(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

(19) World Intellectual Property Organization
International Bureau

(43) International Publication Date
01 July 2021 (01.07.2021)

WIPO | PCT

(10) International Publication Number
WO 2021/133253 A1

(51) International Patent Classification:
G06N 3/02 (2006.01) *G06Q 50/06* (2012.01)
G06Q 10/04 (2012.01)

(21) International Application Number:
PCT/SG2020/050775

(22) International Filing Date:
23 December 2020 (23.12.2020)

(25) Filing Language: English

(26) Publication Language: English

(30) Priority Data:
201911358181.4 25 December 2019 (25.12.2019) CN

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(81) Designated States *(unless otherwise indicated, for every kind of national protection available)*: AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CZ, DE, DJ, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IR, IS, IT, JO, JP, KE, KG, KH, KN, KP, KR, KW, KZ, LA, LC, LK, LR, LS, LU, LY, MA, MD, ME, MG, MK, MN, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PA, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SA, SC, SD, SE, SG, SK, SL, ST, SV, SY, TH, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, WS, ZA, ZM, ZW.

(84) Designated States *(unless otherwise indicated, for every kind of regional protection available)*: ARIPO (BW, GH, GM, KE, LR, LS, MW, MZ, NA, RW, SD, SL, ST, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, RU, TJ, TM), European (AL, AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MC, MK, MT, NL, NO, PL, PT, RO, RS, SE, SI, SK, SM, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, KM, ML, MR, NE, SN, TD, TG).

Published:
— *with international search report (Art. 21(3))*

(54) **Title:** METHOD AND APPARATUS FOR PREDICTING ENERGY CONSUMPTION, AND DEVICE AND STORAGE MEDIUM THEREOF

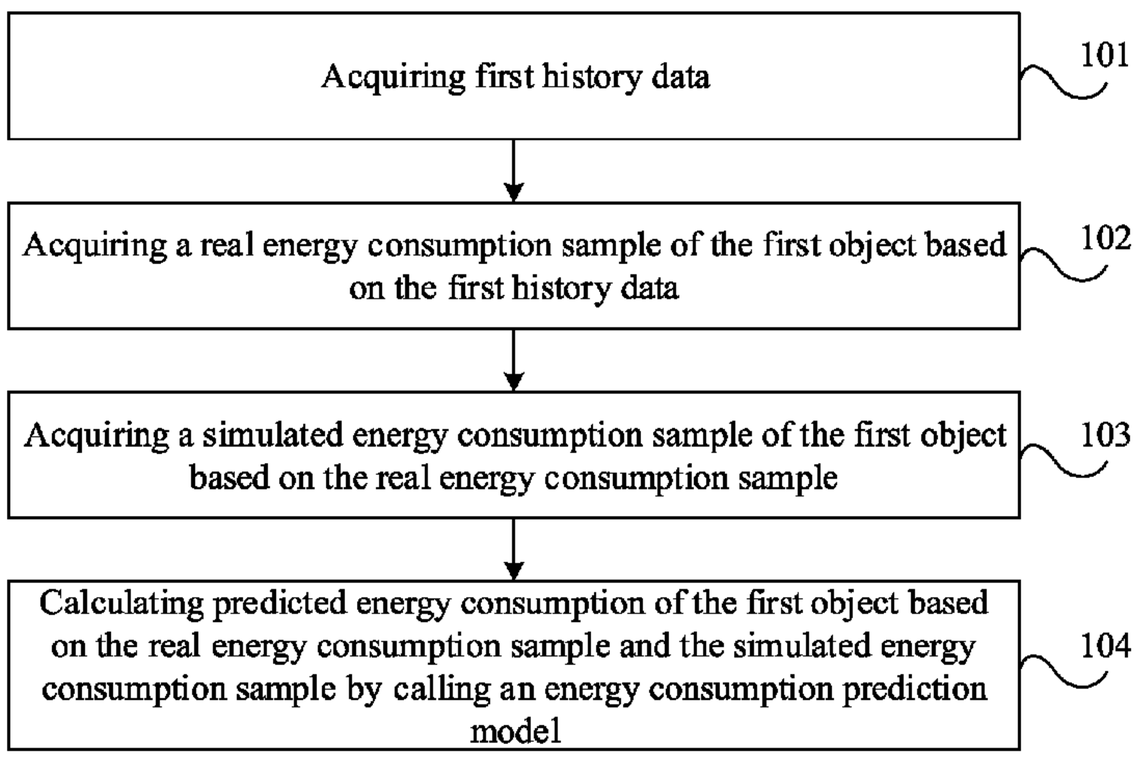


FIG. 1

(57) **Abstract:** Disclosed are a method and apparatus for predicting energy consumption. The method includes: acquiring first history data; acquiring a real energy consumption sample of a first object based on the first history data; acquiring a simulated energy consumption sample of the first object based on the real energy consumption sample; and calculating predicted energy consumption of the first object based on the real energy consumption sample and the simulated energy consumption sample by calling an energy consumption prediction model.

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METHOD AND APPARATUS FOR PREDICTING ENERGY CONSUMPTION, AND DEVICE AND STORAGE MEDIUM THEREOF

TECHNICAL FIELD

[0001] Embodiments of the present disclosure relate to the field of energy Internet technologies, and in particular, relate to a method and apparatus for predicting energy consumption, and a device and a storage medium thereof.

BACKGROUND

[0002] Currently, energy consumption prediction is an indispensable part of the energy Internet.

[0003] Before prediction of energy consumption in a specific region, it is possible to acquire corresponding predicted energy consumption by predicting energy consumption conditions of this region in a future time period based on a large amount of history energy consumption data in this region, such as a history electricity consumption amount.

[0004] However, energy consumption prediction results of newly-built enterprises are inaccurate due to insufficient history energy consumption data of these enterprises.

SUMMARY

[0005] Embodiments of the present disclosure provide a method and apparatus for predicting energy consumption, and a device and a storage medium thereof, which may solve the technical problem that energy consumption prediction results of newly-built enterprises are inaccurate in the related art.

[0006] In one aspect, embodiments of the present disclosure provide a method for predicting energy consumption. The method is applicable to a computer device, and includes:

[0007] acquiring first history data, wherein the first history data includes history energy consumption data of a first object;

[0008] acquiring a real energy consumption sample of the first object based on the first history data;

[0009] acquiring a simulated energy consumption sample of the first object based on the real energy consumption sample, wherein the simulated energy consumption sample includes virtual energy consumption data acquired by expansion based on the real energy consumption sample;

and

[0010] calculating predicted energy consumption of the first object based on the real energy consumption sample and the simulated energy consumption sample by calling an energy consumption prediction model.

[0011] In another aspect, embodiments of the present disclosure provide an apparatus for predicting energy consumption. The apparatus is applicable to a computer device, and includes:

[0012] a first data acquiring module, configured to acquire first history data, wherein the first history data includes history energy consumption data of a first object;

[0013] a real sample acquiring module, configured to acquire a real energy consumption sample of the first object based on the first history data;

[0014] a simulated sample acquiring module, configured to acquire a simulated energy consumption sample of the first object based on the real energy consumption sample, wherein the simulated energy consumption sample includes virtual energy consumption data acquired by expansion by a generative adversarial network based on the real energy consumption sample; and

[0015] a first energy consumption predicting module, configured to calculate predicted energy consumption of the first object based on the real energy consumption sample and the simulated energy consumption sample by calling an energy consumption prediction model.

[0016] In still another aspect, embodiments of the present disclosure provide a computer device. The computer device includes a processor and a memory storing a computer program. The computer program, when loaded and run by the processor, causes the processor to perform the above method.

[0017] In yet still another aspect, embodiments of the present disclosure provide a non-transitory computer-readable storage medium. The storage medium stores a computer program. The computer program, when loaded and run by a processor, causes the processor to perform the above method.

[0018] In yet still another aspect, embodiments of the present disclosure provide a computer program product. The computer program product, when loaded and run by a computer device, causes the computer device to perform the above method.

