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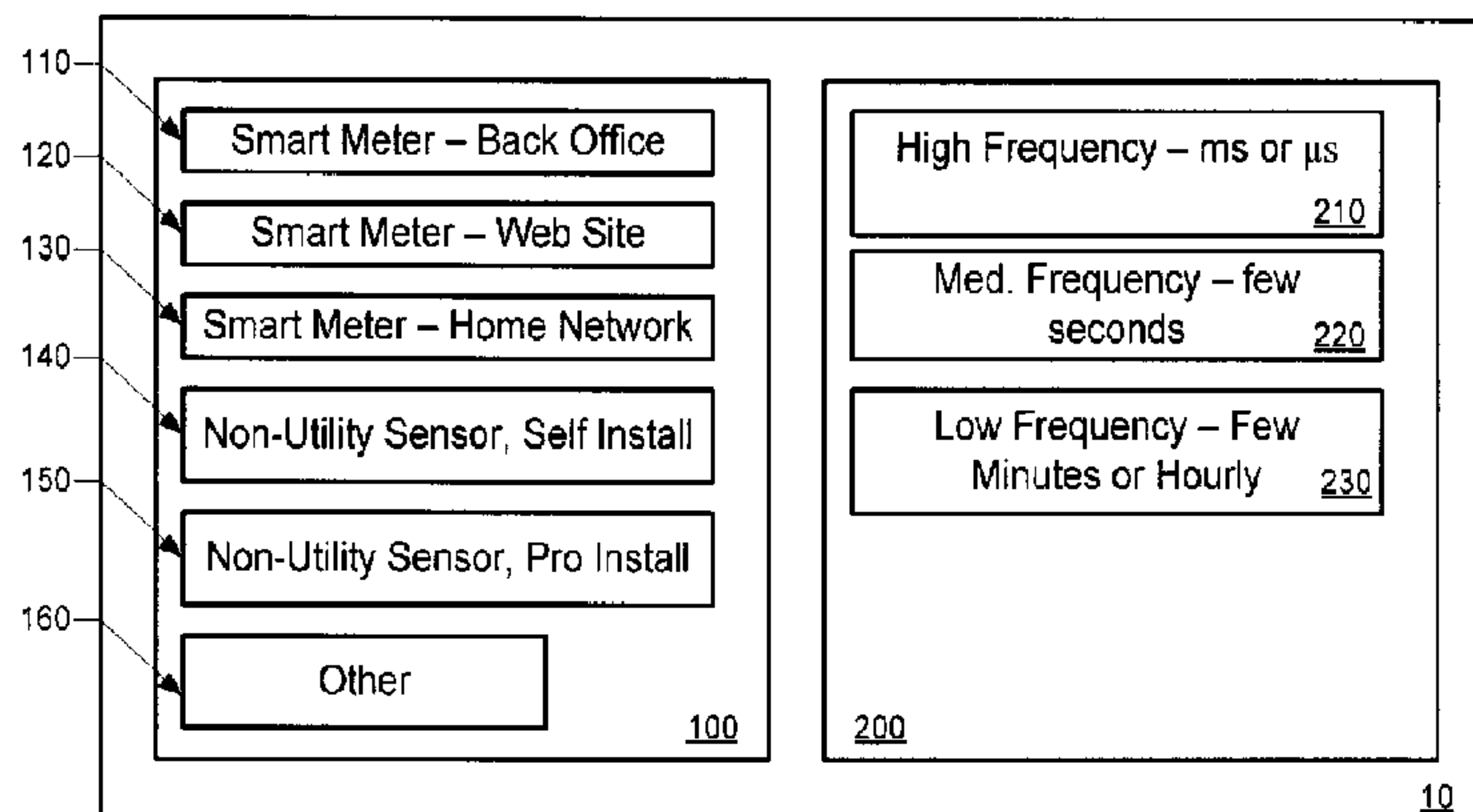
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(72) Inventeurs/Inventors:
 GUPTA, ABHAY, US;
 KHARBOUCH, ALAA, US;
 GARUD, VIVEK, US;
 CHENG, HSIEN-TENG, US

(73) Propriétaire/Owner:
 BIDGELY INC., US

(74) Agent: BERESKIN & PARR LLP/S.E.N.C.R.L.,S.R.L.

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 (54) Title: ENERGY DISAGGREGATION TECHNIQUES FOR LOW RESOLUTION WHOLE-HOUSE ENERGY CONSUMPTION DATA



(57) **Abrégé/Abstract:**

The present invention is generally directed to methods of disaggregating low resolution whole-house energy consumption data. In accordance with some embodiments of the present invention, methods may include steps of: receiving at a processor the low resolution whole house profile; selectively communicating with a first database including non-electrical information; selectively communicating with a second database including training data; and determining by the processor based on the low resolution whole house profile, the non-electrical information and the training data, individual appliance load profiles for one or more appliances.

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- (71) Applicant: **MYENERSAVE, INC.** [US/US]; 20278 Clay Street, Cupertino, CA 95014 (US).
- (72) Inventors: **Abhay Gupta**; 20278 Clay Street, Cupertino, CA 95014 (US). **Alaa Kharbouch**; 1652 Hope Drive, Santa Clara, CA 95054 (US). **GARUD, Vivek**; 7513 Heatherwood Drive, Cupertino, CA 95014 (US). **Hsien-Ting Cheng**; 577 Montego Terrace, Sunnyvale, CA 94089 (US).
- (74) Agent: **MURPHY, Gregory, M.**; Landmark Intellectual Property Law, PC, 23 Seascapes Village, Aptos, CA 95003 (US).

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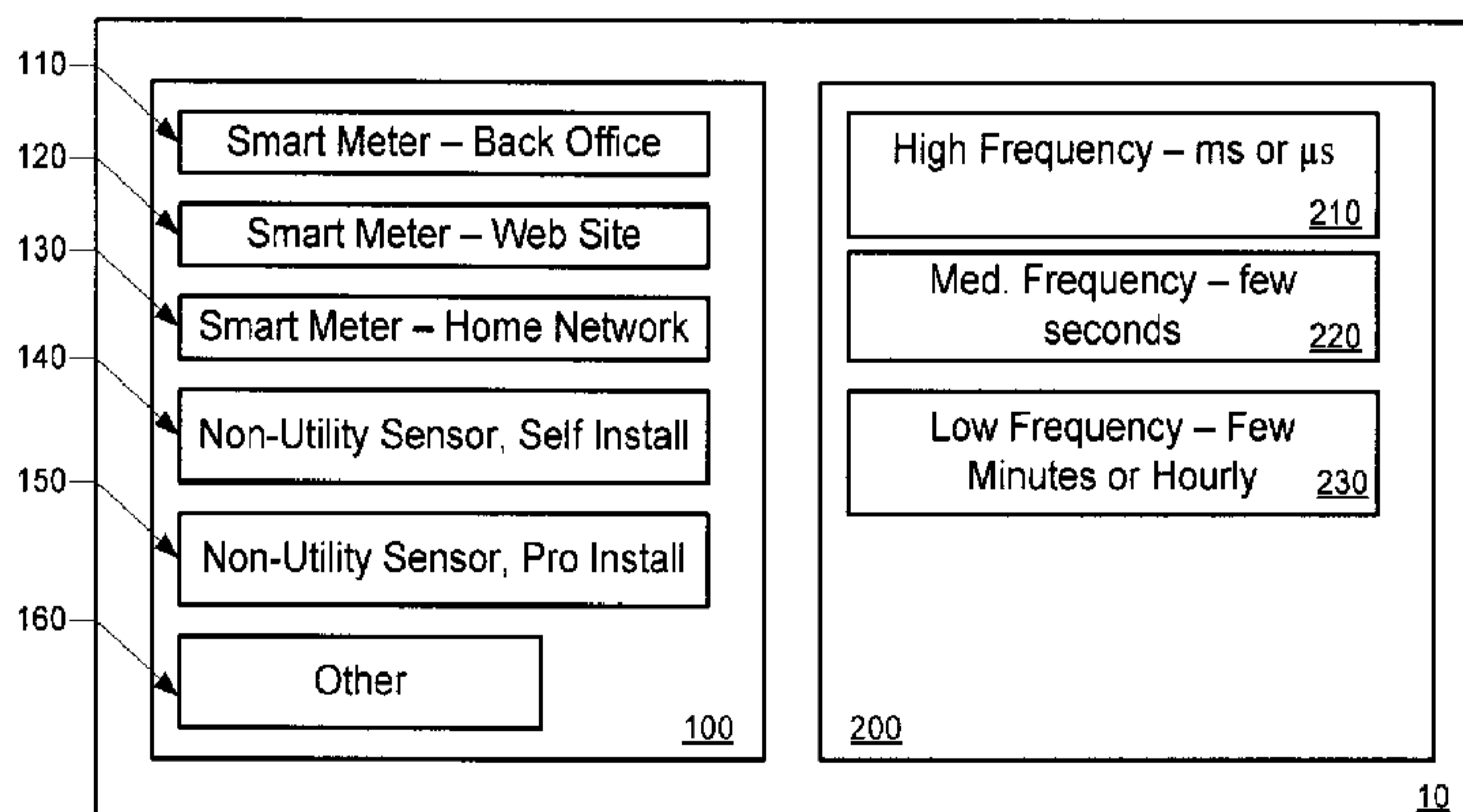
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(54) Title: ENERGY DISAGGREGATION TECHNIQUES FOR LOW RESOLUTION WHOLE-HOUSE ENERGY CONSUMPTION DATA

FIGURE 1



(57) Abstract: The present invention is generally directed to methods of disaggregating low resolution whole-house energy consumption data. In accordance with some embodiments of the present invention, methods may include steps of: receiving at a processor the low resolution whole house profile; selectively communicating with a first database including non-electrical information; selectively communicating with a second database including training data; and determining by the processor based on the low resolution whole house profile, the non-electrical information and the training data, individual appliance load profiles for one or more appliances.

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1 **ENERGY DISAGGREGATION TECHNIQUES FOR LOW RESOLUTION**
2 **WHOLE-HOUSE ENERGY CONSUMPTION DATA**

3 **RELATED APPLICATIONS**

4 [0001] This application claims priority to U.S. Provisional Patent Application Serial No.
5 61/638,265, filed on April 25, 2012, entitled “Smart Meters Energy Load Profile - Use of
6 Training Data Set with High Information Content to Generate Value out of Test Data Set with
7 Low Information Content.” This application also claims priority to U.S. Provisional Patent
8 Application Serial No. 61/754,436 filed on January 18, 2013, entitled “Novel Applications Using
9 Appliance Load Profiles Generated from Non-Intrusive Load Monitoring.”

10 **BACKGROUND OF THE INVENTION**

11 [0002] The present invention is generally directed to systems and methods of non-intrusive
12 appliance load monitoring (“NIALM”). Specifically, the present invention is directed to
13 different techniques for disaggregating low resolution data to determine certain or specific
14 appliance usage.

15 [0003] Appliance load monitoring is an effective way to communicate to users the amount of
16 energy usage required by various appliances. Presenting users with such information in an
17 understandable format allows users to take appropriate action to actively reduce total energy
18 consumption. Moreover, providing itemized information per specific appliance also permits
19 users to determine if acquiring a new or replacement appliance (for example, through purchase,
20 lease, or rental) would reduce energy costs sufficient to validate the price of purchase, lease, or
21 rental. NIALM enables the breakdown of electricity usage for a property without entering the
22 property or applying any sub-metering devices on the individual appliances/devices/loads inside

1 the property. In general, NIALM is known in the prior art. For example, U.S. Patent No.
2 4,858,141 to Hart *et al.* (“Hart”) discusses basic techniques for performing NIALM. Hart
3 teaches generating and using appliance load signatures to extract information for individual loads
4 from whole property load profile data measured by the utility meter. As taught by Hart,
5 information extracted from the utility meter may comprise: power consumption; times when the
6 appliance/load was turned on and off; and appliance/load health.

