

METHOD AND SYSTEM FOR ENERGY MANAGEMENT BY ENERGY USAGE IDENTIFICATION AND VISUALIZATION

TECHNICAL FIELD

[0001] The present invention generally relates to energy management, and more particularly relates to method and systems for energy management by energy usage identification and visualization.

BACKGROUND OF THE DISCLOSURE

[0002] With the rising cost of energy, energy management is essential to controlling costs. Energy usage is critical to energy management as varying usage of energy can vary energy costs. Also, improved energy management has environmental benefits in conservation of energy producing fuel and reducing light and heat pollution. Yet, energy management of large office and housing buildings of tens or hundreds of units and large common areas presents challenges.

[0003] One way to obtain information to manage energy costs is to observe the total energy used from a main power source for a facility. In a small building with one or only a few units, this may be manageable. However, with increased size, such energy management schemes based only on raw data from a main power source becomes unmanageable. It is fairly impossible to tell which energy drawing loads are responsible for which parts of the energy usage.

[0004] Another way would be to monitor energy usage of individual energy drawing loads. While individual units in large office and housing buildings have energy usage monitored for billing purposes, the common areas of such buildings include energy drawing loads such as elevators, lighting and heating, ventilation and air conditioning

(HVAC) equipment. Monitoring of each of these energy drawing loads in such buildings could lead to an unmanageable level of information.

[0005] Thus, there is a need for methods and systems for energy management by energy usage identification and visualization which overcome the drawbacks of the prior art. Furthermore, other desirable features and characteristics will become apparent from the subsequent detailed description and the appended claims, taken in conjunction with the accompanying drawings and this background of the disclosure.

SUMMARY

[0006] According to at least one aspect of the present embodiments, a method for training an energy usage identification system is provided. The method includes dividing a measurement log of aggregate energy usage data corresponding to energy usage of a plurality of loads into a plurality of training samples, each of the plurality of training samples comprising energy data sequences. The method further includes constructing a set of multiple neural network models, extracting a mini-batch of samples and a test sample from the plurality of training samples, and simultaneously training each of the set of multiple neural network models with the mini-batch of samples to derive inferred load-based energy usage data of one or more of the plurality of loads. In addition, the method includes determining an accuracy of the inferred load-based energy usage data for each of the multiple neural network models in response to the test sample, and eliminating from the set of multiple neural network models ones of the set of multiple neural network models exhibiting one or more of a set of poor result criteria. Finally, the method includes repeating simultaneously training of remaining ones of the set of multiple neural network models until an optimal one of the set of multiple neural network models for inferred load-based energy management is

identified in response to determining whether or not an accuracy target difference between actual load-based energy usage data and the inferred load-based energy usage data generated by one of the multiple neural networks using the test sample is met.

[0007] According to an additional aspect of the present embodiments, a first training sample extraction method is provided. The method includes selecting a first one of a plurality of training samples from a measurement log, and selecting subsequent ones of the plurality of training samples from the measurement log in accordance with a stochastic gradient descent stride scheme, wherein the stochastic gradient descent stride scheme requires a subsequent stride between a selected training sample and a next selected training sample be less than previous stride between the selected training sample and a previous selected training sample.

[0008] According to a further aspect of the present embodiments, a second training sample extraction method is provided. The method includes selecting a first one of a plurality of training samples from a measurement log, and selecting subsequent ones of the plurality of training samples from the measurement log in accordance with a scattered selection scheme, wherein the measurement log has a start measurement and a finish measurement. In accordance with this method, the scattered selection scheme requires two of the subsequent ones of the plurality of training samples to be selected alternatively from a front portion of the measurement log and a back portion of the measurement log relative to an immediately previous training sample immediately previous to a first of the two of the subsequent ones of the plurality of training samples, wherein the front portion of the measurement log is a portion of the measurement log between the start measurement and the immediately previous training sample and the back portion of the measurement log is a portion of the measurement log between the finish measurement and the immediately previous training sample.

[0009] According to another aspect of the present embodiments, a system for identification and visualization of energy usage is provided. The system includes a first sensor connected to a main input electrical signal for sensing the main input electrical signal, one or more second sensors connected to one of one or more electrical loads coupled to the main input electrical signal, and an energy usage identification module coupled to the first sensor and the one or more second sensors. The energy usage identification module includes a sample extraction module, a neural network modelling module and an evaluator and training controller and is configured to operate in an inference mode and a training mode. In the inference mode, the energy usage identification module is configured to disaggregate electrical signals for the one or more electrical loads in accordance with trained energy usage inference for each of the one or more electrical loads. In the training mode, the energy usage identification module is configured to train usage inference for each of the one or more electrical loads utilizing the sample extraction module, the neural network modelling module and the evaluator and training controller. The sample extraction module divides a measurement log of recorded aggregate energy usage data corresponding to energy usage of the one or more electrical loads over a period of time into a plurality of training samples, each of the plurality of training samples comprising energy data sequences. The sample extraction module also extracts a mini-batch of samples and a test sample from the plurality of training samples. The neural network modelling module constructs a set of multiple neural network models and simultaneously trains each of the set of multiple neural network models with the mini-batch of samples to derive inferred load-based energy usage data of one or more of the plurality of loads. The evaluator and training controller determines an accuracy of the inferred load-based energy usage data for each of the multiple neural network models in response to the test sample, eliminates from