[0019] The technical solutions according to the embodiments of the present disclosure achieve the following beneficial effects.

[0020] The simulated energy consumption sample is acquired by expansion of the real energy consumption sample, such that the technical problem that energy consumption prediction results of newly-built enterprises are inaccurate due to less history energy consumption data of these enterprises in related art is solved and the number of samples that can be used by the energy

consumption prediction model is increased. Therefore, the accuracy of the energy consumption prediction result is improved.

BRIEF DESCRIPTION OF THE DRAWINGS

[0021] For clearer descriptions of the technical solutions in the embodiments of the present disclosure, the following briefly introduces the accompanying drawings required for describing the embodiments. Apparently, the accompanying drawings in the following description show merely some embodiments of the present disclosure, and a person of ordinary skill in the art may still derive other drawings from these accompanying drawings without creative efforts.

[0022] FIG. 1 is a flowchart of a method for predicting energy consumption according to an embodiment of the present disclosure;

[0023] FIG. 2 exemplarily shows a diagram of a method for storing first history data;

[0024] FIG. 3 exemplarily shows a diagram of a method for generating a simulated energy consumption sample;

[0025] FIG. 4 exemplarily shows a diagram of an energy consumption prediction model;

[0026] FIG. 5 exemplarily shows a diagram of the training of a neural network;

[0027] FIG. 6 exemplarily shows a diagram of a method for training a generative adversarial network;

[0028] FIG. 7 is a block diagram of an apparatus for predicting energy consumption according to an embodiment of the present disclosure;

[0029] FIG. 8 is a block diagram of an apparatus for predicting energy consumption according to an embodiment of the present disclosure; and

[0030] FIG. 9 is a structural block diagram of a computer device according to an embodiment of the present disclosure.

DETAILED DESCRIPTION

[0031] For clearer descriptions of the objectives, technical solutions and advantages in the present disclosure, embodiments of the present disclosure are described in detail below in combination with the accompanying drawings.

[0032] In the technical solutions according to the embodiments of the present disclosure, a generative adversarial network is configured to perform data extension on a first object. In some embodiments, the generative adversarial network acquires a corresponding simulated energy consumption sample of the first object based on a real energy consumption sample of the first object so as to achieve the purpose of data extension. In some embodiments, the generative

adversarial network includes a generator network and a discriminator network. The generator network is configured to generate a candidate simulated energy consumption sample and the discriminator network is configured to determine whether the authenticity of the candidate simulated energy consumption sample satisfies the condition of being a simulated energy consumption sample based on the real energy consumption sample.

[0033] An energy consumption prediction model involved in the embodiment of the present disclosure refers to a machine learning model acquired by machine learning training and configured to predict energy consumption of the first object. The energy consumption prediction model may be a deep-learning energy consumption prediction model, i.e., an energy consumption prediction model constructed based on a deep neural network, such as an energy consumption prediction model constructed based on a deep convolutional neural network. This classification task model may be configured to predict energy consumption of any object, which is not limited in the embodiment of the present disclosure.

[0034] In the method according to the embodiment of the present disclosure, an execution subject of various steps may be a computer device. The computer device refers to an electronic device having data calculation, processing and storage capabilities, such as a personal computer (PC) or a server. It should be noted that the generative adversarial network and the energy consumption prediction model may be disposed on the same computer device or disposed on different computer devices, which is not limited in the embodiment of the present disclosure.

[0035] Referring to FIG. 1, which shows a flowchart of a method for predicting energy consumption according to an embodiment of the present disclosure, the method may include the following steps (101-104).

[0036] In step 101, first history data is acquired.

[0037] The first history data refers to history energy consumption data of a first object. The history energy consumption data refers to history energy consumption amount of the first object. The energy may be electric energy, water energy, fuel, or the like, which is not limited in the embodiments of the present disclosure. The first object includes a region using the energy, which may be an enterprise, a plant, a residential area or the like. In the embodiments of the present disclosure, the computer device determines the first object according to a region in which energy consumption is predicted. Exemplarily, when energy consumption is predicted in a region A, if there is an enterprise a in the region A, the first object is the enterprise a. The computer device acquires predicted energy consumption of the region A by predicting energy consumption of the enterprise a. If both the enterprise a and a plant b exist in the region A, the first object is the enterprise a or the plant b. The computer device may predict energy consumption of the

enterprise a and the plant b respectively and then the sum of predicted energy consumption of the enterprise a and the plant B is predicted energy consumption of the region A; or the first object is the enterprise a and the plant b, and the computer device may acquire predicted energy consumption of the region A by predicting energy consumption of the enterprise a and the plant b as a whole.

[0038] In some embodiments, the first history data is acquired by a load meter. For example, the history electricity consumption data of the first object is acquired by a load electric meter. For example, the history water consumption data of the first object is acquired by a load water meter. Optionally, after acquiring the first history data, the load meter sends the first history data to the computer device at certain time interval over a network. In some embodiments, the time interval is determined by the computer device according to actual conditions, and may be 10 ms, 1 hour, 1 day, 7 days, 14 days or the like, which is not limited in the embodiments of the present disclosure. For the accuracy of predicted energy consumption, the first history data may further include, but is not limited to, at least one of weather, information about holidays and festivals, temperature, and the like.

[0039] It should be noted that the computer device records a time period corresponding to the first history data while acquiring the first history data. In some embodiments, referring to FIG. 2, by taking the first history data being the history electricity consumption data as an example, the first history data may be stored in a coordinate system 20 constructed by the computer device. In the coordinate system 20, the abscissa represents time and the ordinate represents real history electricity consumption of the first object.

[0040] In step 102, a real energy consumption sample of the first object is acquired based on the first history data.

[0041] The real energy consumption sample includes real history energy consumption data of the first object. In some embodiments, after acquiring the first history data, the computer device acquires the corresponding real energy consumption sample by standardization and time period division on the first history data.

[0042] A method for acquiring the real energy consumption sample by the computer device based on the first history data is introduced hereinafter. In some embodiments, step 102 includes the following sub-steps.

[0043] 1. The first history data is standardized.

[0044] The standardizing is to map the history energy consumption of the first object into a preset value range. The preset value range is determined by the computer device according to actual conditions, and may be (0, 1), (0, 2), (1, 2), or the like, which is not limited in the

embodiments of the present disclosure. It should be noted that the standardizing is only directed to history energy consumption data corresponding to the first history data.

[0045] In some embodiments, by taking the preset value range being (0, 1) as an example, x represents any history energy consumption corresponding to the first history data, such as history energy consumption corresponding to a point 21 in FIG. 2. The any history energy consumption standardized x_{scaled} is

[0046]
$$x_{scaled} = \frac{x - x_{\min}}{x_{\max} - x_{\min}},$$

[0047] wherein $x_{\max}$ represents the maximum history energy consumption in the first history data and $x_{\min}$ represents the minimum history energy consumption in the first history data.

[0048] 2. A prediction time period corresponding to the predicted energy consumption is acquired.

[0049] The predicted energy consumption includes future energy consumption data acquired by predicting energy consumption of the first object. The prediction time period includes a time period in which the first object uses the predicted energy consumption. The prediction time period may be 1 hour, 1 day, 7 days, 14 days or the like, which is not limited in the embodiments of the present disclosure. In some embodiments, after standardizing the first history data, the computer device acquires the corresponding prediction time period based on the predicted energy consumption of the first object.

[0050] 3. The real energy consumption sample is acquired by segmenting the standardized first history data based on the prediction time period.

[0051] The real energy consumption sample includes a history energy consumption sample acquired by standardizing and segmenting the history energy consumption data corresponding to the first object. It should be noted that the real energy consumption sample includes at least one item of real energy consumption data. A duration corresponding to the real energy consumption data is the same as the duration of the prediction time period. In some embodiments, the computer device acquires the duration of the prediction time period based on the prediction time period and segments the standardized first history data.

