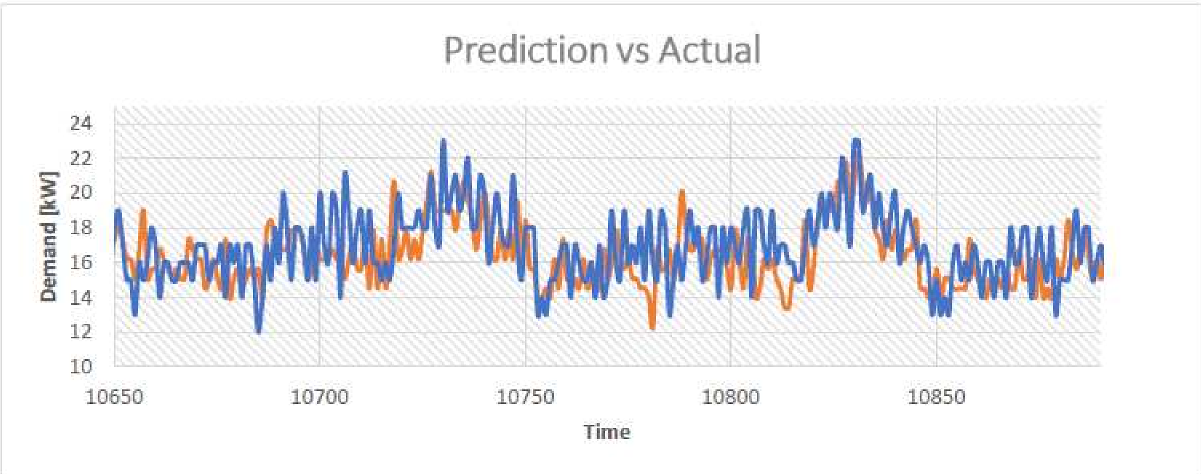


Figure 12: Model prediction (Orange) vs. measured energy demand (Blue) for Tower # 2