7 [0004] There has been research in the area of NIALM and various papers have been published
8 on techniques used to define load signatures and run pattern recognition algorithm on the load
9 profile of the property under inspection. Typically, a software analysis is performed on past data
10 collected. Therefore such prior art techniques may be useful in breaking down the energy usage
11 or itemizing the electric energy bill post-consumption, but fail to provide near real-time
12 information that may immediately empower users to modify their energy usage. With regard to
13 appliances such as heating or air conditioning – for which usage is based upon immediate
14 conditions – such data of previous usage may provide limited assistance in modifying present
15 behavior and usage.

16 [0005] Moreover, most published techniques use data at a high sampling rate (ranging from one
17 sample every second to one million or more samples per second). However, several available
18 sources of energy use data do not provide such high resolution data that typically enables specific
19 appliance signatures to be extracted. For example, while utility companies collect data usage, this
20 is typically performed for validation of billing cycles, and is generally collected at a fifteen (15)
21 minute or one hour interval. Accordingly, this data is generally not specific enough for most
22 published NIALM techniques to perform a useful energy disaggregation and generate a clear
23 appliance signature.

1 [0006] While the prior art may teach various devices for monitoring and determining power
2 usage (for example, U.S. Patent Application Publication No. 2009/0045804 to Durling *et al.*
3 (“Durling”)), such devices generally require additional components to be installed or specific
4 devices to be utilized. In addition, prior art techniques and devices have drawbacks in that such
5 devices and techniques generally provide a relatively low confidence level of identifying specific
6 appliances. Such techniques and devices typically do not utilize the most knowledgeable party –
7 the user himself -- and also generally fail to account for additional non-electrical information that
8 may be available.

9 [0007] Moreover, prior art techniques and methodologies may provide users with some basic
10 information regarding their power consumption – but fail to provide the user with any additional
11 advice or counseling as to how to effectively use the information to reduce energy consumption.
12 Rather, the user is left with the notion that he or she should simply use particular appliances less
13 often. This information is relatively meaningless with regard to appliances that users generally
14 must use – for example, refrigerators, electric ranges, washing machines, dryers, etc. In addition,
15 with regard to economic efficiency, the time of energy usage may dictate the cost of such usage.
16 For example, during peak energy usage times, utility companies may charge increased rates than
17 during low usage times. Merely changing the time of day a particular appliance is used may
18 result in significant cost savings.

19 [0008] Accordingly, it is desirable to provide systems and methods that can provide energy
20 disaggregation on low resolution data. More specifically, it is desirable to provide systems and
21 methods to perform NIALM on data sampled at a rate of approximately one (1) minute or larger.

22 **SUMMARY OF THE INVENTION**

1 [0009] Some aspects of the present invention may include methods for creating an appliance
2 signature based upon a low resolution whole house profile, comprising: receiving at a processor
3 the low resolution whole house profile; selectively communicating with a first database
4 comprising non-electrical information; selectively communicating with a second database
5 comprising training data; and determining by the processor based on the low resolution whole
6 house profile, the non-electrical information and the training data, individual appliance load
7 profiles for one or more appliances.

8 [00010] Other aspects of the present invention may comprise methods for creating an
9 appliance signature based upon a low resolution whole house profile, comprising: receiving at a
10 processor the low resolution whole house profile; selectively communicating with a database
11 comprising: non-electrical information comprising community specific parameters and specific
12 home parameters; and training data; and determining by the processor based on the low
13 resolution whole house profile, the non-electrical information and the training data, individual
14 appliance load profiles for one or more appliances, wherein the determination comprises:
15 receiving electric data associated with one or more appliances in the whole house profile from
16 sensors or other recording means; recording the electric data and the one or more appliances as
17 training data in the second database; receiving the whole house profile and determine, based on
18 resulting models, identify incidences of occurrence and/or usage of various appliances identified
19 in the training data; and applying information received from any other sensors or users, if
20 any, to increase the accuracy of the identified incidences of occurrence and/or usage.

21 [00011] These and other aspects will become apparent from the following description of
22 the invention taken in conjunction with the following drawings, although variations and

1 modifications may be effected without departing from the scope of the novel concepts of the
2 invention.

3 **BRIEF DESCRIPTION OF THE DRAWINGS**

4 [00012] The present invention can be more fully understood by reading the following
5 detailed description together with the accompanying drawings, in which like reference indicators
6 are used to designate like elements. The accompanying figures depict certain illustrative
7 embodiments and may aid in understanding the following detailed description. Before any
8 embodiment of the invention is explained in detail, it is to be understood that the invention is not
9 limited in its application to the details of construction and the arrangements of components set
10 forth in the following description or illustrated in the drawings. The embodiments depicted are to
11 be understood as exemplary and in no way limiting of the overall scope of the invention. Also, it
12 is to be understood that the phraseology and terminology used herein is for the purpose of
13 description and should not be regarded as limiting. The detailed description will make reference
14 to the following figures, in which:

15 [00013] Figure 1 depicts sources and resolution of data sets that may be used in
16 accordance with some embodiments of the present invention.

17 [00014] Figure 2A depicts a test data set, in accordance with some embodiments of the
18 present invention.

19 [00015] Figure 2B depicts a test data set, in accordance with some embodiments of the
20 present invention.

21 [00016] Figure 2C depicts a training data set, in accordance with some embodiments of
22 the present invention.

1 [00017] Figure 3 depicts exemplary parameters used in energy disaggregation, in
2 accordance with some embodiments of the present invention.

3 [00018] Figure 4 illustrates an exemplary method of user specific training, in accordance
4 with some embodiments of the present invention.

5 [00019] Figure 5 illustrates an exemplary matrix for an appliance category, in accordance
6 with some embodiments of the present invention.

7 [00020] Figure 6 illustrates an exemplary correlation home from a training home for an
8 appliance category, in accordance with some embodiments of the present invention.

9 [00021] Figure 7 illustrates a process that may be used to determine energy savings, in
10 accordance with some embodiments of the present invention.

11 [00022] Figure 8 illustrates an exemplary energy disaggregation technique for a pool
12 pump, in accordance with some embodiments of the present invention.

13 [00023] Figure 9 illustrates an exemplary method of two-step training, in accordance with
14 some embodiments of the present invention.

15 [00024] Before any embodiment of the invention is explained in detail, it is to be
16 understood that the present invention is not limited in its application to the details of construction
17 and the arrangements of components set forth in the following description or illustrated in the
18 drawings. The present invention is capable of other embodiments and of being practiced or being
19 carried out in various ways. Also, it is to be understood that the phraseology and terminology
20 used herein is for the purpose of description and should not be regarded as limiting.

21 **DETAILED DESCRIPTION**

22 [00025] The matters exemplified in this description are provided to assist in a
23 comprehensive understanding of various exemplary embodiments disclosed with reference to the

accompanying figures. Accordingly, those of ordinary skill in the art will recognize that various changes and modifications of the exemplary embodiments described herein can be made without departing from the claimed invention. Descriptions of well-known functions and constructions are omitted for clarity and conciseness. Moreover, as used herein, the singular may be interpreted in the plural, and alternately, any term in the plural may be interpreted to be in the singular. Reference figures preceded with "S" (e.g., S100) indicates a step.

[00026] Note that while the preceding and following disclosure primarily discusses monitoring and reporting electric usage, it is fully contemplated by the applicants that such systems and methods disclosed herein may also be used to monitor other types of energy consumption - for example natural gas, propane, and water consumption.

[00027] Current government policies and the consumer attitudes are driving the electric, gas and water utilities to make the consumer energy, water and gas consumption data available. This information may be used by the consumers or consumer authorized third parties for specific presentation and analytics. At least one goal of the availability of such information is to empower consumer with actionable information and influence consumer behavior to participate in energy saving actions.

[00028] Yet, the consumption data collected by utilities may not always have the highest resolution and therefore information may be lost when the data is sampled. For example, this may result when data is collected at large time intervals or low frequency sampling.

[00029] However, utilizing methods and systems disclosed herein and according to some embodiments of the present invention, the consumption data captured by utilities may be analyzed, possibly with the aid of separately collected high resolution data. The analytics

1 generated and results or conclusions may be applied to the low resolution data, therefore making
2 it possible to help consumers save energy on a larger scale. This may be accomplished even
3 though the data from utilities alone may not include information specific enough to generate
4 same analytical results.

5 [00030] With reference to Figure 1, sources of data 100 and exemplary resolution of such
6 data 200 will now be discussed. Sources of data 100 may vary, and may comprise elements such
7 as: information from a processing utility 110 (which may be thought of as “back office”
8 information, or information that is used by the utility typically for billing purposes, note that
9 customer consent is likely need to obtain this information); information from a utility web site
10 120 (for example a customer may download account information and provide the same;
11 alternatively, the customer may provide a third party with access and the third party may
12 “scrape” the website of the utility); directly from the smart meter if there is a home area network
13 130; an additional, consumer installed, meter or usage sensor 140; an additional meter or usage
14 sensor installed by a third party (not the utility) 150; or any other sort of data input 160.

15 [00031] The resolution of the data 200 may, in general, be divided into three categories of
16 high resolution 210, medium resolution 220, and low resolution 230. High resolution data 210
17 may be sampled at a higher frequency, for example every millisecond or microsecond. Medium
18 resolution data 220 may be sampled at a frequency of around every few seconds. Low resolution
19 data 230 may be sampled at a low frequency, for example every several minutes or every hour.

20 [00032] In order to provide reliable, reasonably specific NILM on low frequency data,
21 several overarching techniques may be used. For example, a first technique may comprise
22 estimating a portion of energy from the whole house waveform that is attributed to a specific
23 appliance category. Some appliances – for example: pool pumps, air conditioners, furnaces, etc.

1 – may be able to be culled out of the whole house waveform. A second technique may be to use
2 a training set to assist the system in learning the energy consumption patterns of various
3 appliance categories in relation to specific signatures and/or parameters.

4 [00033] In order to properly “train” a system to disaggregate results from low resolution
5 data, training data may be utilized. Training data may comprise a data set with medium or high
6 resolution, and comprising information required to process non-intrusive load monitoring
7 (“NILM”) in order to extract information associated with individual appliances.

8 [00034] In contrast to the training data, actual data (or “test data”) may comprise a low
9 resolution data set that may not have sufficient content to process NILM algorithms. Such test
10 data may be used to process high-level analysis, but results are generally inferior to analyses that
11 process medium or high resolution data.

12 [00035] Note that training data can be data received from the actual home in question – for
13 example, through user training directed at specific appliances in the home – or can be data
14 associated with any number or plurality of other homes, neighborhoods, communities or other
15 information. For example, in order to obtain more accurate results, a user can train appliances in
16 his or her home. This data directly corresponds to the appliances used in the home. Accordingly,
17 even when low resolution data is received, medium or high resolution training data provided by
18 the user can be used to determine individual and/or specific appliance load profiles.

19 [00036] Alternatively, a user may not undergo the time or effort of training, instead relying
20 upon a larger database of both non-electric data and training data received from others. In this
21 situation, various features of the user’s home (which may, for example, be identified through the
22 use of non-electrical data, such as square footage, age of construction, heating or cooling degree
23 days, etc.) may be identified in the training data.