[0052] In some embodiments, the computer device statically segments the standardized first history data based on the duration of the prediction time period, namely, segments the first history data based on a time sequence. For example, if the duration of the predication time period is 7 days and the duration corresponding to the first history data is 14 days, the real energy

consumption sample acquired by segmenting the first history data includes two items of real energy consumption data, the first real energy consumption data is energy consumption data of the first 7 days, and the second real energy consumption data is energy consumption data of the 8th to 14th days. In another possible embodiment, the computer device dynamically segments the standardized first history data based on the duration of the prediction time period, namely, randomly segments the first history data based on a preset time period. For example, if the duration of the predication time period is 7 days and the duration corresponding to the first history data is 14 days, the real energy consumption sample acquired by segmenting the first history data includes eight items of real energy consumption data, the first real energy consumption data is energy consumption data of the first 7 days, the second real energy consumption data is energy consumption data of the 3rd to 8th days, the third real energy consumption data is energy consumption data of the 3rd to 9th days, and by such analogy, the eighth real energy consumption data is energy consumption data of the 8th to 14th days.

[0053] In step 103, a simulated energy consumption sample of the first object is acquired based on the real energy consumption sample.

[0054] The simulated energy consumption sample includes virtual energy consumption data acquired by expansion on the basis of the real energy consumption sample and includes at least one item of simulated energy consumption data. In some embodiments, the amount of the simulated energy consumption data in the simulated energy consumption sample may be the same or different from the amount of the real energy consumption data in the real energy consumption sample. In some embodiments, the computer device calculates the simulated energy consumption sample based on the real energy consumption sample by calling a generative adversarial network.

[0055] A method for acquiring the simulated energy consumption sample is introduced below. In some embodiments, step 103 includes the following several sub-steps.

[0056] 1. A first randomly-generated noise vector is acquired.

[0057] The first noise vector refers to a random vector for generating the simulated energy consumption sample. In some embodiments, the first noise vector may be a 16-dimensional vector or a 32-dimensional vector generated by a distribution function. The first noise vector may also be a 16-dimensional vector or a 32-dimensional vector generated randomly.

[0058] 2. The simulated energy consumption sample is generated based on the first noise vector by a generator network in the generative adversarial network.

[0059] In some embodiments, the generative adversarial network includes the generator network and a discriminator network. In the embodiment of the present disclosure, after acquiring the first noise vector, the computer device generates a candidate simulated energy consumption

sample based on the first noise vector by the generator network. The candidate simulated energy consumption sample includes at least one item of candidate simulated energy consumption data, the amount of which may be the same or different from the amount of the real energy consumption data in the real energy consumption sample.

[0060] It should be noted that before the generative adversarial network generates the simulated energy consumption sample, the generative adversarial network needs to be trained. A method for training the generative adversarial network is introduced herein in detail, which is not repeated herein.

[0061] In step 104, predicted energy consumption of the first object is calculated based on the real energy consumption sample and the simulated energy consumption sample by calling an energy consumption prediction model.

[0062] In some embodiments, after acquiring the simulated energy consumption sample, the computer device calculates predicted energy consumption of the first object based on the real energy consumption sample and the simulated energy consumption sample by calling the energy consumption prediction model. The energy consumption prediction model is acquired by training based on history energy consumption data of other objects.

[0063] A method for training the energy consumption prediction model is introduced below. Optionally, the following several steps are further included before step 104.

[0064] 1. Second history data is acquired.

[0065] The second history data includes history energy consumption data of other objects associated with the first object. The other objects include objects having the same feature as the first object. The feature may be an actual function, a people flow density, a geographical location or the like, which is not limited in the embodiment of the present disclosure. For example, if the first object is an enterprise A, the other objects may be other enterprises having the same actual function as the enterprise A or other enterprises having similar staff to the enterprise A. In some embodiments, the computer device acquires the second history data by the load meter.

[0066] 2. An initial energy consumption prediction model is acquired by training based on the second history data.

[0067] In the embodiments of the present disclosure, the computer device acquires the initial energy consumption prediction model by training the second history data. In some embodiments, the computer device constructs a recurrent neural network and acquires the initial energy consumption prediction model by training the second history data.

[0068] 3. A bottom-layer parameter of the initial energy consumption prediction model is fixed, and the energy consumption prediction model is acquired by fine-adjusting a high-layer

parameter of the initial energy consumption prediction model based on the simulated energy consumption sample.

[0069] In the embodiments of the present disclosure, after acquiring the initial energy consumption prediction model, the computer device fixes the bottom-layer parameter of the initial energy consumption prediction model. Further, the computer device acquires the energy consumption prediction model of the first object by fine-adjusting the high-layer parameter of the initial energy consumption prediction model based on the simulated energy consumption sample. It should be noted that for different first objects, energy consumption prediction models acquired finally have different parameters.

[0070] In some embodiments, referring to FIG. 3, the energy consumption prediction model includes an encoding network 31 and a decoding network 32. The computer device acquires a parameter of the encoding network 31 based on the second history data of other objects, further fix the parameter of the encoding network 31, and acquires the energy consumption prediction model of the first object by fine-adjusting a parameter of the decoding network 32 by the simulated energy consumption sample of the first object. In some embodiments, the parameter of the encoding network 31 is a weight of the encoding network. The encoding network 31 and the decoding network 32 are connected by an encoder state diagram 33. In some embodiments, parameters 1, 2, and 3 are input to the encoding network 31 and parameters 1, 2 and 3 are output from the decoding network 32.

[0071] It should be noted that the training of the neural network is as follows: first a network weight of each layer is calculated forward, and then reverse calculation is performed. In some embodiments, referring to FIG. 4, z1 and z3 of the first-layer encoding network are fixed; and during reverse calculation, weights of z1 and z3 are not updated again, and all that is needed is to calculate from z5 to z3.

[0072] In summary, in the technical solutions according to the embodiments of the present disclosure, the simulated energy consumption sample is acquired by expansion of the real energy consumption sample, such that the technical problem that energy consumption prediction results of newly-built enterprises are inaccurate due to less history energy consumption data of these enterprises in related art is solved and the number of samples that can be used by the energy consumption prediction model is increased. Therefore, the accuracy of the energy consumption prediction result is improved. As the predicted energy consumption is acquired by the energy consumption predication model, high convenience and efficiency are achieved and the processing overhead for energy consumption prediction by the computer device is reduced.

[0073] In addition, the real energy consumption sample is acquired by standardizing and

segmenting the first history data. Thus, it is ensured that the energy consumption amount of the real energy consumption sample is in the same standard, which is convenient for the generative adversarial network to use the first history data for training. Therefore, the reliability of the generative adversarial network is improved.

[0074] In addition, after the candidate simulated energy consumption sample is generated by the generator network of the generative adversarial network, the similarity between the simulated energy consumption sample and the real energy consumption sample is improved, thereby ensuring the reliability of the simulated energy consumption sample.

[0075] In some embodiments, as shown in FIG. 5, the method according to the embodiment of the present disclosure may further include the following steps.

[0076] In step 501, a second randomly-generated noise vector is acquired.

[0077] The second noise vector refers to a random vector for training the generative adversarial network. In some embodiments, the second noise vector may be a 16-dimensional vector or a 32-dimensional vector generated by a distribution function. The second noise vector may also be a 16-dimensional vector or a 32-dimensional vector generated randomly.

[0078] In step 502, the generative adversarial network is constructed.

[0079] In the embodiments of the present disclosure, the computer device constructs the generative adversarial network. The generative adversarial network includes the generator network and the discriminator network.

[0080] In step 503, a trained generative adversarial network is acquired by training the generative adversarial network based on the second noise vector and the real energy consumption sample.

[0081] In some embodiments, the computer device trains the generative adversarial network based on the second noise vector and the real energy consumption sample.

[0082] In some embodiments, the training of the generative adversarial network includes the following several steps.

[0083] 1. A first loss function and a second loss function are acquired.