the set of multiple neural network models ones of the set of multiple neural network models exhibiting one or more of a set of poor result criteria, and forwards remaining ones of the set of multiple neural network models back to the neural network modelling module for the neural network modelling module to repeat simultaneously training of the remaining ones of the set of multiple neural network models until the evaluator and training controller identifies an optimal one of the set of multiple neural network models for inferred load-based energy management. The evaluator and training controller identifies an optimal one of the set of multiple neural network models for inferred load-based energy management in response to determining whether or not an accuracy target difference between actual load-based energy usage data and the inferred load-based energy usage data generated by one of the multiple neural networks using the test sample is met.

BRIEF DESCRIPTION OF THE DRAWINGS

[0010] The accompanying figures, where like reference numerals refer to identical or functionally similar elements throughout the separate views and which together with the detailed description below are incorporated in and form part of the specification, serve to illustrate various embodiments and to explain various principles and advantages in accordance with present embodiments.

[0011] FIG. 1 depicts a schematic illustration of a system for energy usage identification and visualization in accordance with present embodiments.

[0012] FIG. 2 depicts a schematic illustration of the system for energy usage identification and visualization of FIG. 1 in a training mode in accordance with present embodiments.

[0013] FIG. 3 depicts a flow diagram of a machine learning operation for training of the energy usage identification module of the system of FIG. 2 in the training mode in accordance with the present embodiments.

[0014] FIG. 4 depicts a portion of a measurement log for use by the machine learning operation of FIG. 3 in accordance with the present embodiments.

[0015] FIG. 5, comprising FIGs. 5A and 5B, depicts illustrations of extraction of training samples from the measurement log of FIG. 4 for use in the machine learning operation of FIG. 3 in accordance with the present embodiments, wherein FIG. 5A depicts overlapped training samples and FIG. 5B depicts non-overlapped training samples selected with a progressively diminishing stride.

[0016] FIG. 6 depicts an illustration of extraction of training samples from multiple measurement logs for use in the machine learning operation of FIG. 3 in accordance with the present embodiments

[0017] FIG. 7, comprising FIGs. 7A and 7B, depicts illustrations of operation of the machine learning of FIG. 3 in accordance with the present embodiments, wherein FIG. 7A depicts a modular illustration of the operation of the machine learning and FIG. 7B depicts a flowchart of the operation of the machine learning.

[0018] FIG. 8 depicts an illustration of a neural network structure in accordance with the present embodiments.

[0019] FIG. 9 depicts an illustration of operation within a layer of the neural network structure of FIG. 8 in accordance with the present embodiments.

[0020] And FIG. 10 depicts an illustrative example of user-defined energy usage visualization in accordance with the present embodiments.

[0021] Skilled artisans will appreciate that elements in the figures are illustrated for simplicity and clarity and have not necessarily been depicted to scale.

DETAILED DESCRIPTION

[0022] The following detailed description is merely exemplary in nature and is not intended to limit the invention or the application and uses of the invention. Furthermore, there is no intention to be bound by any theory presented in the preceding background of the invention or the following detailed description. It is the intent of present embodiments to present methods and systems for energy usage identification and visualization as well as methods and systems for energy management utilizing energy usage identification and visualization in accordance with present embodiments.

[0023] Referring to FIG. 1, a schematic illustration 100 depicts a system for energy usage identification and visualization in accordance with the present embodiments. A power switch board 102 is coupled to an incoming main which receives power from the grid and/or alternate power sources and provides the power to a plurality of loads 104. A sensor module 106 is coupled to the power switch board 102 and connected to the incoming main by, for example, current transformer (CT) sensor clamps to monitor a main input electrical signal for aggregate energy usage. The CT sensor clamps provide a non-invasive way to monitor energy usage by clamping around, not on, the main input power supply cable to measure the electromagnetic field around a power cable. The power switch board 102 could be coupled to a power supply for a building having one or a few units, a building having many, even hundreds, of units, or for a plurality of buildings, such as a facility having many buildings either co-located or not. In accordance with the present embodiments, the power switch board 102 is coupled to a plurality of loads 104 and the sensor module 106 monitors energy usage for the plurality of loads 104 from an aggregated electrical signal passing through the power switch board 102.