1 [00037] Groupings of the training data may be utilized to provide a feature classification
2 based upon the most comparable data. For example, home size may provide grouping. Data
3 associated with a 1200 square foot home may not provide sufficiently comparable data to
4 determine the load on a heating or cooling system used in a 4500 square foot home. Similarly,
5 homes built during the same time period in the same geographic area are likely to have
6 comparable insulation. Even the number of residents of a home may provide information useful
7 in grouping the data. A home with two adults and five children will generally require laundry
8 machines to run more often than single-person homes. Homes with pools may require the use of
9 a periodic pool pump. Each of these features can be associated with stored training data.

10 [00038] Accordingly, low resolution data can be processed through a trained classifier or a
11 regression model to determine the likely presence and operation of one or more specific
12 appliances. The use of a trained classifier and/or regression model is discussed in further detail
13 below.

14 [00039] With reference to Figures 2A – 2C the difference between low resolution test data
15 and high resolution training data can be seen. Figure 2A illustrates low resolution test data
16 sampled at a frequency of once every hour (or every sixty (60) minutes). It can be seen that the
17 waveform offers little details from which to determine specific appliance usage. Figure 2B also
18 illustrates low resolution test data, this time sampled at ten (10) minute intervals. While the
19 waveform is more specific and certain aspects of NILM may be applied, the results would very
20 high-level and not offer any degree of specificity.

21 [00040] In contrast, Figure 2C illustrates a training data set comprising high resolution
22 data. It can be seen that the information present in the waveform of Figure 2C may be used in
23 NILM techniques to disaggregate the waveform and determine specific appliance loads.

1 [00041] With reference to Figure 3, different parameters that may be used in an energy
2 disaggregation algorithm 300 will now be discussed. Energy disaggregation algorithm 300 may
3 utilize various inputs, which may generally be broken into two categories: community
4 parameters 310 and household parameters 320. Community parameters 310 may comprise
5 elements such as, but not limited to, the time (e.g., the month, week, day, hour, minute) 311 of
6 the sample; the weather conditions (e.g., the temperature, humidity, dew point, barometric
7 pressure, recorded cloud coverage, sunrise/sunset times, etc.) 312, and even community
8 demographics (eg., the average income and home profiles of the community, town, city, zip code,
9 etc., the average age of family units in the community, etc.) 313.

10 [00042] Household parameters 320 may comprise attributes of a specific household, such
11 as but not limited to: appliance profiles of the home 321, water and gas usage of the home 322,
12 thermostat inputs from the home 323 (for example, thermostat set points, start and end times,
13 temperature change rate, etc.), user provided training (discussed in greater detail below) 324,
14 and/or any other sensor that may indicate when an appliance is turned on or off 325.

15 [00043] Note that other information may also be used, for example information referred to
16 as “non-electrical information” in U.S. Application No. 13/366,850 filed on February 06, 2012
17 and entitled “Systems and Methods for Improving the Accuracy of Appliance Level
18 Disaggregation in Non-Invasive Appliance Load Monitoring Techniques,”. Other such
19 information may be satellite imagery of the specific house, neighboring demographics,
20 tax records, determination of building mass and insulation levels, etc.

21

22 [00044] Regardless of whether the energy data is low, medium, or high resolution, the
23 information and factors set forth in Figure 3 may be utilized in NILM techniques.

1 [00045] **Household-Specific Inputs and Training**

2 [00046] Additional information may be desired in order to improve the accuracy of NILM
3 techniques on low or medium resolution data. For example, the presence of a sensor to measure
4 various appliance activity – or the use of user provided system training may provide additional
5 accuracy in energy disaggregation. For example, inputs from a user or a sensor specifying the
6 turn on and off times of a specific appliance may assist the system with learning the require
7 power level, run time(s), cycle time(s), and/or other electrical and/or consumer use behavior.
8 Because specific appliance information – and specific consumer behavior -- often vary from
9 household to household, such information can assist in generating accurate results from the
10 disaggregation. In some situations, training may be provided on a recurring basis (for example,
11 through the use of a permanently installed sensor, or through the repeated behavior of a user), or
12 may only occur one or more times when the information is provided for future use.

13 [00047] **User-Provided Training**

14 [00048] Current methods of disaggregating a whole house waveform into individual
15 appliances loads are generally based on obtaining accurate signatures of appliances for pattern
16 matching in the whole house waveform obtained outside the property. Since the accuracy of the
17 detection of appliances in current methods is dependent on matching the generic appliance
18 signatures to the actual appliances in the property, it is often beneficial to have the user provide
19 system level training to gather the property specific appliance signatures. This may be
20 accomplished in several ways. Generally, methods of user training employed in the prior art
21 require high level of effort by user to train the system and therefore run the risk of losing user
22 interest in the system altogether. However, in accordance with some embodiments of the present

1 invention, methods of gathering appliance signatures supported by user involvement will be
2 discussed.

3 [00049] Specifically, a user providing feedback on energy disaggregation results
4 indicating whether results were correct or marking periods using interactive charts or forms
5 informing when a specific appliance was used. For example, with reference to Figure 4, a user
6 may train the system in real time by using a training mode. When the system goes into training
7 mode, the user may turn an appliance on and off and the system may therefore learn the
8 appliance signature in real time. With continued reference to Figure 4, an exemplary method of
9 user specific training 40 will now be discussed.

10 [00050] At step 410, a user may start the training mode. Starting the training mode may
11 require the user to initiate a training sequence for the system, which may be performed by
12 communicating with the system. This may be accomplished through user input into a website,
13 application on a smart phone, thermostat input, telephone call, email, short messaging services,
14 or any other sort of information. It is also contemplated that a user may record a training session
15 on a device (such as a smart phone, tablet, laptop, or other electronic device) and may later
16 upload the training session to the system after the training session is complete.

17 [00051] Regardless of whether the training session is indicated before the data is recorded
18 or uploaded after the recordation of data, at step 420 the user may select an appliance that is
19 going to be covered or used in the training. This selection may be through the selection on a
20 website, application, etc. In accordance with some embodiments of the invention, this selection
21 may be physically recorded by the user (i.e., written down) and later conveyed to the system or
22 to a representative of the system.

1 [00052] At step 430 the user may start the appliance and allow the appliance to run
2 through its normal cycle. It is also contemplated that a user may initiate an abbreviated or
3 elongated appliance cycle in order to capture more, less, or different information than a normal
4 cycle. At step 450 the appliance cycle may end, and if the user is conducting a real-time training
5 or recording the training session, the training mode may be exited. At step 470 the system may
6 determine if a good appliance signature was captured by the training session. If the appliance
7 signature was not sufficient, a communication may be sent to the user requesting the user re-train
8 the system with the specific appliance. Such communication may request additional actions, for
9 example that the user cease using another appliance during training, or that the user allow the
10 appliance to run through a full cycle. If a good appliance signature is not captured, the method
11 may return to step 430 where the user starts the appliance for training again.

12 [00053] If a good appliance signature was captured, at step 480 the system may be
13 successfully trained to identify the specific appliance. Note that in accordance with some
14 embodiments of the present invention, optional step 440 may be used. Optional step 440 may
15 comprise a user using an additional aid or input in the training session. For example, an
16 application on a smart phone may be used (the application, may, for example, utilize the various
17 sound, motion, and attitude sensors of the smart phone). For example, during the training mode,
18 the smart phone can be placed on or near the appliance (or affected areas that indicate appliance
19 operation) and real time behavior of the appliance may be recorded. Examples of such additional
20 inputs may include, but are not limited to:

- 21 a. Sensing the vibration of a clothes dryer;
- 22 b. Determining HVAC usage by recording the sound of airflow through a
23 HVAC vent using a microphone;

- 1 c. Providing specific appliance information by utilizing the camera function
2 to provide pictures of the appliance, or the appliance label, to determine
3 make, model, functions, etc.
- 4 d. Determining when lights in a house are used through a light sensor;
- 5 e. Determining indoor temperature and set points using a temperature sensor;
- 6 f. Utilizing the GPS coordinates of a user's phone to deduce when a user is
7 not at home, and using such information to correlate energy use with
8 house occupancy.

9 [00054] In addition to user training, information may also be received from one or more
10 various sensors installed temporarily or permanently in the household. Such sensors may provide
11 various inputs that can be used in disaggregation of the overall house energy data. For example,
12 information may be obtained from a thermostat, plug sensors, and/or voltage noise signature
13 sensors.

14 [00055] Thermostats may, for example, provide set points, start and end times, and indoor
15 and/or outdoor temperature. Plug sensors are temporary or permanent installed plug-level
16 sensors that may indicate cycle times for appliances. Voltage noise signature sensors may be
17 sensors installed on a wall plug that may detect when an appliance is turned on and off. Such
18 sensors may also measure the cycle times of various appliance and may measure voltage noise
19 signatures that can be used in NILM disaggregation systems.

20 [00056] With reference to Figure 5, a feature matrix 510 may be generated for each
21 appliance category. In general, an overall data set 520 may be analyzed and various features may
22 be determined or generated 530. Features may be generated for each type of appliance category

1 531, 532, 533. Accordingly, an appliance feature matrix for a specific appliance category for a
2 given data set 510 may be generated.

3 [00057] With reference to Figure 6, training data 610 for each appliance category 611,
4 612, 613 may be gathered and correlated with test data 620. Test data 620 may be obtained
5 through any number of the methods discussed above, or any combination of the methods
6 discussed above. A correlation matrix 630 between the test data and the training data may then
7 be performed to find the best match for each appliance category. In this manner, the training data
8 can be used to properly identify appliance categories found in the test data.

9 [00058] With reference to Figure 7, a method of using training data sets to derive
10 appliance energy information in accordance with some embodiments of the present invention
11 will now be discussed. Test data 710 – which may be low resolution test data – may be
12 compared with a database of medium or high frequency training data 720. The database of
13 training data 720 may comprise training data for different appliance categories 721, 722, 723. At
14 730, the test data 710 and the training data 721, 722, 723 may be compared to see if there is any
15 match. If a match is found, at 740 energy saving recommendations may be determined based
16 upon appliance energy itemization. In addition to passing on this information to a user, the
17 results may also be cycled back into the test data (and potentially the database (not shown)) in
18 order to provide a machine-learning environment that can iteratively improve its determinations
19 and findings.

20 [00059] **Energy Disaggregation Methods and Components**

21 [00060] Once the data is captured – both test data and training data – various methods,
22 models, and algorithms may be utilized to disaggregate the energy data into specific appliance

1 loads. For example, Factorial Hidden Markov Models (HMM) may be utilized, as well as sparse
2 approximation.

3 [00061] Factorial Hidden Markov Model

4 [00062] Using an HMM approach, A hidden Markov model may be used to uncover which
5 appliances were turned on during each sampling interval. Each hidden state may correspond to a
6 different combination of a limited number of appliances being on or off. For example, one state
7 can represent the combination of a dryer and water heater in the on state, and the air conditioner
8 off. It follows that the observed variable, the whole-house usage in the sampling period, is
9 dependent of the state since it is dependent on which appliances are on. The HMM can use
10 training data for various aspects of the model, e.g. the emission probability distributions for each
11 state. However, HMM analysis may be performed without training data as well.

12 [00063] Note that an additive factorial HMM may allow the tracking of each appliance
13 using its own Markov chain, with the observable variable (representing the whole-house power)
14 equal to the sum of the state-dependent-output of the individual appliance/category chains. A
15 noise variable or similar consideration may be used to account for any usage outside of the
16 modeled appliances.

17 [00064] Sparse Approximation

18 [00065] Using a sparse approximation approach, a whole-house time series may be
19 represented as a linear combination of a collection of signals (time-series), called a dictionary.
20 Each signal or dictionary may represent the usage of an appliance across one or more sampling
21 intervals. By enumerating various possible patterns for an appliance (e.g. an on-cycle start time),
22 the dictionary can be constructed to represent all appliances. Therefore, under this method the
23 whole house energy usage time series can be seen as a sum of signals, each corresponding to a

1 usage of a particular appliance during a period of time. Alternatively, the section of a dictionary
2 corresponding to each appliance may be a set of vectors obtained using training data for that
3 appliance and a dictionary learning method. A sparse least square representation may be
4 computed, and the coefficient vector may therefore explain which appliances occurred, the
5 timing of such appliances, and the time-averaged usage or amplitude of such appliances.