[0084] The first loss function is a loss function of the discriminator network and the second loss function is a loss function of the generator network. Exemplarily, assuming that the discriminator network is $D(x)$, the first loss function L_1 is:

[0085] $$L_1 = \max_D E_{x\sim p_r}[\log D(x)] + E_{x\sim p_g}[\log(1 - D(x))]$$, and

[0086] the second loss function L_2 is:

[0087] $$L_2 = \min_g \max_D E_{x\sim p_r}[\log D(x)] + E_{x\sim p_g}[\log(1 - D(x))]$$;

[0088] wherein p_r represents the real energy consumption sample and p_g represents the simulated energy consumption sample. It should be noted that the higher the distinction ability of the discriminator network is, the greater the values of the left and right sides of the first loss function are.

[0089] 2. A parameter of the generator network is fixed and the discriminator network is trained.

[0090] In some embodiments, after constructing the generative adversarial network, the computer device fixes the parameter of the generator network and trains the discriminator network.

[0091] 3. A parameter of the discriminator network is fixed and the generator network is trained if the first loss function satisfies a first preset condition.

[0092] In some embodiments, when the first loss function corresponding to the discriminator network satisfies the first preset condition, the training of the discriminator network is completed and the computer device fixes the parameter of the trained discriminator network and trains the generator network. The first preset condition means that a loss value of the discriminator network acquired based on the first loss function is maximized.

[0093] 4. It is determined that the training of the generator network is completed if the second loss function satisfies a second preset condition.

[0094] In some embodiments, after acquiring the trained discriminator network, the computer device fixes the parameter of the discriminator network and trains the generator network. If the second loss function corresponding to the generator network satisfies the second preset condition, it is determined that the training of the generator network is completed. In some embodiments, the second preset condition means that a loss value of the second loss function is minimized. At this time, the second loss function is a convergent function.

[0095] If the second loss function does not satisfy the second preset condition, the computer device adjusts the parameter of the generator network, and again performs the procedure from the step that the discriminator network is trained.

[0096] In some embodiments, referring to FIG. 6, a method for training the generative adversarial network is introduced hereinafter. The generator network 61 generates the simulated energy consumption sample 63 based on the second noise vector 62. Further, the discriminator network 64 determines the authenticity of the simulated energy consumption sample 63 based on the simulated energy consumption sample 63 and the real energy consumption sample 65. For example, assuming that the simulated energy consumption sample 63 is marked as "false" and the real energy consumption sample 65 is marked as "true," if the discriminator network 64 determines that the simulated energy consumption sample 63 is "false," it is determined that the

training of the discriminator network 64 is completed; and if the discriminator network 64 determines that the simulated energy consumption sample 63 is "true," the parameter of the discriminator network 64 is modified to continuously determine the authenticity of the simulated energy consumption sample 63 until the training of the discriminator network 64 is completed. After the training of the discriminator network 64 is completed, the generator network 61 is continued to be trained, the simulated energy consumption sample 63 is continuously generated based on the generator network 61, and the trained discriminator network 64 discriminates the simulated energy consumption sample. For example, assuming that the simulated energy consumption sample 63 is marked as "false" and the real energy consumption sample 65 is marked as "true," if the discriminator network 64 determines that the simulated energy consumption sample 63 is "true," it is determined that the training of the generator network 61 is completed; and if the discriminator network 64 determines that the simulated energy consumption sample 63 is "false," the parameter of the generator network 61 is modified to continuously generate the simulated energy consumption sample 63, and the discriminator network 64 discriminates the authenticity of the simulated energy consumption sample 63 until the training of the generator network 61 is completed. In addition, in the process of training the generator network and the discriminator network, the steps may be repeated until the loss value of the first loss function corresponding to the discriminator network 64 is maximized, and the second loss function corresponding to the generator network 61 is the convergent function.

[0097] In summary, in the technical solution according to the embodiment of the present disclosure, the generative adversarial network is trained based on the second noise vector and the real energy consumption sample, such that the reliability of the generator network used when the simulated energy consumption sample is generated is ensured, and the accuracy of the simulated energy consumption sample is improved.

[0098] In addition, the generative adversarial network is trained alternately by the first loss function and the second loss function. Thus, the accuracy of the simulated energy consumption sample acquired by the trained generative adversarial network is further ensured.

[0099] Hereinafter, apparatus and device embodiments of the present disclosure are described. The apparatus and device may be configured to perform the methods according to the method embodiments of the present disclosure. For the details not disclosed in the apparatus and device embodiments of the present disclosure, reference may be made to the method embodiments of the present disclosure.

[00100] Referring to FIG. 7, which shows a block diagram of an apparatus for predicting energy consumption according to an embodiment of the present disclosure, the apparatus has the

function of practicing the above method examples. The function may be implemented by hardware or implemented by executing corresponding software by hardware. The apparatus may be a computer device or may be disposed in a computer device. The apparatus 700 may include a first data acquiring module 701, a real sample acquiring module 702, a simulated sample acquiring module 703 and a first energy consumption predicting module 704.

[00101] The first data acquisition module 701 is configured to acquire first history data, wherein the first history data refers to history energy consumption data of a first object.

[00102] The real sample acquiring module 702 is configured to acquire a real energy consumption sample of the first object based on the first history data.

[00103] The simulated sample acquiring module 703 is configured to acquire a simulated energy consumption sample of the first object based on the real energy consumption sample, wherein the simulated energy consumption sample includes virtual energy consumption data acquired by expansion based on the real energy consumption sample.

[00104] The first energy consumption predicting module 704 is configured to calculate predicted energy consumption of the first object based on the real energy consumption sample and the simulated energy consumption sample by calling an energy consumption prediction model.

[00105] In some embodiments, the real sample acquiring module 702 is configured to standardize the first history data, wherein the standardizing is to map the history energy consumption of the first object into a preset value range; acquire a prediction time period corresponding to the predicted energy consumption; and acquire the real energy consumption sample by segmenting the standardized first history data based on the prediction time period.

[00106] In some embodiments, the simulated sample acquiring module 703 is configured to acquire a first randomly-generated noise vector; and generate the simulated energy consumption sample based on the first noise vector by a generator network in a generative adversarial network.

[00107] In some embodiments, the generative adversarial network includes a generator network and a discriminator network. As shown in FIG. 8, the apparatus 700 further includes a candidate sample generating module 705, an authenticity calculating module 706, and a simulated sample determining module 707.

[00108] The candidate sample generating module 705 is configured to generate a candidate simulated energy consumption sample based on the first noise vector by the generator network.

[00109] The authenticity calculating module 706 is configured to calculate authenticity of the candidate simulated energy consumption sample by the discriminator network based on the real energy consumption sample and the candidate simulated energy consumption sample.

[00110] The simulated sample determining module 707 is configured to determine the candidate

simulated energy consumption sample as the simulated energy consumption sample if the authenticity is greater than a preset threshold.

[00111] In some embodiments, as shown in FIG. 8, the apparatus 700 further includes a second vector acquiring module 708, a neural network constructing module 709, and a neural network training module 710.

[00112] The second vector acquiring module 708 is configured to acquire a second randomly-generated noise vector.

[00113] The neural network constructing module 709 is configured to construct the generative adversarial network.

[00114] The neural network training module 710 is configured to acquire a trained generative adversarial network by training the generative adversarial network based on the second noise vector and the real energy consumption sample.

[00115] In some embodiments, the neural network training module 710 is configured to: acquire a first loss function and a second loss function, wherein the first loss function is a loss function of the discriminator network and the second loss function is a loss function of the generator network; fix a parameter of the generator network and train the discriminator network; fix a parameter of the discriminator network and train the generator network if the first loss function satisfies a first preset condition; determine that the training of the generator network is completed if the second loss function satisfies a second preset condition; and adjust the parameter of the generator network if the second loss function does not satisfy the second preset condition, and perform the procedure again from the step of training the discriminator network.

[00116] In some embodiments, as shown in FIG. 8, the apparatus 700 further includes a second data acquiring module 711, a prediction model training module 712 and a model parameter fine-adjusting module 713.