[0024] The sensor module 106 is connected to a router 108 which is coupled to an energy usage identification module 110 via the cloud 112. The sensor module 106 measures parameters of energy usage from electrical signals measured by the CT clamps such as voltage, current, active power, reactive power, apparent power, power factor and date and time of such electrical signal measurements. The data comprising the measured electrical signal parameters is stored in files in storage 109 in the cloud 112 and/or a storage device in the energy usage identification module 110. The energy usage identification module 110 has two operation modes: a training mode and an inference mode. In the inference mode (which can only occur after the training mode), the module 110 disaggregates the main input electrical signal forwarded from the sensor module 106 via the router 108 or downloaded from the storage 109 in order to identify energy usage of each of the plurality of loads 104. In the training mode, as discussed hereinafter, the energy usage identification module 110 uses machine learning to develop a disaggregation scheme to identify the energy usage of each of the plurality of loads 104 or a subset number of the plurality of loads 104 from within the main input electrical signal.

[0025] In addition, in the inference mode, the energy usage identification module 110 retrieves the data from the stored files in the storage 109. After inference of energy usage of the loads 104, the energy usage information is incorporated into a user-defined individualized visualization format by the visualization module 114 in the cloud 112 and the user-defined formatted energy usage information is provided to each end user 116 when requested. While the illustration 100 depicts a single power switch board 102 coupled to the energy usage module 110, in accordance with the present embodiments, the energy usage identification module 110 can be coupled to a multiplicity of buildings, multi-building facilities or other energy using structures (e.g., a manufacturing facility

such as a chemical processing plant) or combination of structures (e.g., a plurality of co-owned or co-operated residential or business complexes in various parts of a city or state) to monitor energy usage within such buildings, facilities or combination of structures.

[0026] Referring to FIG. 2, a schematic illustration 200 depicts the system for energy usage identification and visualization 100 in a training mode in accordance with present embodiments. In addition to the sensor module 106 being connected to the router 108, during the training mode, CT clamps or other energy monitoring sensors 105 are coupled to sub-circuit cables/wires for each of the plurality of loads 104 or a subset number of the plurality of loads 104 to be identified from within the main input electrical signal sensed by the sensor module 106. Electrical signals from the multiple sensors 105 on the load outgoing cables are also connected to the router 108. The energy usage identification module 110 is set to the training mode and is coupled to the router 108 via the cloud 112 to receive, either directly or as stored in the storage 109, electrical signals from the sensor module 106 and the electrical signals 105 from the ones of the plurality of loads 104 to be identified from within the main input electrical signal.

[0027] Referring to FIG. 3, a flow diagram 300 depicts operation of the energy usage identification module 110 in the training mode in accordance with the present embodiments. Initially, at step 310, data on electrical signals from the sensor modules 105, 106 are loaded into a computing device memory of the module 110 from stored files. These could be files stored within a storage means in the module 110 and/or files stored within the storage 109 in the cloud 112 which include data collected over a period of time (called a measurement log) when the system 300 was in the training mode and collecting electrical signals from the sensor module 106 and from the ones of the plurality of loads 104 to be identified from within the main input electrical signal via the sensor module 105.

[0028] At step 320, in order to clean and prepare the data of the electrical signals from the sensor module 106 for feeding into a neural network, non-valid data points are discarded 322, the data is augmented to generate additional data with patterns not identified by the existing data sets 324, and the data may be converted to the log scale standardized and divided into sequences 326. At step 330, hyperparameters are selected for the neural network 332, the neural network is constructed 334, and the neural network is trained until an accuracy metric goes flat 336. If it appears that the accuracy metric will not converge within a targeted accuracy, all or part of step 320 is repeated with different parameters and step 330 is repeated. This is reiterated until the accuracy target is achieved.

[0029] Referring to FIG. 4, a time series 400 depicts a portion of a measurement log wherein time is plotted along the x-axis 402 and power usage is plotted along the y-axis. A measurement log is a contiguous time series of power meter reading values. The readings are separated by a fixed interval (for example, one second). The whole measure log may span a duration of one to ten days, or even longer. Let a total number of readings within the measurement log be L . For example, a forty-seven-hour measurement log with one-second intervals will contain 169200 readings. The time series 400 shows unaligned load power meter measurements 410 and aligned load power meter measurements 420, as well as a total power meter measurement 430 for all of the loads.

[0030] For training purposes, the measurement log is divided into training samples. A training sample is a small contiguous subset of the measurement log. In accordance with the present embodiment, each training sample contains a fixed number of readings called a timestep, T . The value of the timestep depends on load dynamics, but should preferably be a small fraction of the duration of the measurement log. This duration may vary from fifty seconds to one thousand seconds, or higher.

[0031] Referring to FIGs. 5A and 5B, illustrations 500, 550 depict selection of training samples. Training samples are usually extracted from a measurement log in a sequential manner, which may or may not involve overlapping regions, depending on the stride ΔT which is the number of readings separating the starting points of two consecutive samples. Referring to the illustration 500, three overlapping training samples 510, 520, 530 are depicted having a stride ΔT .