6 [00066] Temperature Based Heating and Cooling Estimation

7 [00067] In addition to HMM and sparse approximation approaches, estimations may also
8 be made based on temperature-based heating and cooling. In other words, the energy used by air
9 conditioners or heating-related devices are generally intimately tied to temperature. Using this
10 methods, a starting point is the representation of the whole-house usage as a combination of (i)
11 temperature-dependent components, each of which corresponds to AC or heating usage; and (ii)
12 another component that generally does not vary with temperature.

13 [00068] The first component may then be extracted from the data based upon, at least in
14 part, the temperature based heating and cooling. Temperature data may be converted to a variant
15 of cooling or heating degree days, which may represent the need for cooling or heating in a given
16 day or period. For example, the cooling degree days generally increase with every hour when
17 the temperature exceeds a certain reference temperature (e.g. 65 F). This increase is generally
18 proportional to the difference between external temperature and that baseline. A similar
19 calculation may be used to compute heating degree days. The whole-house usage over several
20 weeks/months may then be explained using a model based on heating and cooling degree days.

21 [00069] In the simplest case, where a linear dependency is assumed, a simple linear least
22 squares regression may be used to separate the AC/heating. However, nonlinear analysis may
23 also be used. In addition, regularizers may be used in the regression process (e.g. penalizing the

1 squared norm of the linear weight vector) to significantly improve the solution. In the same vein,
2 the optimization over the fitting error (often the total square error) can also be constrained (e.g.
3 to produce nonnegative heating/cooling degree coefficients) to provide more stable and sensible
4 solutions given the interpretation of the output.

5 [00070] Steps to discover or incorporate time of day or house occupancy patterns,
6 determine the set point (set temperature) of a building, and/or any other non-electrical
7 information as discussed above may be added to improve accuracy for a specific house.

8 [00071] In many cases, high/low temperatures during a certain period have little to no
9 effect on cooling/heating usage, whereas deviation from the set temperature during other periods
10 will result in a larger increase in heating/cooling energy use. A specific strategy is to break up the
11 “cooling degree” calculations to correspond to different periods of the day (i.e. use only the
12 temperature during certain hours for the calculation). In the example of linear regression, the
13 whole house usage is represented as a linear combination which includes terms that relate to
14 heating or cooling at different times of day. This not only allows for more accurate
15 heating/cooling usage estimation, it can produce additional insight into to how this usage is
16 distributed across different periods of time.

17 [00072] A similar breakup of the explanatory variables into heating/cooling degree
18 calculations based on different reference temperatures can also be used to account for different
19 set temperature settings across homes, and allow the system to search over models corresponding
20 to more than one possible set temperature. As the number of regression features or explanatory
21 variables increases, feature selection in some form may become crucial. For example, the model
22 should not need to incorporate two features that both correspond to heating during the same

1 hours (although some overlap in time may be acceptable). In the linear case, a norm penalty can
2 ensure sparsity of the weight/coefficient vector.

3 [00073] Again, non-electrical data, such as learning from other similar homes (for
4 example, according to certain criteria such as size, neighborhood, date of construction, etc.) may
5 be used to help determine a recipe for extracting AC/heating usage. Moreover, the results may
6 be refined with an iterative process, where the solution is designed to improve based on solution
7 from previous iterations. An example of this, in accordance with some embodiments of the
8 present invention, is to determine which data points are more relevant for analysis, or place
9 different weights on different samples.

10 [00074] Estimations from Baseload Levels

11 [00075] Utilizing a base-load approach, an “always on” level estimate may be made for
12 each house. This base-load of “always on” may then be subtracted from each home’s data to
13 remove one source of inter-house variation before further processing to extract other information.
14 Base-load estimation may be used in conjunction with any of the methods discussed above in
15 order to obtain more accurate or specific results.

16 [00076] In accordance with some embodiments of the present invention, the base-load
17 may be calculated as a minimum value over a certain period, often one (1) day or longer. More
18 broadly, the base-load estimated may be based on examining a subset corresponding to the
19 lowest hourly usage. Such distribution of hourly usage may be analyzed to produce a base-load
20 estimate (e.g. a mean). Note that it is contemplated that actual hourly usage may, at times, dip
21 below the determined base-load. Accordingly, in accordance with some embodiments of the
22 present invention, algorithms used may remove and/or ignore certain outlier data points. Also

1 note that due to changing seasonal conditions, a separate base-load estimate may be made for
2 each day/week/month etc.

3 [00077] Identifying Pool Pumps

4 [00078] In determining specific appliance loads from a whole house profile, it may be
5 advantageous to remove loads from identified appliances. Pool pumps may often be recognized
6 by their specific wave form and load characteristics. Removal of pool pumps from composite
7 data may also assist in obtaining a more accurate or specific appliance load identification.

8 [00079] With regard to pool pumps, it can often be assumed that the pool pump will start
9 and end at approximately the same time every day for some period of time (2 weeks, a month, a
10 year, etc.). To infer the start time, duration, or amplitude of the pool pump data can be combined
11 from several days, such that the pool pump usage becomes more prominent (due to schedule
12 consistency and high amplitude. For example, in accordance with some embodiments of the
13 present invention a match filtering approach may be used to identify the start time, and possible
14 duration of the pool pump. Such filter may have a 24-hour periodicity, and examination of how
15 the periods with the pool pump running differ from those where it is not running may be used to
16 estimate the amplitude/wattage of the pool pump.

17 [00080] With reference to Figure 8, an exemplary energy disaggregation technique 80 for
18 a pool pump, in accordance with some embodiments of the present invention will now be
19 discussed. A one-dimensional low-resolution whole house energy time series data 810 may be
20 rearranged 820 to a two-dimensional “image” 830. For example a one-hour-sampled signal of
21 length n can be rearranged as a $(n/24) \times 24$ image (focusing on the case where n is a multiple of
22 24 with one-hour sampling), in which the i th row represents i th day sequence and “pixel” (i, j)
23 reflects the j th hour energy usage. A higher intensity may represent a higher whole-house usage

1 value. A pool pump edge detection 840 may be processed utilizing a reasonable assumption that
2 the pool pump may start and end approximately the same time everyday across a period of time.
3 Accordingly the pure pool pump pattern in the house energy image may be seen in the edge map
4 850 as a vertical stripe with stripe width approximately matching the duration and stripe length
5 equal to number of days pool pump running consecutively.

6 [00081] Hence the pool pump identification and usage estimation may be seen as a
7 vertical stripe detection problem in the corresponding image. A Sobel-like edge detection 860
8 with pool pump specific kernel design can be applied to find candidates for starting and ending
9 times in the first stage. Each starting time and ending time pair 860 and an associated amplitude
10 may constitute a candidate pump configuration. In the next stage, parameter estimation 870 of
11 the final pool pump starting time, ending time and amplitude may be obtained via a search in that
12 configuration space using candidate start and end times as starting points. This may refine the
13 time estimate with a higher temporal granularity and may simultaneously rate the possible
14 configurations using a numerical criterion. The numerical rating takes into account several
15 factors, including the consistency of individual rising or falling pool pump edges, and how often
16 a rising/falling edge pair coincide (occur on the same days). In addition, there may be a
17 particularly high penalty if the usage falls below a minimum pool pump usage threshold dictated
18 by the amplitude of a candidate configuration. A final pool pump estimation 880 may thus be
19 obtained.

20 [00082] Note that the pool pump estimation routine discussed above may only be invoked
21 when it is believed that a given house or user has a pool pump that is contributing to the total
22 energy usage. The presence of a pool pump may be indicated by user input or obtained from
23 other sources, such as a real estate or tax database. The source of this information can be

1 indirect, requiring a layer of analysis before a conclusion about whether a pool pump is active in
2 a house can be reached, e.g. via the processing of satellite images. However, even in the absence
3 of the aforementioned inputs, automatic pool pump detection (i.e. whether the house has a pool
4 pump) can be attempted using only the whole-house low frequency usage data. Variations may
5 occur; for example, the process of pool pump usage and parameter estimation may be extended
6 to use a similar numerical rating for the best configuration found to determine whether it
7 corresponds to an actual pool pump. Various criteria computed in the search for a configuration
8 or some variations may also be used as features in a supervised learning model that may be
9 designed to determine whether a user even has a pool pump. When it is known whether the pool
10 pump is present for a house then its data can be included in the training set. This approach may
11 also be extended to determine the number of pool pumps present, even in the case where the
12 number is greater than one.

13 [00083] Supervised Learning Based Energy Disaggregation

14 [00084] In addition to the methods and techniques discussed above, supervised learning
15 may be used to perform one or more steps of energy disaggregation. Supervised learning may
16 refer herein to an approach where another data set including single-appliance usage (i.e. labels)
17 may be leveraged to learn a method. Training data (as discussed above) may come from the same
18 household or from other households. Ground-truth information may be obtained by several
19 means, including the output of disaggregation using higher-resolution data (e.g. with a one-
20 second energy usage sampling period, this labeling can be imperfect), or the placement of
21 individual plug-level sensors for each appliance.

22 [00085] In accordance with some embodiments of the invention, an approach to
23 supervised learning may comprise the estimation of consumption of an appliance during an

1 interval. As a non-limiting example, for data sampled at 1-hour intervals, an estimate can be
2 made for every hour. The total consumption during that given period, as well as information
3 about how that consumption changes before and after such period, may be used to make an
4 estimate.

5 [00086] Such information may be preprocessed, encoded or transformed in several
6 possible ways (for example, but not limited to a Fourier Transform, determining the difference
7 between nearby data points, etc.). In addition, other vital information associated with the
8 period/home, such as temperature, time of day, humidity, and other information discussed above
9 may be used by a trained supervised learning algorithm (classification or regression) to output
10 information about appliance-level activity in a given period (outside of the training set). The time
11 data may therefore be transformed to reflect circular distance in the 24-hour-cycle (e.g. 23:00 is
12 just as close to 00:00 as it is to 22:00). In accordance with this method, the single-appliance
13 usage over a longer period may be obtained by aggregating over usage over the smaller intervals
14 comprising it. The data can be used as a feature (variable or observable) directly, or it can be
15 exploited in other ways, such as segmenting homes into groups based on certain attributes. The
16 motivation behind this is to use training data only from homes in a similar category for
17 disaggregation analysis in a given home, which are likely to share some characteristics or usage
18 patterns on a whole-house or single-appliance level.

19 [00087] Grouping can be based on household size, amplitude of dryers, geographical area
20 (zip code) and so on. Therefore, some of the available data fields, including those in List 2, can
21 also be used for segmentation or clustering as a processing step, rather than a direct input or
22 feature in supervised regression or classification. Moreover, other analysis such as the
23 unsupervised approach in section 3.3.3 can be used to segment or group homes based on heating

1 and cooling usage. As an example, the temperature-based method can be used to identify homes
2 which do not have any electric heating or cooling, and a separate model can be built and used for
3 this class of homes. While this is an illustrative example, this may be applied more broadly – for
4 example to segment homes based on heating /cooling characteristics and needs. Similarly, the
5 output of other forms of analysis can be used as a means for home or user segmentation.

6 [00088] Alternatively, for the direct estimation of total usage during a longer period (e.g.
7 week/month) by individual appliances, a variation of this approach which featurizes the whole-
8 house time series (and others such as temperature) during that period using other methods.
9 Examples of this include signal transforms, estimation of usage density for sampling period,
10 smoothing, and other techniques to summarize activity without large sensitivity to small
11 temporal variations in appliance cycle occurrence.