[00117] The second data acquiring module 711 is configured to acquire second history data, wherein the second history data refers to history energy consumption data of other objects associated with the first object.

[00118] The prediction model training module 712 is configured to acquire an initial energy consumption prediction model by training based on the second history data.

[00119] The model parameter fine-adjusting module 713 is configured to fix a bottom-layer parameter of the initial energy consumption prediction model, and acquire the energy consumption prediction model by fine-adjusting a high-layer parameter of the initial energy consumption prediction model based on the first history data.

[00120] In summary, in the technical solutions according to the embodiments of the present

disclosure, the simulated energy consumption sample is acquired by expansion of the real energy consumption sample, such that the technical problem that energy consumption prediction results of newly-built enterprises are inaccurate due to less history energy consumption data of these enterprises in related art is solved and the number of samples that can be used by the energy consumption prediction model is increased. Therefore, the accuracy of the energy consumption prediction result is improved.

[00121] It should be noted that the apparatus according to the above embodiment is only illustrated by the division of various functional modules when implementing its function. In practical application, the functions may be assigned to be completed by different functional modules according to actual needs. That is, the internal structure of the device is divided into different functional modules to complete all or part of the functions described above. In addition, the apparatus and the method according to the above embodiments are based on the same inventive concept, and details of the apparatus are detailed in the method embodiment, which are not repeated herein.

[00122] Referring to FIG. 9, which shows a structural block diagram of a computer device 900 according to an embodiment of the present disclosure, the computer device is configured to perform the method for predicting energy consumption according to the above embodiments. The computer device may be any electronic device having data processing and storage capabilities.

[00123] Specifically, the computer device 900 includes a processing unit, such as a central processing unit (CPU), a graphics processing unit (GPU), and a field-programmable gate array (FPGA) 901, a system memory 904 including a random-access memory (RAM) 902 and a read-only memory (ROM) 903, and a system bus 905 connecting the system memory 904 and the central processing unit 901. The computer device 900 further includes a basic input/output (I/O) system 906 configured to facilitate information transmission between various components within the computer device, and a high-capacity storage device 907 configured to store an operating system 913, an application 914 and other program modules 915.

[00124] The basic input/output system 906 includes a display 908 configured to display information and an input device 909, such as a mouse and a keyboard, configured to input information of a user. Both the display 908 and the input device 909 are connected to the central processing unit 901 by an input/output controller 910 connected to the system bus 905. The basic input/output system 906 may also include the input/output controller 910 configured to receive and process inputs from a plurality of other devices, such as the keyboard, the mouse, or an electronic stylus. Similarly, the input/output controller 910 further provides output to the display, a printer or other types of output devices.

[00125] The high-capacity storage device 907 is connected to the central processing unit 901 by a high-capacity storage controller (not shown) connected to the system bus 905. The high-capacity storage device 907 and a computer-readable medium associated therewith provide non-volatile storage for the computer device 900. That is, the high-capacity storage device 907 may include the computer-readable medium (not shown), such as a hard disk or a compact disc read-only memory (CD-ROM) driver.

[00126] Without loss of generality, the computer-readable medium may include a computer storage medium and a communication medium. The computer storage medium includes volatile and non-volatile, removable and non-removable media implemented in any method or technology for storage of information such as a computer-readable instruction, a data structure, a program module or other data. The computer storage medium includes a RAM, a ROM, an erasable programmable read only memory (EPROM), an electrically erasable programmable read only memory (EEPROM), a flash memory or other solid-state storage technologies, a CD-ROM, a digital video disc (DVD) or other optical storage, a tape cartridge, a magnetic tape, a disk storage or other magnetic storage devices. It will be known by a person skilled in the art that the computer storage medium is not limited hereto. The system memory 904 and the high-capacity storage device 907 may be collectively referred to as the memory.

[00127] According to the embodiments of the present disclosure, the computer device 900 may also be connected to a remote computer on a network by the network, such as the Internet, for operation. That is, the computer device 900 may be connected to the network 912 by a network interface unit 911 connected to the system bus 905, or may be connected to other types of networks or remote computer systems (not shown) with the network interface unit 911.

[00128] The memory further includes at least one instruction, at least one program, a code set, or an instruction set. The at least one instruction, the at least one program, the code set, or the instruction set, when loaded and executed by one or more processors, causes the one or more processors to perform the above method.

[00129] An embodiment of the present disclosure provides a non-transitory computer-readable storage medium. The computer-readable storage medium stores at least one instruction, at least one program, a code set, or an instruction set therein. The at least one instruction, the at least one program, the code set, or the instruction set, when loaded and executed by a processor, causes the processor to perform the above method.

[00130] In some embodiments, the non-transitory computer-readable storage medium may include a ROM, a RAM, a solid state drive (SSD), an optical disc or the like. The random-access memory may include a resistance random-access memory (ReRAM) and a dynamic

random-access memory (DRAM).

[00131] In some embodiments, a computer program product is further provided. When executed by a processor, the computer program product is configured to implement the above method.

[00132] It should be understood that the term "a plurality of" herein refers to two or more. The term "and/or" describes an association relationship between associated objects and indicates that there may be three relationships. For example, A and/or B may indicate that there are three cases where A exists separately, A and B exist at the same time, and B exists separately. The character "/" generally indicates that an "or" relationship exists between contextual objects. In addition, step numbers described herein merely show exemplarily a possible execution sequence of steps. In some other embodiments, the steps may also be performed out of the number sequence. For example, two steps with different numbers may be performed at the same time or two steps with different numbers may be performed based on a sequence adverse to that shown in the figure, which is not limited in the embodiments of the present disclosure.

[00133] Described above are only exemplary embodiments of the present disclosure, and are not intended to limit the present disclosure. Any modifications, equivalent replacements, improvements and the like made within the spirit and principles of the present disclosure should be included within the scope of protection of the present disclosure.

CLAIMS

What is claimed is:

1. A method for predicting energy consumption, the method being applicable to a computer device, and comprising:

acquiring first history data, wherein the first history data comprises history energy consumption data of a first object;

acquiring a real energy consumption sample of the first object based on the first history data;

acquiring a simulated energy consumption sample of the first object based on the real energy consumption sample, wherein the simulated energy consumption sample comprises an energy consumption sample acquired by expansion based on the real energy consumption sample; and

calculating predicted energy consumption of the first object based on the real energy consumption sample and the simulated energy consumption sample by calling an energy consumption prediction model.

2. The method according to claim 1, wherein acquiring the real energy consumption sample of the first object based on the first history data comprises:

standardizing the first history data, wherein the standardizing is to map history energy consumption of the first object into a preset value range;

acquiring a prediction time period corresponding to the predicted energy consumption; and

acquiring the real energy consumption sample by segmenting the standardized first history data based on the prediction time period.

3. The method according to claim 1, wherein acquiring the simulated energy consumption sample of the first object based on the real energy consumption sample comprises:

acquiring a first randomly-generated noise vector; and

generating the simulated energy consumption sample based on the first noise vector by a generator network in a generative adversarial network.

4. The method according to claim 3, wherein the generative adversarial network comprises the generator network and a discriminator network; and

before generating the simulated energy consumption sample based on the first noise vector by the generator network in the generative adversarial network, the method further comprises:

generating a candidate simulated energy consumption sample based on the first noise vector by the generator network;

calculating authenticity of the candidate simulated energy consumption sample by the discriminator network based on the real energy consumption sample and the candidate simulated energy consumption sample; and

determining the candidate simulated energy consumption sample as the simulated energy consumption sample if the authenticity is greater than a preset threshold.

5. The method according to claim 3, wherein before generating the simulated energy consumption sample based on the first noise vector by the generator network in the generative adversarial network, the method further comprises:

acquiring a second randomly-generated noise vector;

constructing the generative adversarial network; and

acquiring a trained generative adversarial network by training the generative adversarial network based on the second noise vector and the real energy consumption sample.