[0032] For non-overlapped sampling with a stride value $\Delta T=T$, the total number of samples obtainable from a measurement log of L readings will be $\text{int}(L/T)$. For fully overlapped sampling, the stride ΔT equals 1 and the total number of samples obtainable from a measurement log of L readings will be $L-T$. There, of course, are a number of other sampling techniques between these two extremes having other values of ΔT .

[0033] The illustration 550 depicts eight non-overlapping training samples 552, 554, 556, 558, 560, 562, 564, 566 having a minibatch timestep of five are extracted from a measurement log 570 in accordance with the present embodiments. In the measurement log 570, there are 133 readings. As neighboring samples are very similar, training sample extraction in accordance with the present embodiments adopts a minibatch stochastic gradient descent since using minibatches from a single temporal vicinity is likely to hit a local minimum. In addition, since weights may vary drastically from one minibatch to another, especially for loads with larger ON/OFF durations, training samples are selected from the measurement log 570 in a scattered manner as shown in the illustration 550, where the front and back halves of the measurement log 570 is alternatively accessed.

[0034] In addition to alternatively accessing the front and back halves of the measurement log 570, training sample extraction in accordance with the present embodiments adopts a progressively diminishing stride instead of a conventional fixed

stride. Utilization of the diminishing stride ensures that training samples 552, 554 are extracted from the widest separation first to ensure that the training samples do not prematurely fall into a local minimum. As training proceeds, the stride reduces which coincides with a need to fine tune parameters. This can be seen where the stride from training sample 554 to training samples 556, 558 is less than the stride from training sample 552 to training sample 554. The stride is further reduced for training samples 560, 562 from training sample 556 and training samples 564, 566 from training sample 558.

[0035] The scheme in accordance with the present embodiments is advantageously very effective with multiple measurement logs scenario, where some gaps occur between logs due to down time of the loggers. Referring to FIG. 6, an illustration 600 depicts multiple measurement log training sample extraction in accordance with the present embodiments where the training samples are extracted from three separate measurement logs 602, 604, 606. The measurement logs 602, 604, 606 are parsed with the widest strides first as shown in the illustration 610. The measurement logs are then reparsed with progressively smaller strides as shown in the illustrations 620, 630.

[0036] After training samples have been extracted from one or a multiple of measurement logs, the training sample sequences are gathered into mini-batches for training by the energy usage identification module 110 in the training mode in accordance with the present embodiments. Training continues in accordance with the present embodiments until a desired accuracy is obtained. Utilization of training sample extraction in accordance with the present embodiments advantageously enables an optimal stride to be automatically obtained in a single training session. Utilization of the training sample extraction scheme in accordance with the present embodiments beneficially provides a better scheme for extracting optimal training samples from one

or a multiple of measurement logs as compared to conventional training sample extraction schemes such as a trial-and-error approach to determine an optimal stride by performing multiple trainings with training samples extracted with difference strides ΔT .

[0037] The training by the energy usage identification module 110 in the training mode involves processing a large number of training samples. Even dividing the training samples into mini-batches still requires a large amount of serial processing of training samples for machine learning. Accordingly, an advantageous solution for efficiently training the energy management system 200 (FIG. 2) is provided in accordance with the present embodiments which provides a time-efficient, less costly machine learning solution for training of the system 200. The machine learning solution in accordance with the present embodiments utilizes the fact that with the introduction of big data technologies, localized computation costs drop at a much higher rate than data access costs. The novel and improved machine learning training solution is depicted in FIGs. 7A and 7B and, in accordance with present embodiments, rethinks the way neural network training is performed. Instead of completing neural network training with a selected hyperparameter set and then repeating the same process serially through multiple hyperparameter sets, the present embodiments provide a multiple instruction single data approach to machine learning. Thus, training in accordance with the present embodiments advantageously avoids a need to perform neural network training multiple times to find optimal hyperparameters, which can prove costly or impossible.

[0038] Referring to FIG. 7A, a modular illustration 700 depicts operation of the machine learning training in accordance with the present embodiments. As indicated previously, measurement logs are stored in, for example, cloud storage 109. Before

parallel training starts, a N set of hyper parameters are assigned to N neural network models. A sample extractor 710 extracts a mini-batch of S samples and one test sample. Each of the S samples are fed in parallel to all N neural network models 720, 722, 724 for mini-batch parallel neural network training. The test sample is then used for accuracy evaluation after each mini-batch training. The mini-batch accuracy evaluation results are fed into a mini-batch based evaluator and training controller 730 to develop a global picture of all N models. The controller 730 then decides based on mini-batch training of the S sample which neural network models 720, 722, 724 to short-list for further mini-batch training.