12 [00089] Two-Step Supervised Learning

13 [00090] With reference to Figure 9, an exemplary embodiment of two-step learning will
14 now be discussed. In practice, supervised learning may be performed in a two-step process,
15 comprising detection and estimation. In accordance with some embodiments of the invention,
16 the problem may be broken up into a classification stage and another stage to calculate actual
17 appliance usage in KW-hr or other unit of energy. In the classification stage, the supervised
18 learning classifier (e.g. Support Vector Machine) may be used to determine whether an appliance
19 is on or off during a period (e.g. 1-hour for data sampled at 1-hour intervals). This output may
20 then be used in conjunction with whole-house usage at all time points to calculate single-
21 appliance usage in an appropriate energy unit. This process (possibly indirectly) may infer to
22 usage for the intervals when it is on (this is tied to the electric wattage of the appliances).

1 [00091] If the training data for the classifier is obtained from other households, then a
2 home's own whole-house data may be used to make an inference related to an appliance cycle
3 usage level. In one variant, the estimation may be accomplished by solving a system of linear
4 equations with the sum of the appliances that are on during certain intervals on one side, and the
5 whole-house usage during the corresponding intervals on the other side. This may yield a per-
6 interval (e.g. per hour) coefficient that may be useful for aggregating single appliance usage over
7 a period (containing multiple sampling intervals). This process may be further refined by
8 incorporating other information, such as temperature. A separate classifier may be trained for
9 each appliance, but several appliances may be combined and jointly trained for more than one
10 appliance. This may be accomplished by converting it into a multi-class rather than a binary
11 classification. In this case each class may correspond to a different combination of the separate
12 appliances being on or off. Information specifying whether certain appliances are on or off at
13 different times may come from a data source, such as a thermostat, or Mhz-level electric monitor.
14 In such circumstances, the corresponding output of the classifier/detection stage may be replaced
15 with this information thereby removing a source of error. Such confirmation may also be used as
16 another feature or for consistency checks of other methodologies.

17 [00092] User-provided information, such as the data obtained during a training mode, may
18 provide concrete information about the appliance usage when it is on. This may be incorporated
19 into the detection process for more accurate classification, or incorporated into the appliance
20 usage estimation process. As a simple example, if a dryer amplitude or average cycle usage is
21 known, a dryer cycle count in a time interval (e.g. week) may suffice for dryer usage estimation
22 during that interval. This also applies to the approach in the next subsection (direct estimation).

1 [00093] With renewed reference to Figure 9, an exemplary method 90 of a two-step
2 training process will now be discussed. Steps of detection may comprise receiving or using data
3 from a test period 910 or from training data 930. Data received from a test period 910 may be
4 processed to compute feature vectors of the test data 920, as discussed above. Similarly, training
5 data 930 may also be processed to compute feature vectors 940 of the training data. The training
6 data may be further processed through an “on/off” type classifier 950, which may record and
7 indicate known cycles of an appliance. As discussed in more detail below, an on/off classifier
8 950 may receive information and data from different training sources 990.

9 [00094] The feature vectors of the test data 920 and the feature vectors of the training data
10 950 may then be processed to detect hourly appliance usage 960, as noted above. From the
11 hourly appliance usage 960, as well as test data and data from different training sources 990, an
12 appliance usage estimation 970 may be obtained. And from this estimation 970, an appliance
13 level usage for a test period 980 may be determined.

14 [00095] Note that throughout the process, information from training sources 990 may be
15 utilized. Training sources 990 may comprise user training 991 data, as discussed above, input
16 from sensors 992 (such as a smart phone, voltage sensor, etc.), as discussed above, and/or any
17 other type of user input 993 that may assist in identifying the appliance, its timing, cycles, and/or
18 profile.

19 [00096] One-Step Supervised Learning

20 [00097] In accordance with some embodiments of the present invention, a one-step
21 supervised learning method may be employed. In this variation, a single estimation/regression
22 stage using a feature set similar to that described above may be used to directly estimate usage.
23 In this case a supervised machine learning regression algorithm may be used to relate such

variables to single appliance usage during a sampling interval (e.g. one (1) hour). A separate solution may be obtained for each appliance, but multi-label or multi-target regression can jointly learn an estimator for all appliances using the training labels from all appliances. This may exploit relationships between the appliance usages.

[00098] It will be understood that the specific embodiments of the present invention shown and described herein are exemplary only. Numerous variations, changes, substitutions and equivalents will now occur to those skilled in the art without departing from the invention. Accordingly, it is intended that all subject matter described herein and shown in the accompanying drawings be regarded as illustrative only, and not in a limiting sense, and that the scope of the invention will be solely determined by the appended claims.

Claims

1. A method for learning an energy consumption signature associated with a specific appliance from energy consumption interval data sampled ranging from minutely to hourly associated with a specific house, comprising:
 - receiving at a processor the energy consumption interval data;
 - selectively communicating by the processor with a first database comprising non-electrical information;
 - selectively communicating by the processor with a second database comprising training data, the training data comprised at least in part of high resolution energy consumption data sampled periodically with periods of less than one minute, received from a plurality of homes associated with appliances at least some of which are the same type as the specific appliance; and
 - determining a correlation between the energy consumption interval data and the training data;
 - determining based at least in part on the correlation that the specific appliance was running during the interval data; and
 - identifying the energy consumption signature of the specific appliance.
2. The method of claim 1, wherein the low-resolution energy consumption interval data is received from one or more of the group consisting of:
 - a smart meter;
 - a meter data management system from a utility back office;
 - a website of a utility; and
 - a non-utility installed sensor or measuring device.
3. The method of any one of claims 1 and 2, wherein the non-electric information comprises home and community specific attributes comprising one or more of the group consisting of:
 - zip code;
 - local weather;
 - home size;

home age;
information about presence of various appliances in the household;
sensor inputs such as thermostat data;
gas consumption data; and
water consumption data.

4. The method of claim 3, wherein the non-electric information is procured from third party sources.

5. The method of any one of claims 1 to 4, wherein the first and second database are the same database.

6. The method of any one of claims 1 to 5, wherein at least some of the training data in the second database is obtained by:

receiving high frequency energy consumption or power data from a plurality of homes;

running one or more disaggregation algorithms to produce a disaggregated appliance output;

saving the disaggregated appliance output in the second database.

7. The method of any one of claims 1 to 6, wherein at least some of the training data in the second database is obtained from plug-level sensors.

8. The method of any one of claims 1 to 7, wherein at least some of the training data in the second database is obtained from user provided information about start and stop times of appliances in the user's home.

9. The method of any one of claims 1 to 8, wherein the step of identifying occurrences during which the specific appliance was likely running comprises:

segmenting or grouping training data based upon various criteria;

receive the input low resolution energy consumption data and determine a matching segment or group for analysis;
train a classifier based upon the determined matching segment or group;
use the trained classifier to identify occurrences of usage of the specific appliance in the input low resolution energy consumption data.

10. The method of any one of claims 1 to 9, wherein the step of learning the energy consumption signature of the specific appliance comprises:

identifying any scheduling consistency of certain periodic loads in the input low resolution energy consumption data;

determining, based upon non-electrical data, whether the house has a pool;

determining, based on scheduling consistency and the presence of a pool the existence of a pool pump;

determining, based upon the existence of a pool pump and scheduling consistency of certain periodic loads in the input low resolution energy consumption data, the individual energy consumption profile for the pool pump.

11. The method of any one of claims 1 to 10, wherein a confidence level of energy consumption profile for the detected pool pump is calculated based on a number of attributes including a number of days the pattern repeats per day, week, or month

12. The method of any one of claims 1 to 11, wherein the step of estimation of energy consumption by the specific appliance comprises:

receiving a series of detections identified occurrences of the specific appliance;

calculating weights based at least in part on the temperature profile data;

calculating the estimated energy consumption as a weighted sum of the series of detections.

13. The method of claim 12, wherein the step of estimation of energy consumption by the specific appliance comprises searching for a setpoint during the calculation of weights based on temperature profile data.

14. A method for learning the energy consumption signature associated with an appliance from energy consumption interval data sampled ranging from minutely to hourly associated with a specific house, comprising:

receiving temperature data from the specific house for a period of time;

identifying the energy consumption interval data as a combination of temperature dependent and non-temperature dependent components;

using a regression framework, estimating heating, cooling, or heating and cooling energy consumption based at least in part upon:

the identified temperature-dependent components; and

high resolution training data sampled periodically with periods of less than one minute; comprising at least in part feedback by a user through an interactive user interface using interactive charts; and

performing an action of energy management by presenting information regarding the energy consumption signature of the specific appliance to a user.

15. The method of claim 14, wherein the low-resolution energy consumption data is represented as a linear combination of heating or cooling terms at different intervals of the day such as morning, afternoon, evening and night.

16. The method of any one of claims 14 and 15, further comprising:

receiving temperature data from the specific house, as identified by the input low resolution energy consumption interval data for a period of time;

detecting one or more days where daily energy usage profile has a most positive or negative correlation, global and local, with a temperature profile;

running a smoothing filter over a series of the detected days;

using a regression framework, estimating heating, cooling, or heating and cooling energy consumption based upon a correlation coefficient for at least some of the detected days.

17. The method of claim 16, wherein the temperature data is shifted by adding a temporal delay before finding correlation with the energy consumption to account for insulation of the house.

18. The method of claim 17, wherein a search is performed over a domain of delays to find a shift to be applied to the temperature data to maximize a correlation with energy data profile.

19. A method for learning the energy consumption signature associated with an appliance from low resolution energy consumption interval data associated with a specific house, comprising:

receiving at a processor the low-resolution energy consumption interval data, wherein the data is sampled periodically with periods ranging from one or more minutes to hourly;

selectively communicating with a first database comprising non-electrical information;