6. The method according to claim 5, wherein acquiring the trained generative adversarial network by training the generative adversarial network based on the second noise vector and the real energy consumption sample comprises:

acquiring a first loss function and a second loss function, wherein the first loss function comprises a loss function of the discriminator network and the second loss function comprises a loss function of the generator network;

fixing a parameter of the generator network and training the discriminator network;

fixing a parameter of the discriminator and training the generator network if the first loss function satisfies a first preset condition;

determining that the training of the generator network is completed if the second loss function satisfies a second preset condition; and

adjusting the parameter of the generator network if the second loss function does not satisfy

the second preset condition, and performing the procedure again from the step of training the discriminator network.

7. The method according to claim 1, wherein before calculating the predicted energy consumption of the first object based on the real energy consumption sample and the simulated energy consumption sample by calling the energy consumption prediction model, the method further comprises:

acquiring second history data, wherein the second history data refers to history energy consumption data of other objects associated with the first object;

acquiring an initial energy consumption prediction model by training based on the second history data; and

fixing a bottom-layer parameter of the initial energy consumption prediction model, and acquiring the energy consumption prediction model by fine-adjusting a high-layer parameter of the initial energy consumption prediction model based on the simulated energy consumption sample.

8. An apparatus for predicting energy consumption, the apparatus being applicable to a computer device, and comprising:

a first data acquiring module, configured to acquire first history data, wherein the first history data comprises history energy consumption data of a first object;

a real sample acquiring module, configured to acquire a real energy consumption sample of the first object based on the first history data;

a simulated sample acquiring module, configured to acquire a simulated energy consumption sample of the first object based on the real energy consumption sample, wherein the simulated energy consumption sample comprises virtual energy consumption data acquired by expansion by a generative adversarial network based on the real energy consumption sample; and

a first energy consumption predicting module, configured to calculate predicted energy consumption of the first object based on the real energy consumption sample and the simulated energy consumption sample by calling an energy consumption prediction model.

9. A computer device, comprising a processor and a memory storing a computer program, wherein the computer program, when loaded and run by the processor, causes the processor to perform the method as defined in any one of claims 1 to 7.

10. A computer-readable storage medium storing a computer program, wherein the computer program, when loaded and run by a processor, causes the processor to perform the method as defined in any one of claims 1 to 7.

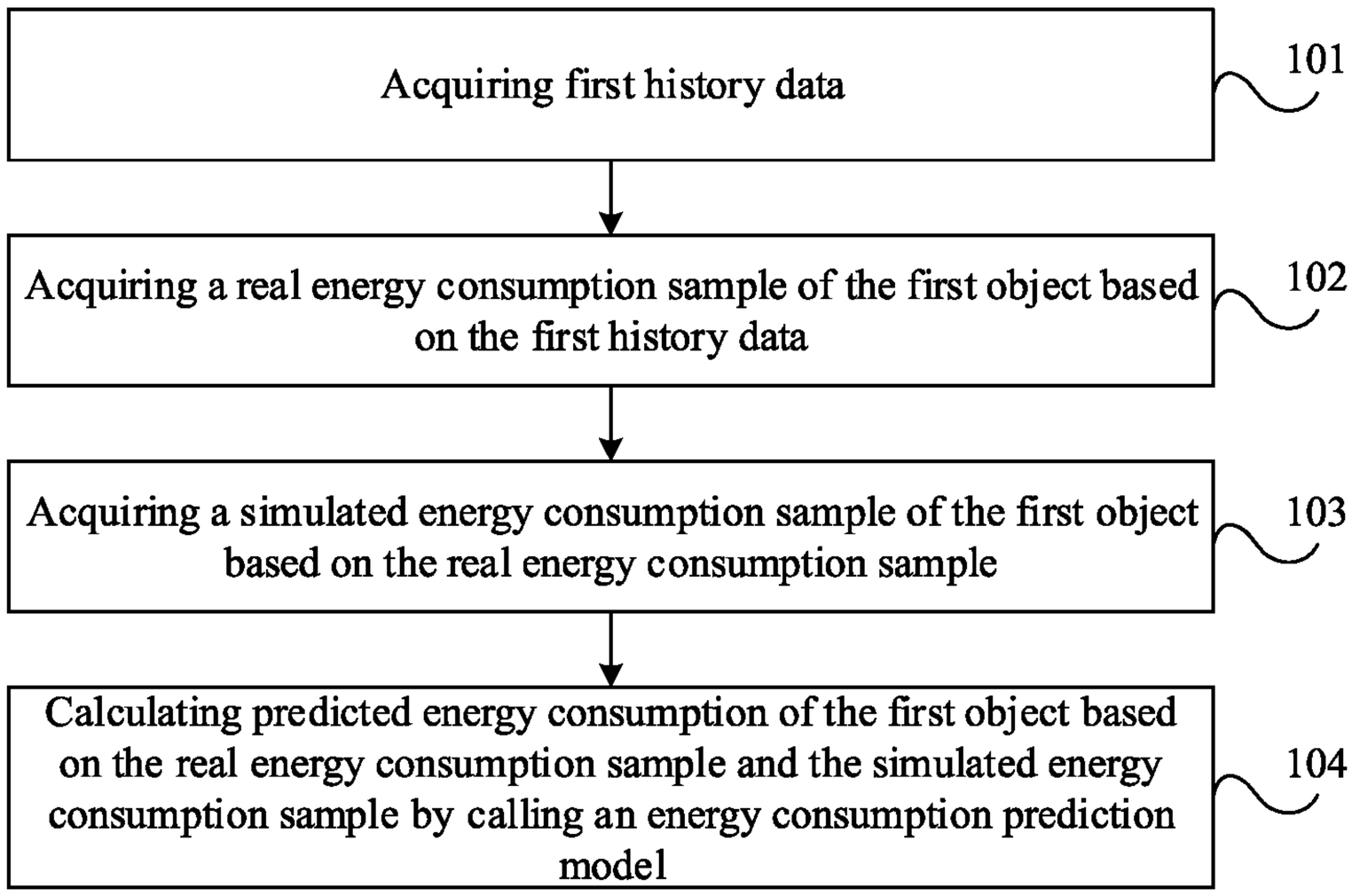

Acquiring first history data
101
Acquiring a real energy consumption sample of the first object based on the first history data
102
Acquiring a simulated energy consumption sample of the first object based on the real energy consumption sample
103
Calculating predicted energy consumption of the first object based on the real energy consumption sample and the simulated energy consumption sample by calling an energy consumption prediction model
104