[0039] In accordance with the present embodiments, the controller 730 can eliminate some of the neural network models 720, 722, 724 from further training when results from such neural network model(s) exhibit divergence in accuracy or has poor results. A next mini-batch can then be extracted for a next iteration of mini-batch parallel neural network training. Such parallel training with a single training batch with selective premature termination of models can advantageously be used with the above-described training sample extraction approach making it less likely for individual neural network model to hit a local minimum in the initial stages of training. By the time a fine-tuning stage is reached, only a selected few neural network models survive. These neural network models can then be quickly trained to identify an optimal neural network model for energy management in accordance with the present embodiments. Premature removal of neural network models with bad hyperparameters from the training process in accordance with the present embodiments allows released computation resources to be reallocated to the remaining models, thus advantageously reducing training time further.

[0040] Referring to FIG. 7B, a flowchart 750 describes the machine learning training process of the energy usage identification module 110 in accordance with the present embodiments. When the energy usage identification module 110 is placed in the training mode 752, the N neural network models 720, 722, 724 (FIG. 7A) are set up 754 with hyperparameter sets. The parameters of the N neural network models 720, 722, 724 are initialized 756 and a mini-batch of S training samples and one test sample are selected 758.

[0041] The N neural network models 720, 722, 724 are parallel trained 760 with the S samples. The mini-batch based evaluator and training controller 730 then evaluates 762 the accuracy of the results of all of the N neural network models 720, 722, 724 using the one test sample and determines 764 if any model needs to be terminated, reallocates computation resources and updates the N neural network model set for further mini-batch training. If the minimum accuracy is not reached 766, processing returns to get a new mini-batch of S training samples and the one test sample 755 for parallel training 760 with the updated N neural network model set. When the minimum accuracy is reached 766, the training is completed 770 and the optimal neural network model is used by the energy usage identification module 110 for disaggregation of energy usage of each of the plurality of loads 104 or a subset number of the plurality of loads 104 from within the main input electrical signal during the inference mode of operation of the energy usage identification module 110.

[0042] The time to train the machine learning operation in accordance with the present embodiments advantageously reduces the time to train the model by simultaneously processing selected samples from disparate locations in the data sequence in multiple neural networks and then testing converging neural networks with a test sample to

determine a trained neural network that provides results within the predetermined accuracy target.

[0043] Referring to FIG. 8, an illustration 760 depicts the parallel training of multiple neural networks 852, 854, 856 constructed in accordance with the present embodiments. The S samples 860 are input into the multiple neural networks 870, 880, 890. The neural networks are multi-layer convolution-based neural networks (i.e., neural networks with convolution layers, such as Convolution Neural Networks (CNN), CNN plus Recurrent neural Networks (CNN + RNN), AutoEncoder, or similar neural networks with convolution layers). At each layer of the neural networks 870, 880, 890, a one-dimensional convolution of the samples one to M 860 with different hyperparameter sets is performed, each layer using the selected layer hyperparameters.

[0044] Referring to FIG. 9, an illustration 900 of operation within an exemplary layer of the neural network structures 870, 880, 890 in accordance with the present embodiments is depicted. For each layer, the signal 902 from the previous layer is provided. This input signal 904 is submitted to a convolution operation 906. The convoluted signal includes NK number of kernels 908, each kernel having a kernel size KS . After the convolution operation, all of the kernels are shifted by a stride S to perform another convolution operation. The kernels are shifted and the convolution operation is performed until the end of the input signal 904. This convoluted signal 906 is then output to the next level. Those skilled in the art realize that the layers of the neural network structures 870, 880, 890 will include one or more of a convolution operation performed in an encoding block and a deconvolution operation performed in a decoding block. Referring back to FIG. 8, the neural networks 870, 880, 890 generate resultant samples 875, 885, 895.

[0045] Referring to FIG. 10, an illustration 1000 depicts an illustrative example of user-defined energy usage visualization in accordance with the present embodiments. After the system 100 has been trained in the training mode, it operates in the inference mode. In the inference mode, the system 100 infers energy usage of each of the plurality of loads 104 from the main input electrical signal sensed by the sensor module 106. The visualization module 114 is configured to receive the inferred energy usage information and a user connected to the cloud 112 can access this information in order to, for example, identify energy usage within their building.

[0046] In accordance with the present embodiments, each user can design their own individualized presentation scheme for energy usage information, the presentation scheme be configured in the visualization module 114. When a user 116 accesses their inferred energy usage information, it is presented to the user in accordance with their individualized presentation scheme stored in the visualization module 114. One such scheme is shown in the illustration 1000 where a first portion 1010 identifies total energy consumption in megawatts hours. A second portion 1020 identifies power usage of various loads over time (in this example, a top graph depicts inferred (disaggregated) energy usage of lights and the bottom graph depicts inferred (disaggregated) energy usage of booster pumps). A third portion 1030 identifies aggregated logger signals and disaggregated inferred signals for one load (in this case elevators/lifts in the building). A fourth portion 1040 summarizes the energy usage of all or a plurality of the loads 104 in a pie chart. The illustration 1000 is merely exemplary and a number of other design schemes for visualizing energy usage can be used. In accordance with the present embodiments, a significant element of each design scheme is that it is user-defined yet capable of receiving and visualizing inferred/disaggregated real time energy usage data

from the energy usage identification module 110 or previously stored energy usage data from the storage 109.