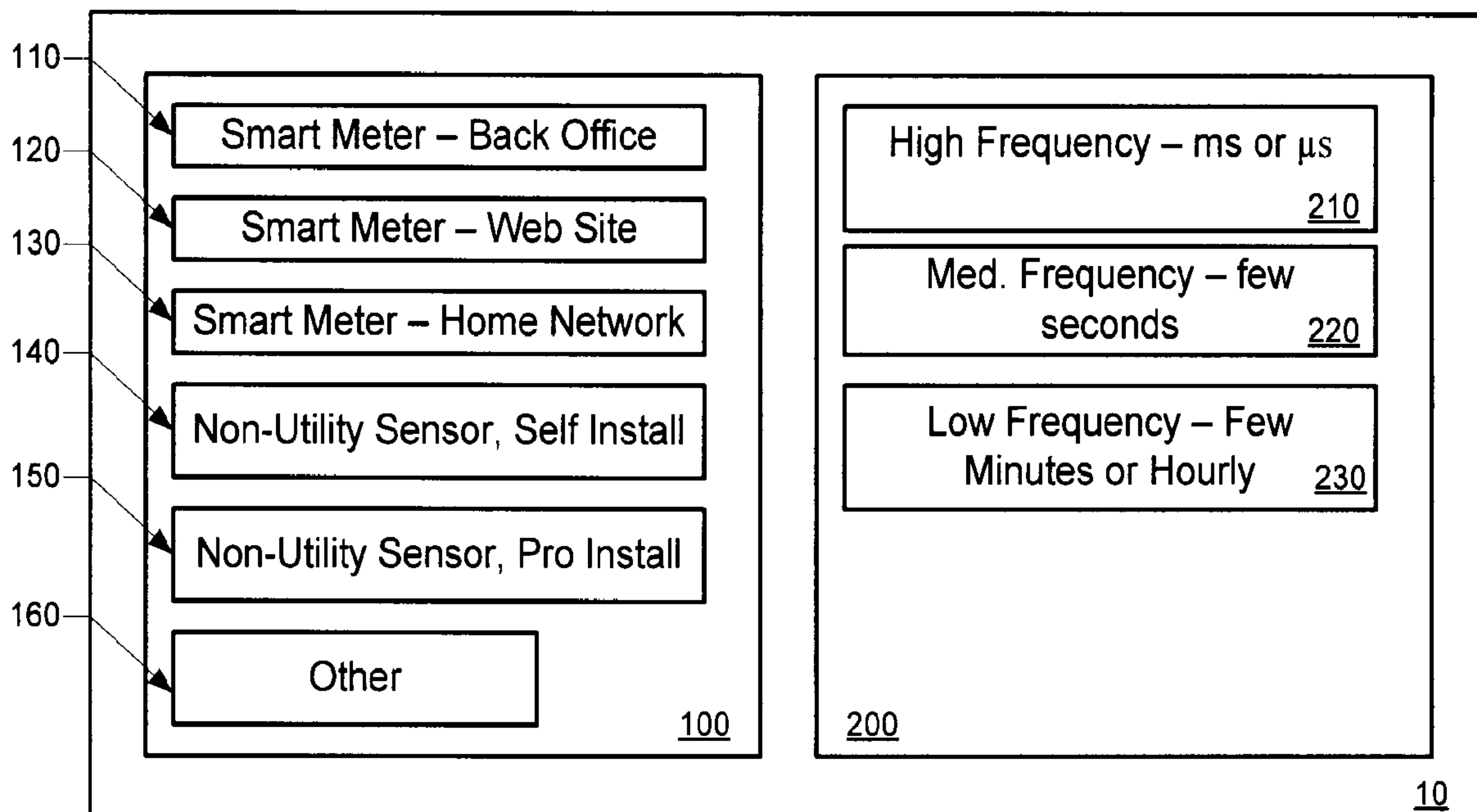
selectively communicating with a second database comprising training data, the training data comprised at least in part of appliance level energy consumption data associated with a plurality of homes; and

finding the closest matching set of homes within the training data where the whole house low-resolution energy consumption interval data for the specific home matches the corresponding whole house interval data;

estimating of the energy consumption by the appliance at a hourly, daily or monthly scale, by combining the energy consumption of that appliances over the closest matching set, thereby learning its energy consumption signature.

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FIGURE 1



SHEET 2 / 8

FIGURE 2A

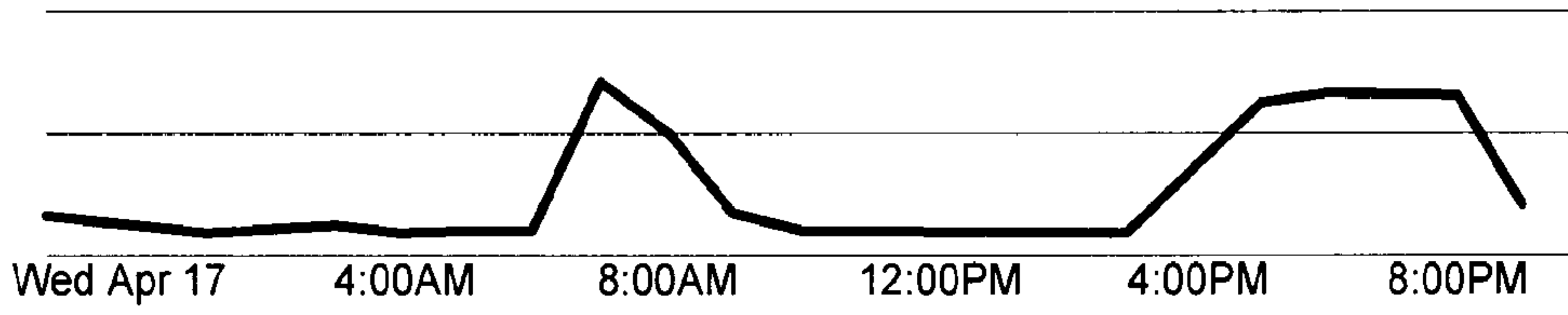


FIGURE 2B

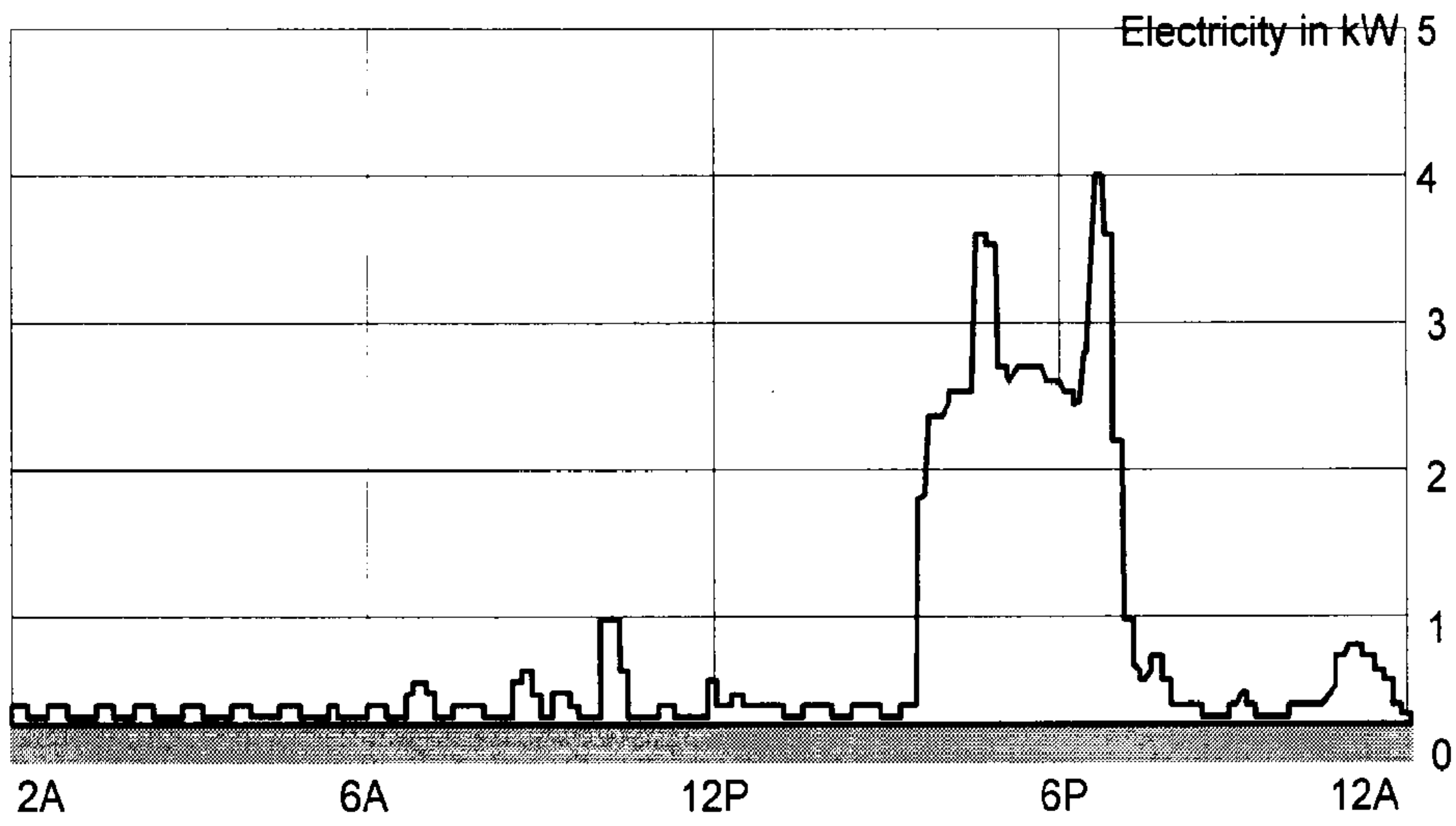
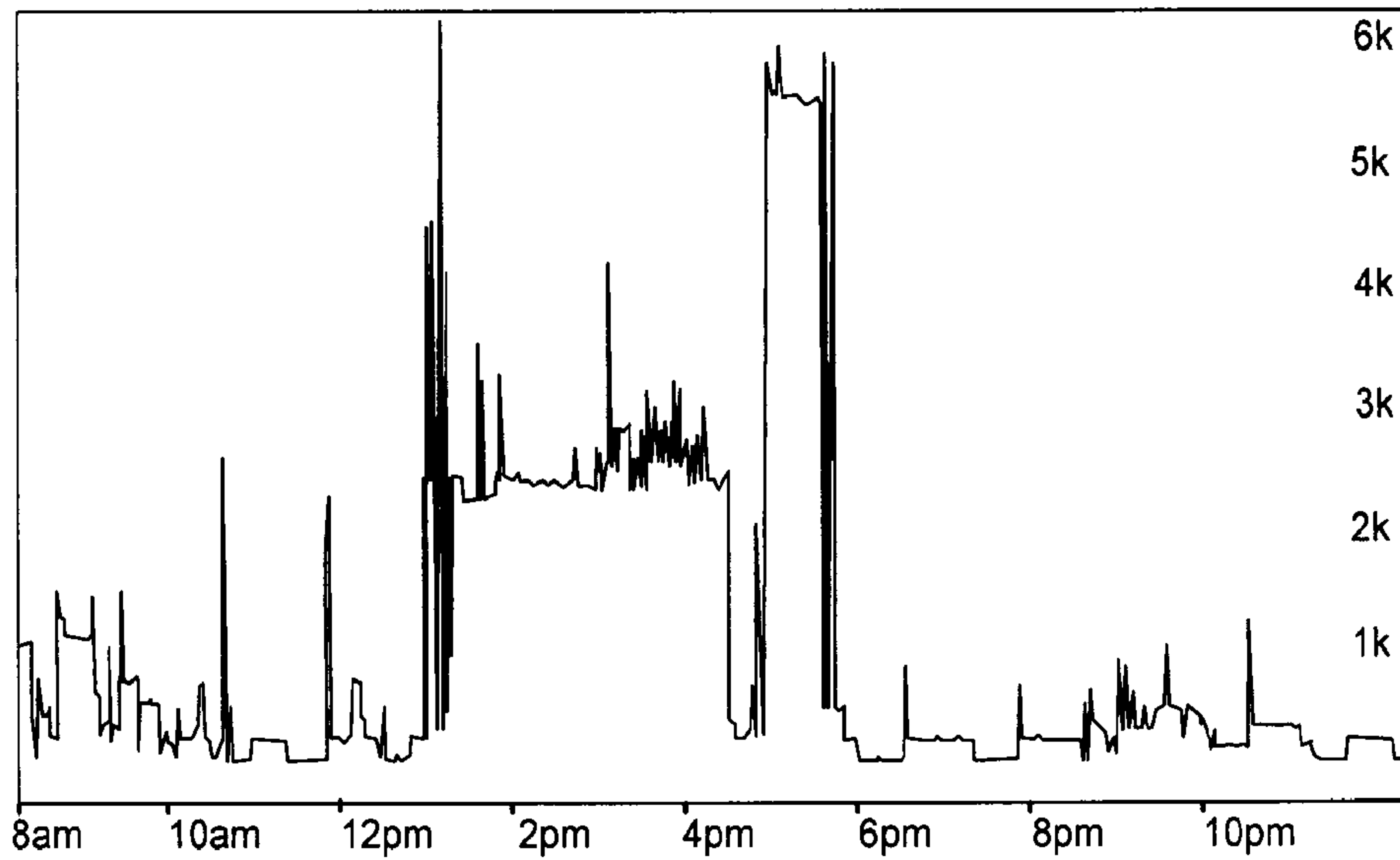
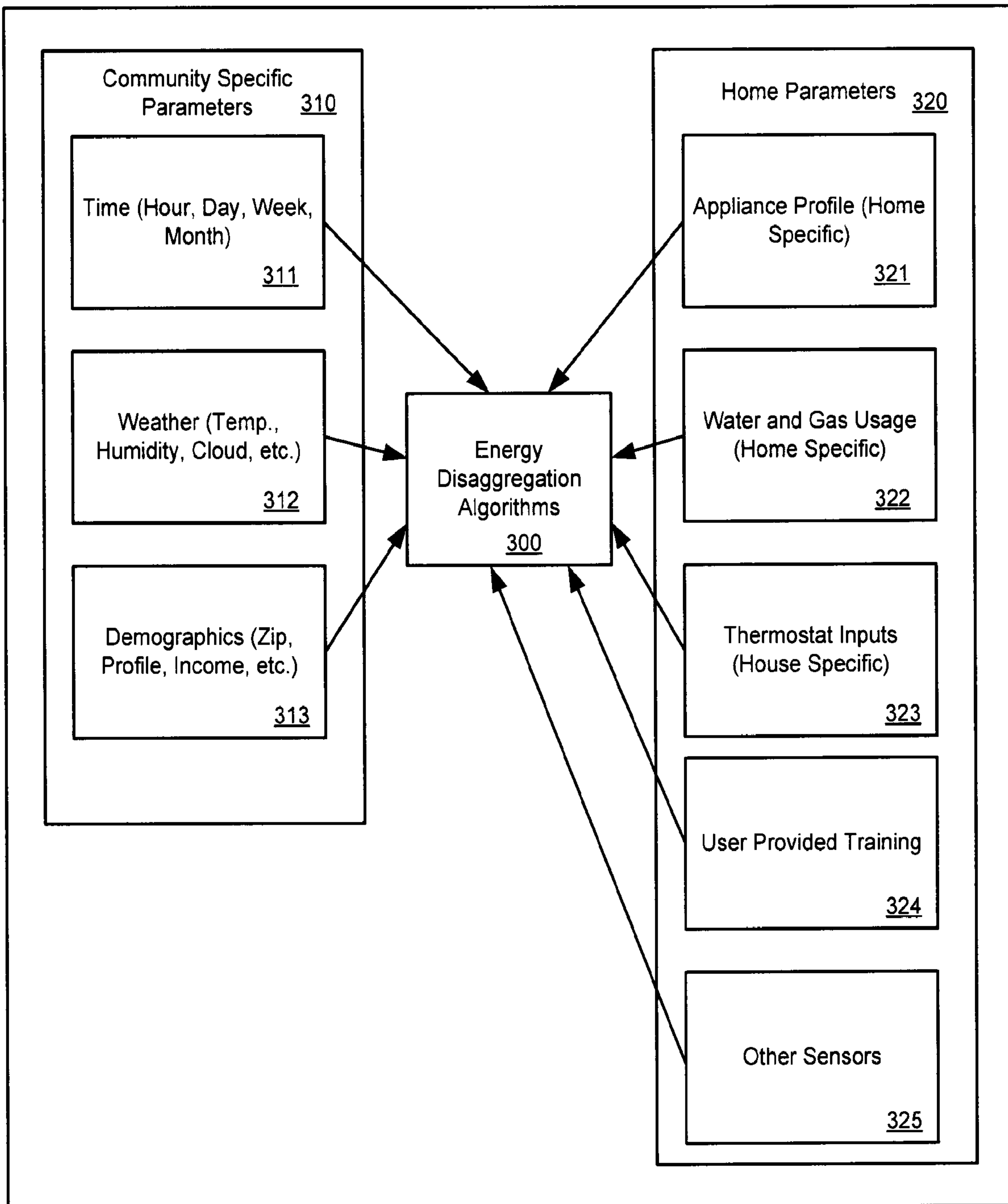