FIG. 1

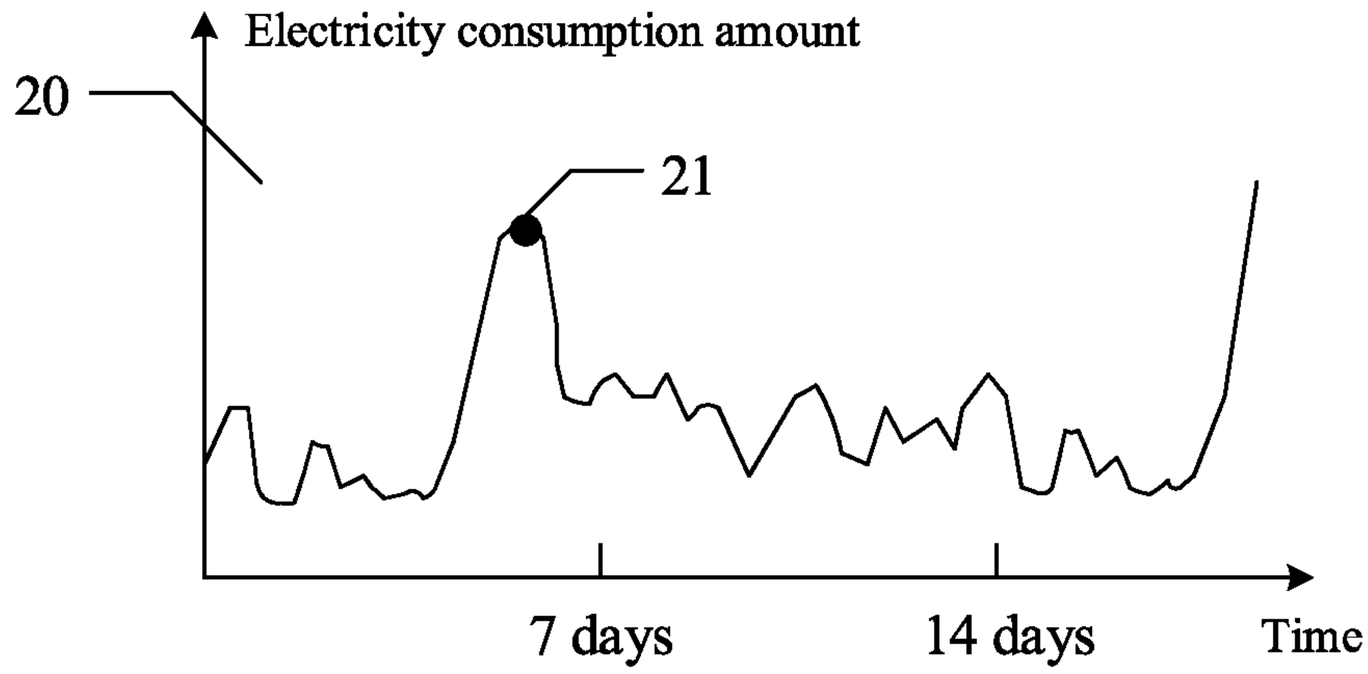

Electricity consumption amount
20
21
7 days
14 days
Time

FIG. 2

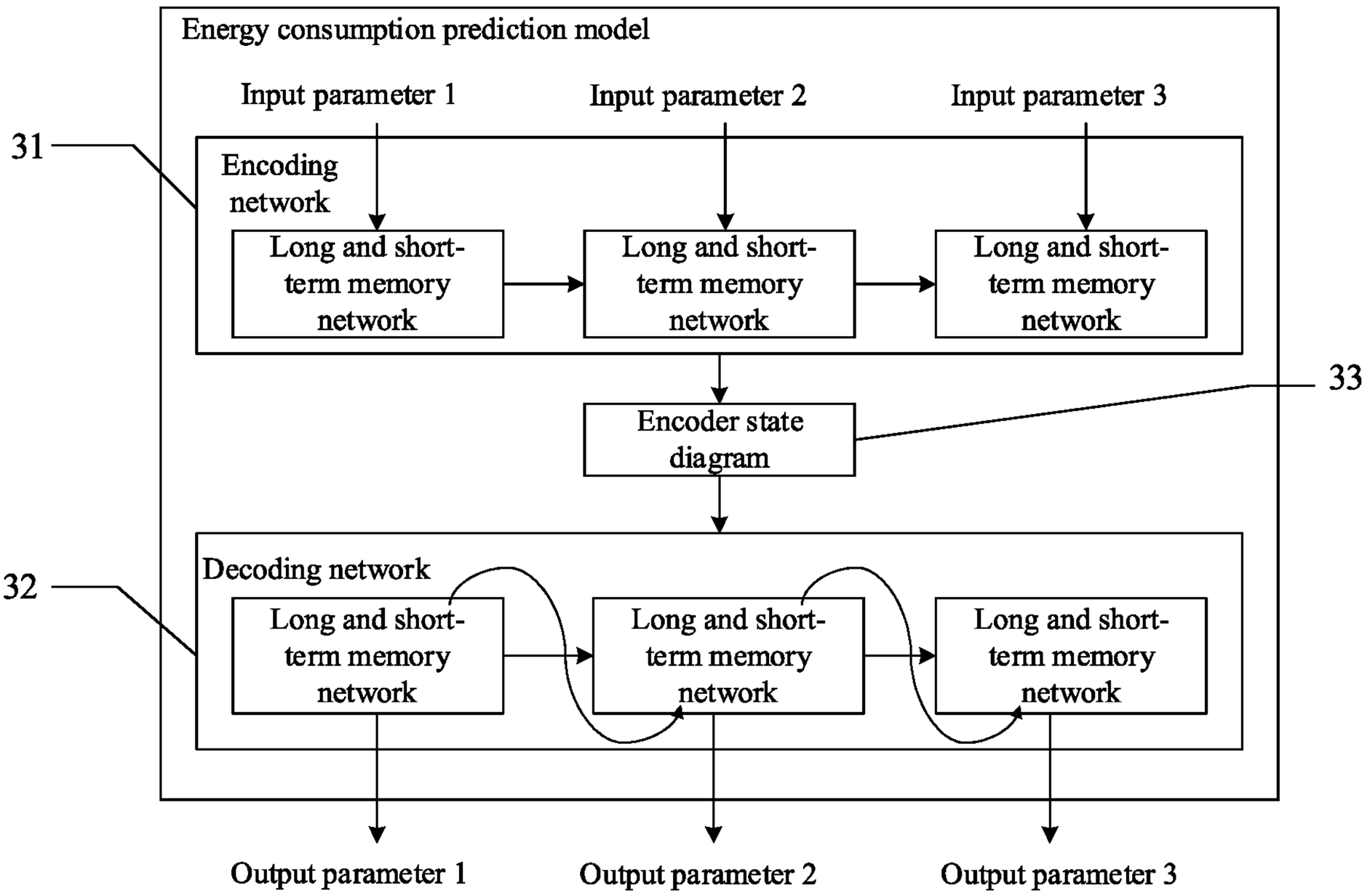

Energy consumption prediction model
Input parameter 1
Input parameter 2
Input parameter 3
31
Encoding network
Long and short-term memory network
Long and short-term memory network
Long and short-term memory network
Encoder state diagram
33
Decoding network
32
Long and short-term memory network
Long and short-term memory network
Long and short-term memory network
Output parameter 1
Output parameter 2
Output parameter 3