[0047] Thus, it can be seen that the present embodiments provide methods and systems for energy management by energy usage identification and visualization. Energy usage can be inferred from a single electrical signal from an input main after training to advantageously disaggregate energy usage of various loads from the single electrical signal. Machine learning is used to train the system to disaggregate each of several identified loads from the single electrical signal, the machine learning constructing neural networks with selected hyperparameters and simultaneously training multiple neural networks with selected samples from data sequences of the electrical parameter signal data. The hyperparameters are advantageously modified in accordance with the present embodiments until an accuracy target. The accuracy target is more quickly met in accordance with the present embodiments because of the simultaneous training of disparate samples of electrical signal parameter data by multiple networks with varying hyperparameters, thereby identifying convergence of a neural network with selected hyperparameters in reduced time.

[0048] While exemplary embodiments have been presented in the foregoing detailed description of the present embodiments, it should be appreciated that a vast number of variations exist. It should further be appreciated that the exemplary embodiments are only examples, and are not intended to limit the scope, applicability, operation, or configuration of the invention in any way. Rather, the foregoing detailed description will provide those skilled in the art with a convenient road map for implementing exemplary embodiments of the invention, it being understood that various changes may be made in the function and arrangement of steps and method of operation described in

the exemplary embodiments without departing from the scope of the invention as set forth in the appended claims.

CLAIMS

What is claimed is:

1. A method for training an energy usage identification system comprising:
 - dividing a measurement log of aggregate energy usage data corresponding to energy usage of a plurality of loads into a plurality of training samples, each of the plurality of training samples comprising energy data sequences;
 - constructing a set of multiple neural network models;
 - extracting a mini-batch of samples and a test sample from the plurality of training samples;
 - simultaneously training each of the set of multiple neural network models with the mini-batch of samples to derive inferred load-based energy usage data of one or more of the plurality of loads;
 - determining an accuracy of the inferred load-based energy usage data for each of the multiple neural network models in response to the test sample;
 - eliminating from the set of multiple neural network models ones of the set of multiple neural network models exhibiting one or more of a set of poor result criteria;
 - and
 - repeating simultaneously training of remaining ones of the set of multiple neural network models until an optimal one of the set of multiple neural network models for inferred load-based energy management is identified in response to determining whether or not an accuracy target difference between actual load-based energy usage data and the inferred load-based energy usage data generated by one of the multiple neural networks using the test sample is met.

2. The method in accordance with Claim 1 wherein determining whether or not an accuracy target difference between actual load-based energy usage data and the inferred load-based energy usage data is met comprises whether the actual load-based energy usage data and the inferred load-based energy usage data differ by less than a predetermined margin.

3. The method in accordance with Claim 1 or Claim 2 wherein each of the set of multiple neural network models are determined to exhibit one or more of a set of poor result criteria in response to the accuracy target difference between actual load-based energy usage data and the inferred load-based energy usage data for the one of the multiple neural network models.

4. The method in accordance with Claim 3 wherein the one of the multiple neural network models exhibits one or more of a set of poor result criteria when the accuracy determined for the one of the multiple neural network models diverges in accuracy as compared to other ones of the set of multiple neural network models.

5. The method in accordance with Claim 3 wherein the one of the multiple neural network models exhibits one or more of a set of poor result criteria when the accuracy determined for the one of the multiple neural network models diverges in accuracy as compared to accuracy determined previously for the one of the set of multiple neural network models.

6. The method in accordance with any of Claims 1 to 5 wherein constructing the set of multiple neural networks comprises assigning a set of hyperparameters to each of the set of multiple neural networks.

7. The method in accordance with any of Claims 1 to 6 wherein each of the set of multiple neural networks comprises multiple layers, and wherein simultaneously training each of the set of multiple neural network models with the mini-batch of samples comprises seeding each of the mini-batch of samples into a first layer of the multiple layers of each of the multiple neural networks.

8. The method in accordance with Claim 7 wherein constructing the set of multiple neural network models comprises constructing a multi-layer convolution-based neural network for each one of the set of multiple neural network models.

9. The method in accordance with Claim 7 or Claim 8 wherein simultaneously training each of the set of multiple neural network models with the mini-batch of samples comprises at each layer of the multiple layers of each of the multiple neural network models performing an operation on an inputted data sample, modifying the data sample in response to the hyperparameters, and providing the modified data sample to the next layer.

10. The method in accordance with any of Claims 7 to 9 wherein the set of hyperparameters comprise one or more selected values for number of kernels, kernel size, stride, or padding for each layer of the multiple layers of each of the set of multiple neural network models.