FIGURE 2C



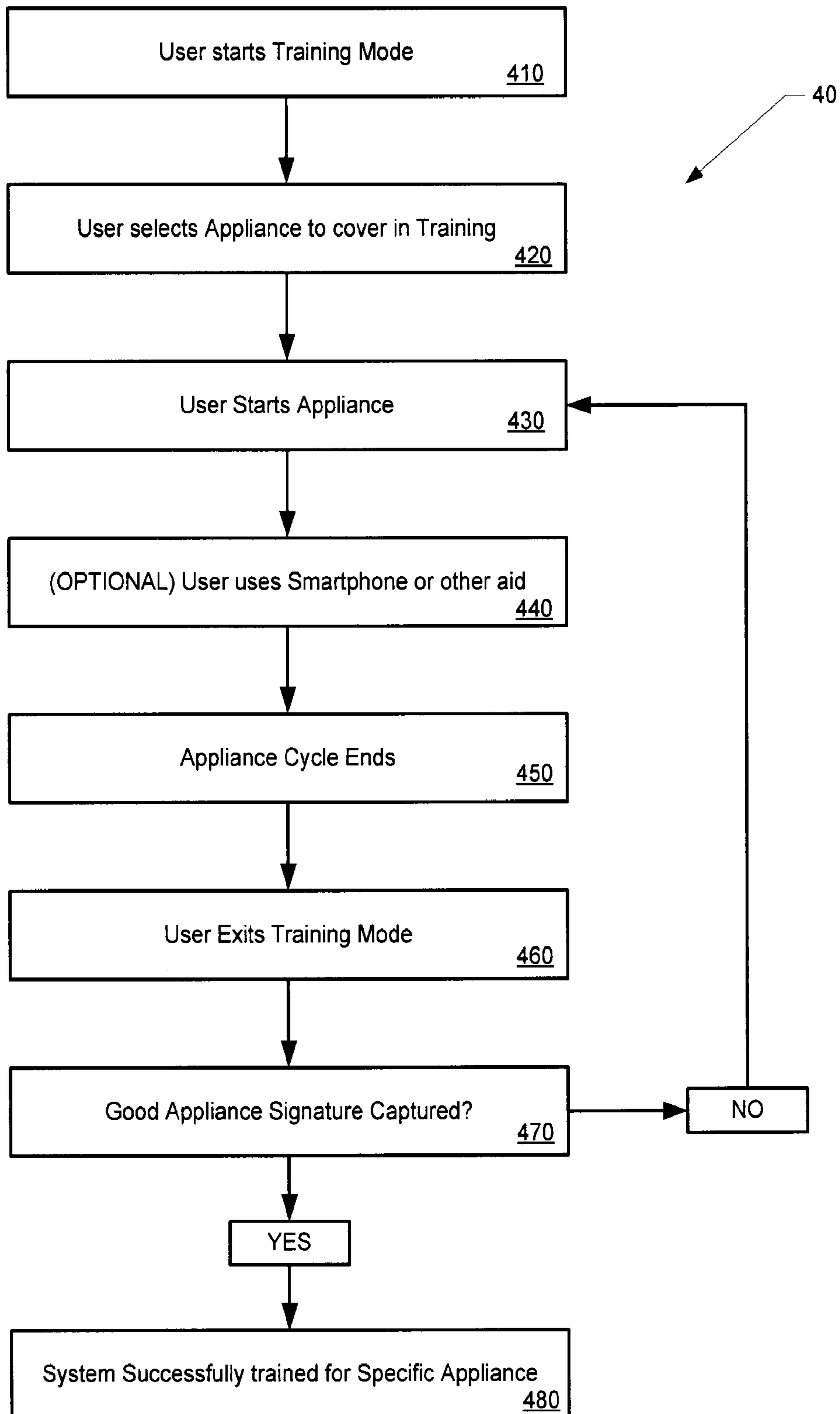
SHEET 3 / 8

FIGURE 3



SHEET 4 / 8

FIGURE 4



SHEET 5 / 8

FIGURE 5

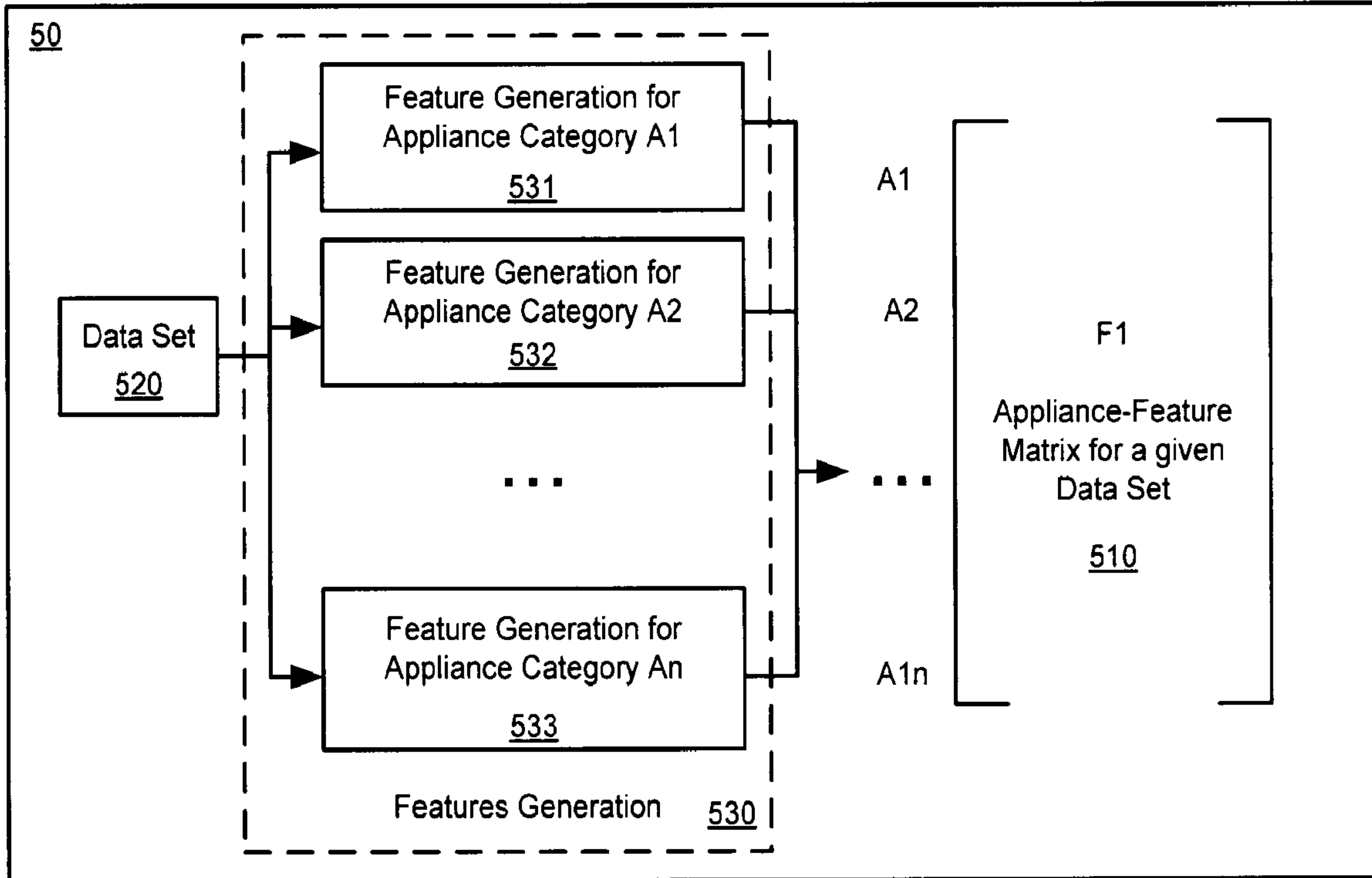
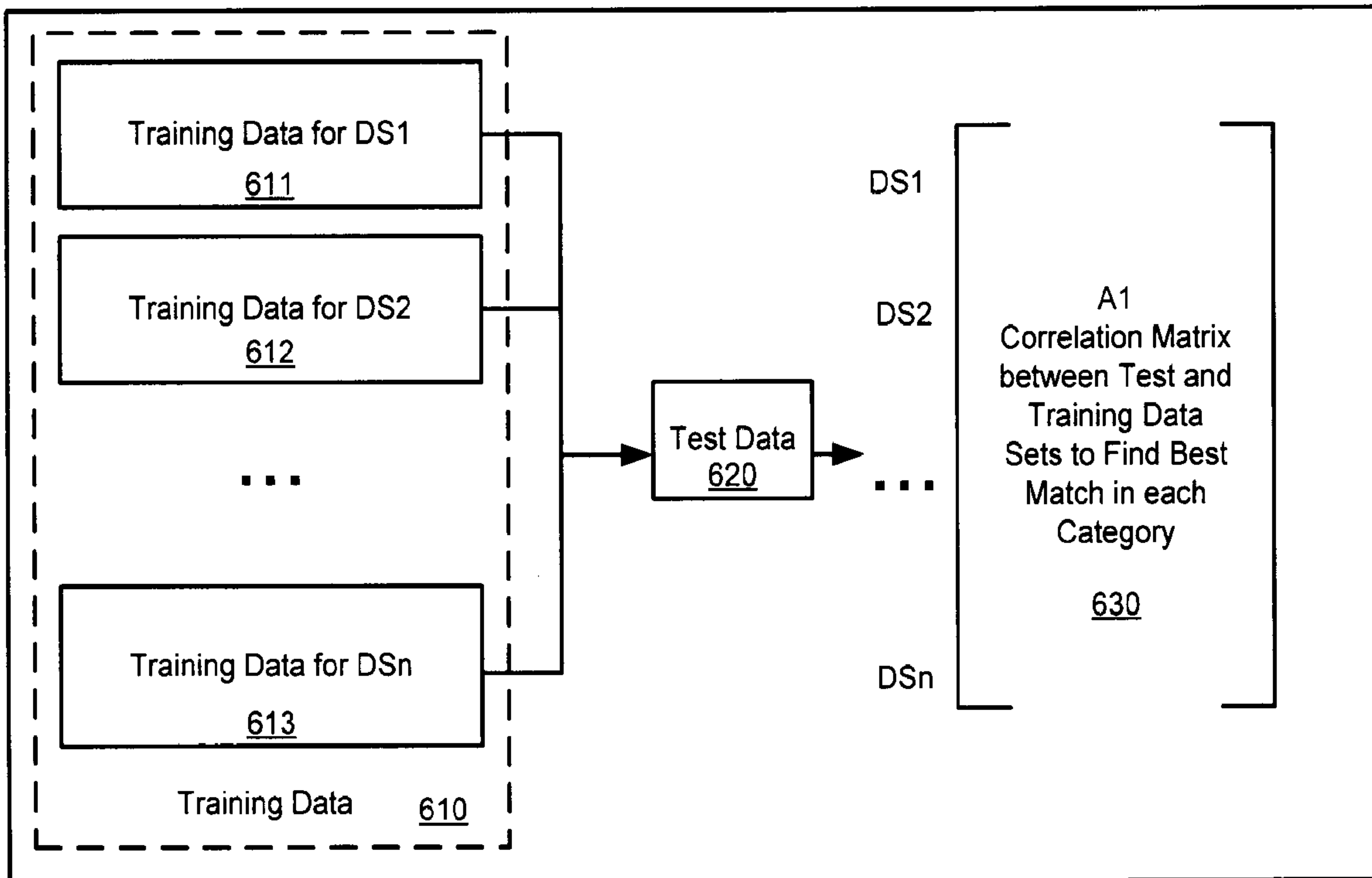