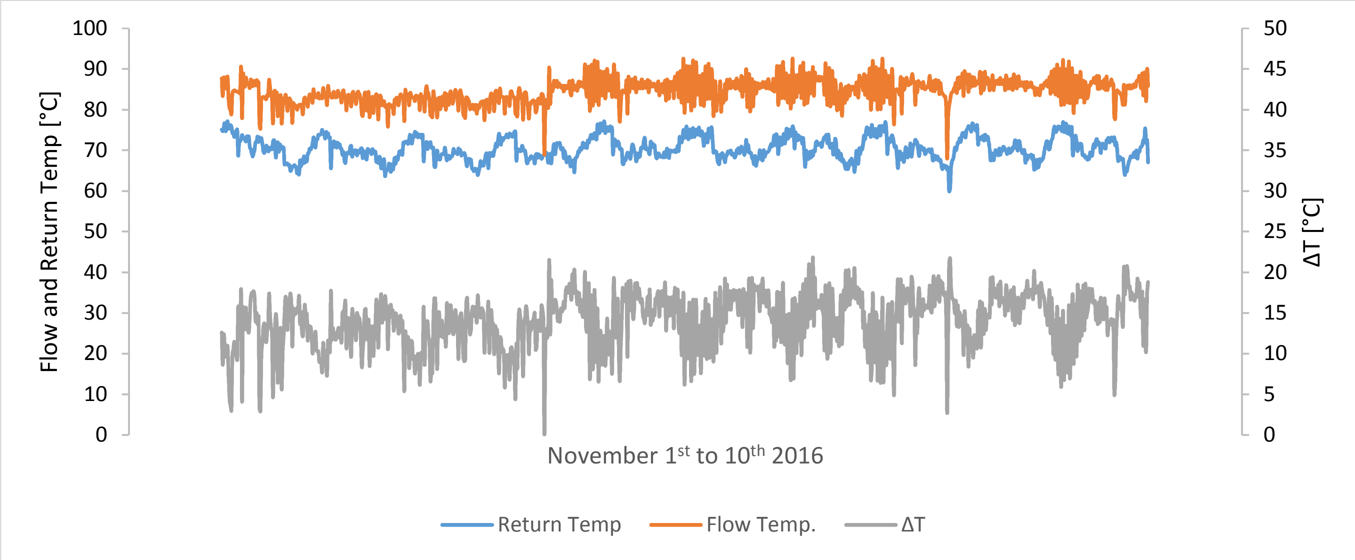


Figure 13: *Underground network's operational temperature*

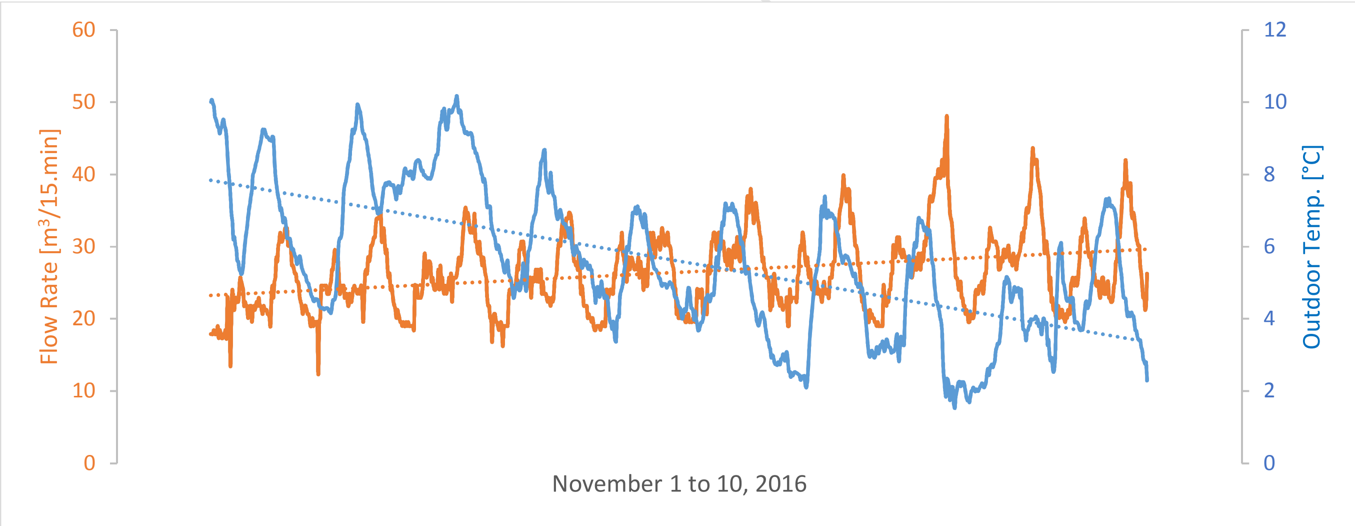


Figure 14: Water flow rate vs. outdoor temperature in the distribution network

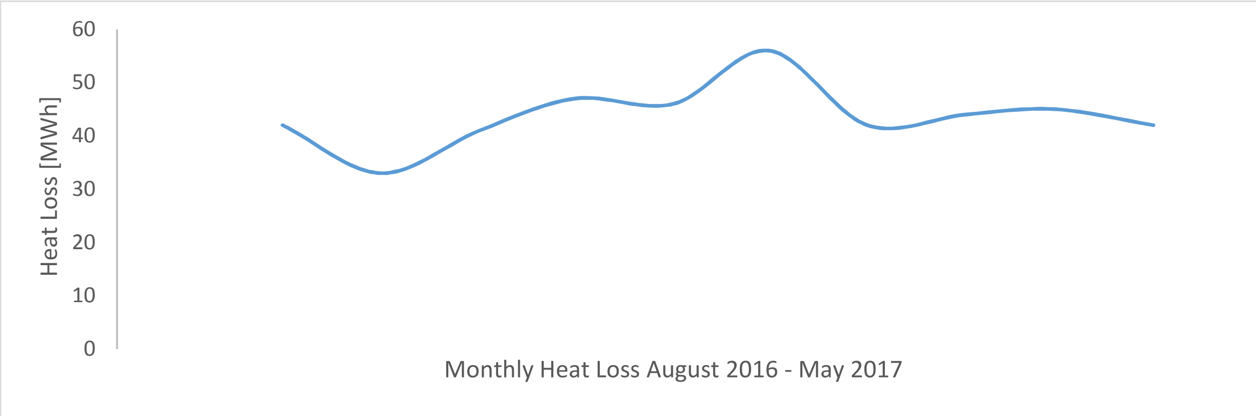


Figure 15: Distribution network's monthly heat loss projection

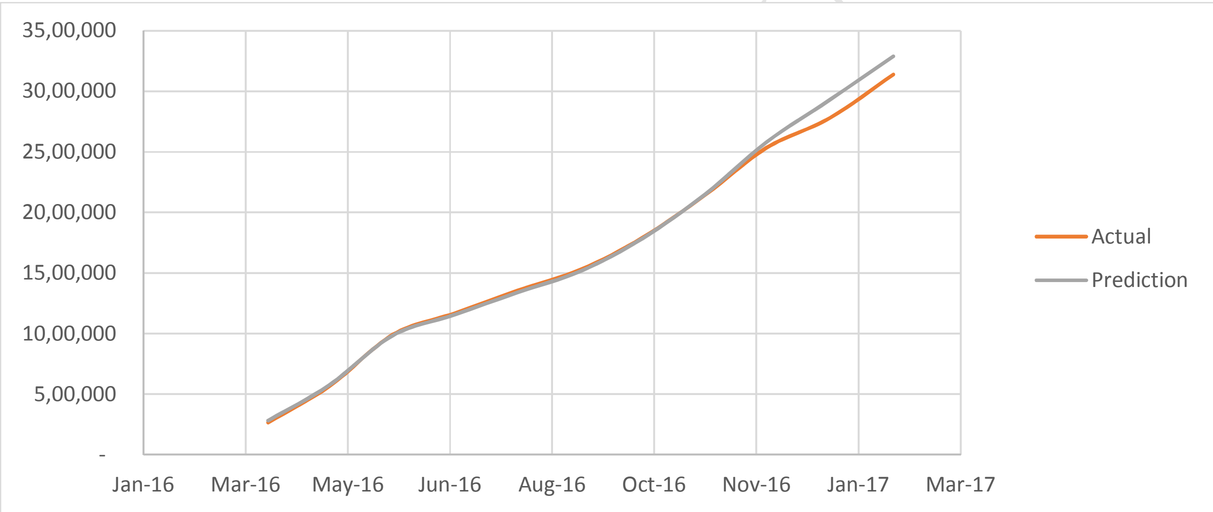


Figure 16: Accumulated predicted energy delivered vs actual generated energy in the boiler house

Highlights

- Simplified method is used to predict the heating load of a mid-size community.
- Clustering approach is used to define the number of archetypes required for the load prediction.
- The simplified model prediction is validated with the measured data.