11. The method in accordance with any of Claims 1 to 10 wherein dividing the measurement log of aggregate energy usage data corresponding to energy usage of the plurality of loads into the plurality of training samples comprises:

selecting a first one of the plurality of training samples from the measurement log; and

selecting subsequent ones of the plurality of training samples from the measurement log in accordance with a scattered selection scheme, wherein the measurement log has a start measurement and a finish measurement, and wherein the scattered selection scheme requires two of the subsequent ones of the plurality of training samples to be selected alternatively from a front portion of the measurement log and a back portion of the measurement log relative to an immediately previous training sample immediately previous to a first of the two of the subsequent ones of the plurality of training samples, and wherein the front portion of the measurement log is a portion of the measurement log between the start measurement and the immediately previous training sample, and wherein the back portion of the measurement log is a portion of the measurement log between the finish measurement and the immediately previous training sample.

12. The method in accordance with Claim 11 wherein selecting subsequent ones of the plurality of training samples comprises selecting subsequent ones of the plurality of training samples from the measurement log in accordance with both the scattered selection scheme and a stochastic gradient descent stride scheme, wherein the stochastic gradient descent stride scheme requires a subsequent stride between a

selected training sample and a next selected training sample be less than previous stride between the selected training sample and a previous selected training sample.

13. The method in accordance with any of Claims 1 to 10 wherein dividing the measurement log of aggregate energy usage data corresponding to energy usage of the plurality of loads into the plurality of training samples comprises:

selecting a first one of the plurality of training samples from the measurement log; and

selecting subsequent ones of the plurality of training samples from the measurement log in accordance with a stochastic gradient descent stride scheme, wherein the stochastic gradient descent stride scheme requires a subsequent stride between a selected training sample and a next selected training sample be less than previous stride between the selected training sample and a previous selected training sample.

14. A training sample extraction method comprising:

selecting a first one of a plurality of training samples from a measurement log; and

selecting subsequent ones of the plurality of training samples from the measurement log in accordance with a stochastic gradient descent stride scheme, wherein the stochastic gradient descent stride scheme requires a subsequent stride between a selected training sample and a next selected training sample be less than previous stride between the selected training sample and a previous selected training sample.

15. A training sample extraction method comprising:

selecting a first one of a plurality of training samples from a measurement log;

and

selecting subsequent ones of the plurality of training samples from the measurement log in accordance with a scattered selection scheme, wherein the measurement log has a start measurement and a finish measurement, and wherein the scattered selection scheme requires two of the subsequent ones of the plurality of training samples to be selected alternatively from a front portion of the measurement log and a back portion of the measurement log relative to an immediately previous training sample immediately previous to a first of the two of the subsequent ones of the plurality of training samples, and wherein the front portion of the measurement log is a portion of the measurement log between the start measurement and the immediately previous training sample, and wherein the back portion of the measurement log is a portion of the measurement log between the finish measurement and the immediately previous training sample.

16. The training sample extraction method in accordance with Claim 15 wherein selecting subsequent ones of the plurality of training samples from the measurement log comprises selecting subsequent ones of the plurality of training samples from the measurement log in accordance with both the scattered selection scheme and a stochastic gradient descent stride scheme, wherein the stochastic gradient descent stride scheme requires a subsequent stride between a selected training sample and a next selected training sample be less than previous stride between the selected training sample and a previous selected training sample.

17. An energy usage identification module comprising a processor configured to operate in an inference mode and a training mode, wherein in the inference mode, the processor is configured to disaggregate electrical signals for a plurality of loads in accordance with trained energy usage inference for each of the plurality of loads, and wherein in the training mode, the processor is configured to train usage inference for each of the plurality of loads in accordance with the method of any of Claims 1 to 13.

18. The energy usage identification module in accordance with Claim 17 in the inference mode the processor is further configured to:

identify subsequent energy usage data in accordance with the training of the energy usage identification system; and

present a visualization of the subsequent energy usage data, wherein a format of the visualization is defined by a user viewing the visualization.

19. A system for identification and visualization of energy usage, wherein the system comprises:

a first sensor connected to a main input electrical signal for sensing the main input electrical signal;

one or more second sensors, each of the one or more second sensors connected to one of one or more electrical loads coupled to the main input electrical signal;

an energy usage identification module coupled to the first sensor and the one or more second sensors and comprising a sample extraction module, a neural network modelling module and an evaluator and training controller, the energy usage

identification module configured to operate in an inference mode and a training mode, wherein in the inference mode, the energy usage identification module is configured to disaggregate electrical signals for the one or more electrical loads in accordance with trained energy usage inference for each of the one or more electrical loads, and wherein in the training mode, the energy usage identification module is configured to train usage inference for each of the one or more electrical loads utilizing the sample extraction module, the neural network modelling module and the evaluator and training controller,

wherein the sample extraction module divides a measurement log of recorded aggregate energy usage data corresponding to energy usage of the one or more electrical loads over a period of time into a plurality of training samples, each of the plurality of training samples comprising energy data sequences and extracts a mini-batch of samples and a test sample from the plurality of training samples, and