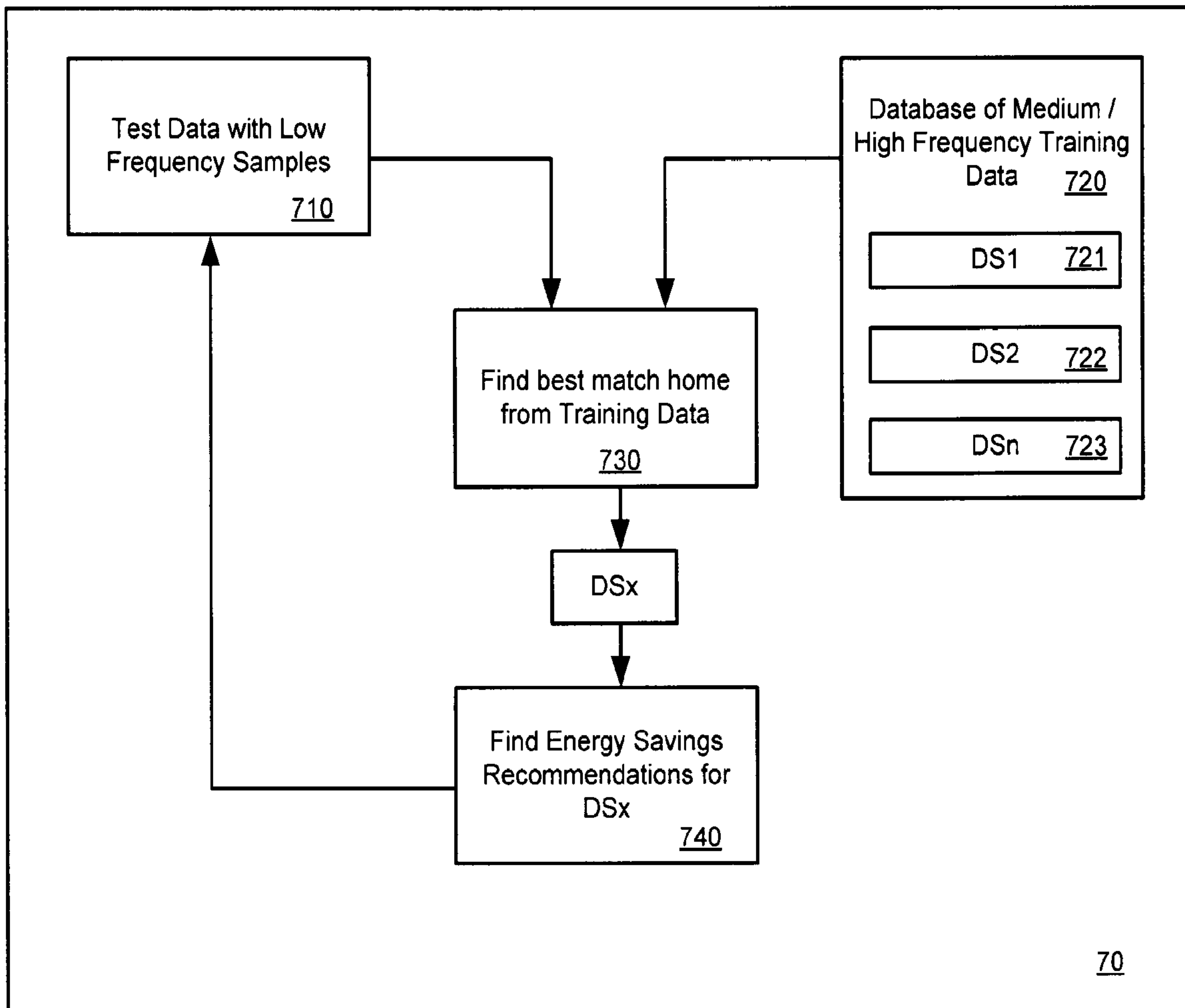


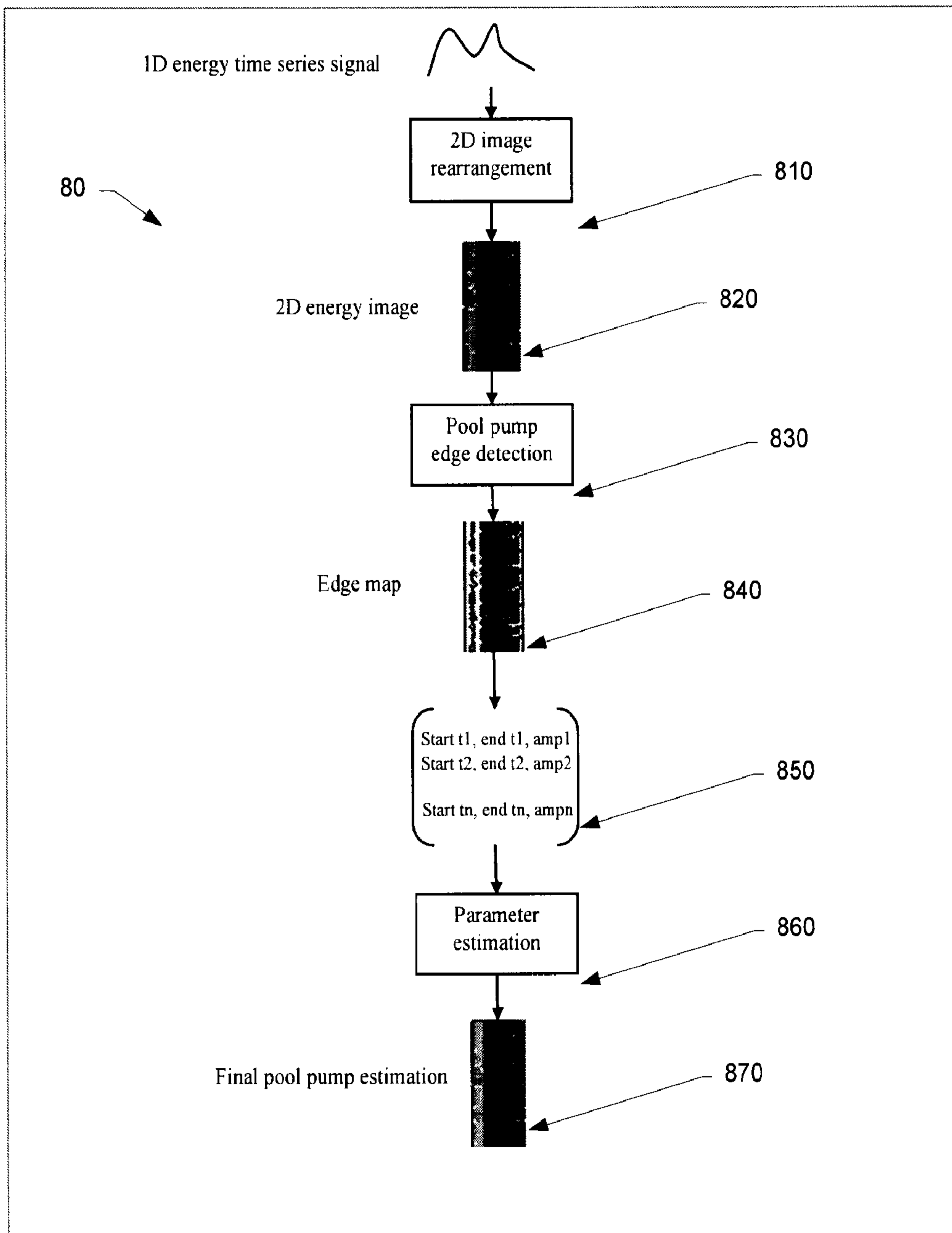
FIGURE 6



SHEET 6 / 8**FIGURE 7**

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FIGURE 8



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FIGURE 9