wherein the neural network modelling module constructs a set of multiple neural network models and simultaneously trains each of the set of multiple neural network models with the mini-batch of samples to derive inferred load-based energy usage data of one or more of the plurality of loads, and

wherein the evaluator and training controller determines an accuracy of the inferred load-based energy usage data for each of the multiple neural network models in response to the test sample, eliminates from the set of multiple neural network models ones of the set of multiple neural network models exhibiting one or more of a set of poor result criteria, and forwards remaining ones of the set of multiple neural network models back to the neural network modelling module for the neural network modelling module to repeat simultaneously training of the remaining ones of the set of multiple neural network models until the evaluator and training controller identifies an optimal one of the set of multiple neural network models for inferred load-based energy

management in response to determining whether or not an accuracy target difference between actual load-based energy usage data and the inferred load-based energy usage data generated by one of the multiple neural networks using the test sample is met.

20. The system in accordance with Claim 19 wherein the evaluator and training controller determines whether or not an accuracy target difference between actual load-based energy usage data and the inferred load-based energy usage data is met comprises whether the actual load-based energy usage data and the inferred load-based energy usage data differ by less than a predetermined margin.

21. The system in accordance with either Claim 19 or Claim 20 wherein the evaluator and training controller determines whether each of the set of multiple neural network models exhibits one or more of a set of poor result criteria in response to the accuracy target difference between actual load-based energy usage data and the inferred load-based energy usage data for the one of the multiple neural network models.

22. The system in accordance with Claim 21 wherein the evaluator and training controller determines whether the one of the multiple neural network models exhibits one or more of a set of poor result criteria when the accuracy determined for the one of the multiple neural network models diverges in accuracy as compared to other ones of the set of multiple neural network models.

23. The system in accordance with Claim 21 wherein the evaluator and training controller determines whether the one of the multiple neural network models exhibits one or more of a set of poor result criteria when the accuracy determined for

the one of the multiple neural network models diverges in accuracy as compared to accuracy determined previously for the one of the set of multiple neural network model.

24. The system in accordance with any of Claims 19 to 23 wherein the evaluator and training controller is configured to discard any one of the neural networks found to not be converging.

25. The system in accordance with any of Claims 19 to 24 wherein the neural network modelling module constructs each of the set of multiple neural networks to include multiple layers and simultaneously trains each of the set of multiple neural network models with the mini-batch of samples by seeding each of the mini-batch of samples into a first layer of the multiple layers of each of the multiple neural networks.

26. The system in accordance with Claim 25 wherein the neural network modelling module constructs the set of multiple neural networks by constructing a multi-layer convolution-based neural network for each one of the set of multiple neural network models.

27. The system in accordance with Claim 25 or Claim 26 wherein the neural network modelling module simultaneously trains each of the set of multiple neural network models with the mini-batch of samples by, at each layer of the multiple layers of each of the multiple neural network models, performing an operation on an inputted data sample, modifying the data sample in response to the hyperparameters, and providing the modified data sample to the next layer.

28. The system in accordance with any of Claims 19 to 27 wherein the sample extraction module selects a first one of the plurality of training samples from the measurement log and selects subsequent ones of the plurality of training samples from the measurement log in accordance with a scattered selection scheme, wherein the measurement log has a start measurement and a finish measurement, and wherein the scattered selection scheme requires two of the subsequent ones of the plurality of training samples to be selected alternatively from a front portion of the measurement log and a back portion of the measurement log relative to an immediately previous training sample immediately previous to a first of the two of the subsequent ones of the plurality of training samples, and wherein the front portion of the measurement log is a portion of the measurement log between the start measurement and the immediately previous training sample, and wherein the back portion of the measurement log is a portion of the measurement log between the finish measurement and the immediately previous training sample.

29. The system in accordance with Claim 27 wherein the sample extraction module selects subsequent ones of the plurality of training samples from the measurement log in accordance with both the scattered selection scheme and a stochastic gradient descent stride scheme, wherein the stochastic gradient descent stride scheme requires a subsequent stride between a selected training sample and a next selected training sample be less than previous stride between the selected training sample and a previous selected training sample.

30. The system in accordance with any of Claims 19 to 29 wherein the first sensor comprises one or more current transformer (CT) clamps coupled to a connection to the main input electrical signal for respective one or more buildings or structures.

31. The system in accordance with any of Claims 19 to 30 wherein each of the one or more second sensors comprise one or more current transformer (CT) clamps coupled to a connection to a a respective one of the one or more electrical loads.

32. The system in accordance with any of Claims 19 to 31 wherein the first sensor and the one or more second sensors are coupled to the energy usage identification module via the cloud.

33. The system in accordance with any of Claims 19 to 32 wherein the energy usage identification module is further configured when operating in the inference mode to identify subsequent energy usage data in accordance with the trained energy usage inference for each of the plurality of loads and present a visualization of the subsequent energy usage data to a user, wherein the visualization is defined by the user.