FIG. 3

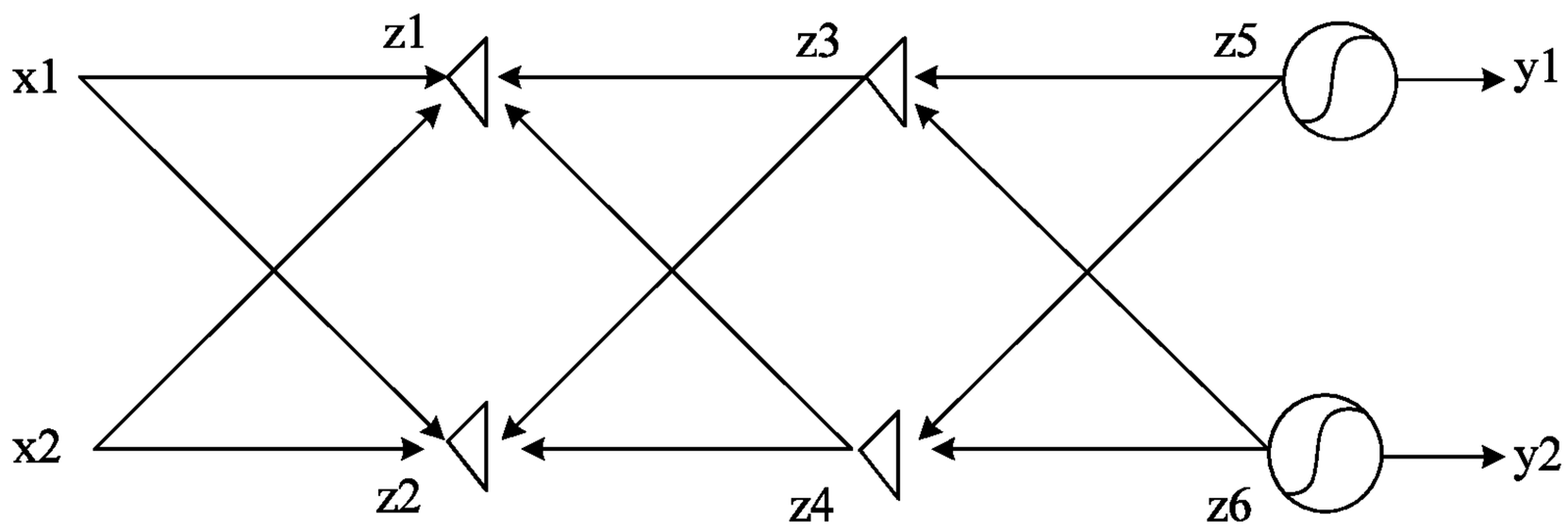

x1
x2
z1
z2
z3
z4
z5
z6
y1
y2

FIG. 4

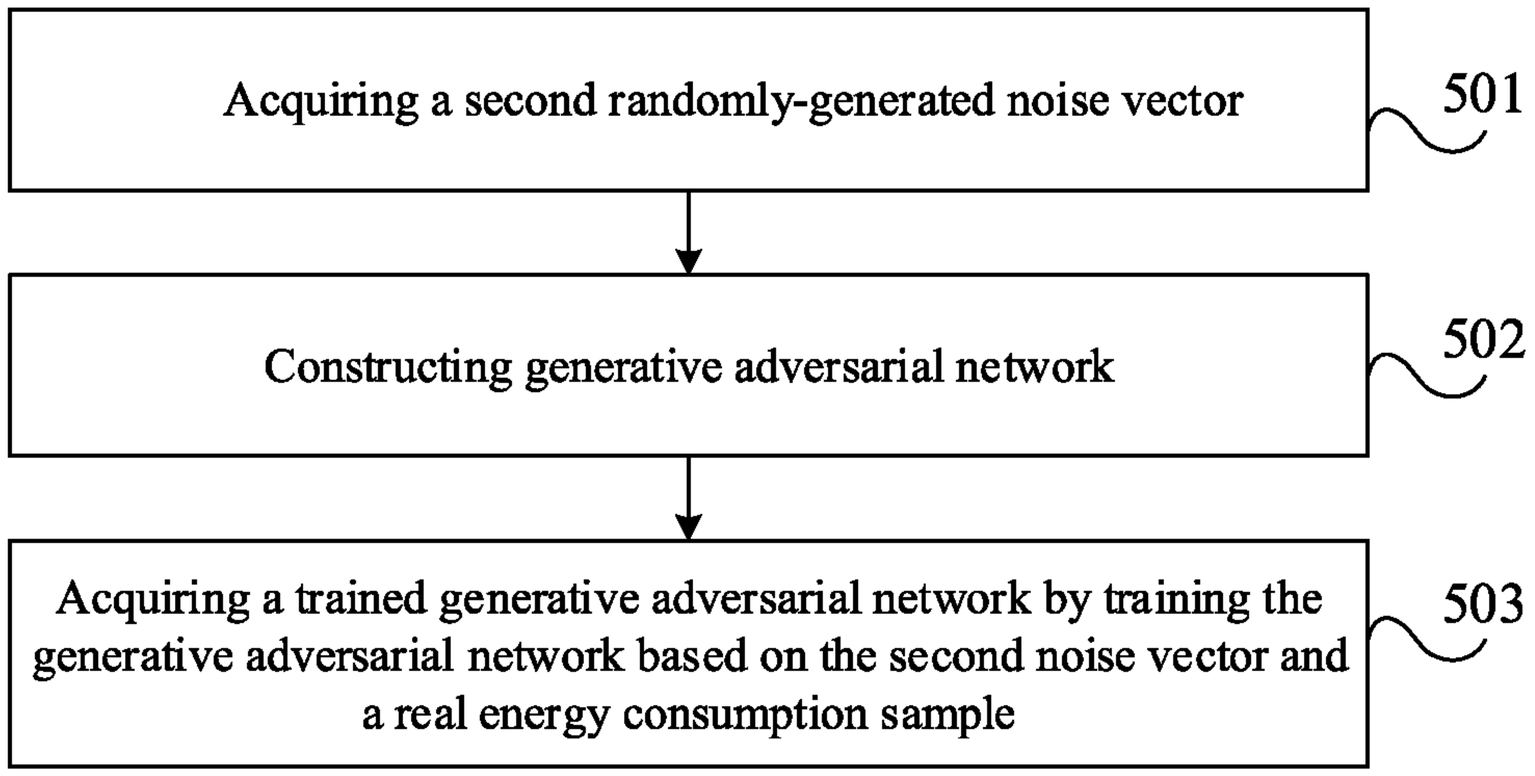

Acquiring a second randomly-generated noise vector
501
Constructing generative adversarial network
502
Acquiring a trained generative adversarial network by training the generative adversarial network based on the second noise vector and a real energy consumption sample
503

FIG. 5

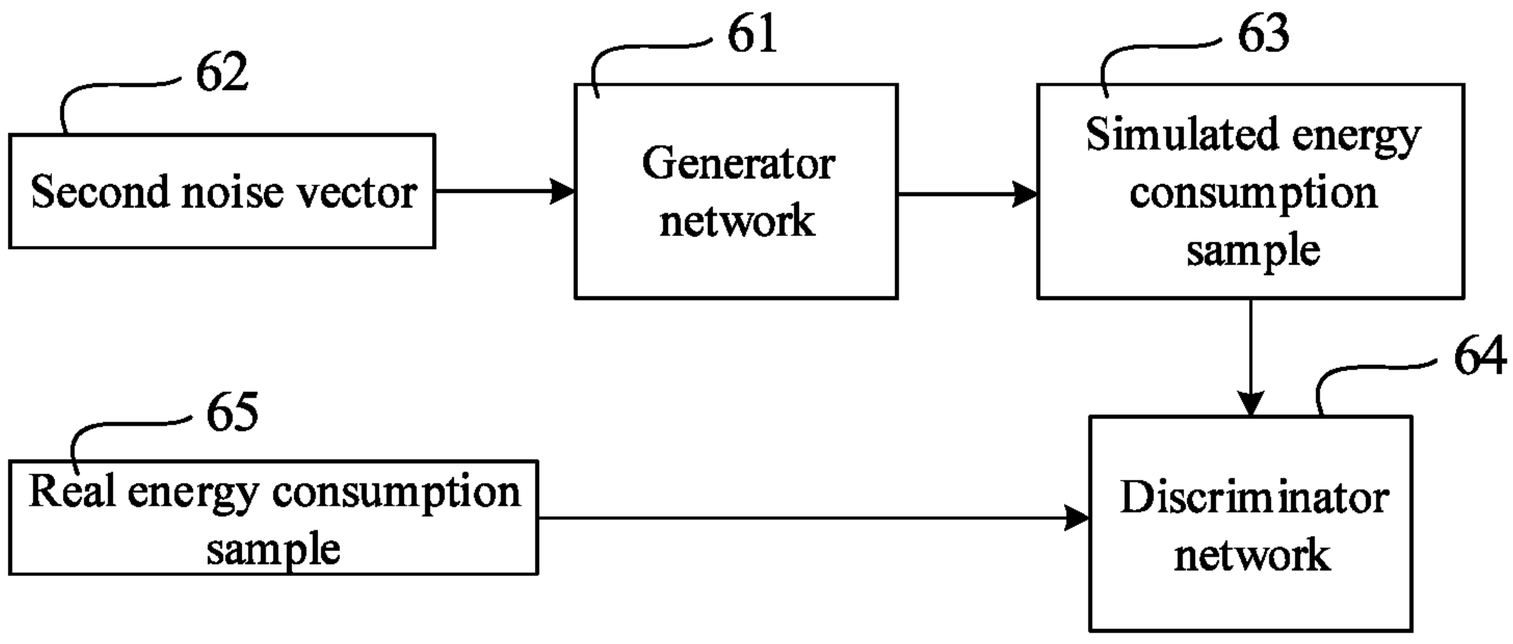

62
Second noise vector
61
Generator network
63
Simulated energy consumption sample
64
65
Real energy consumption sample
Discriminator network

FIG. 6

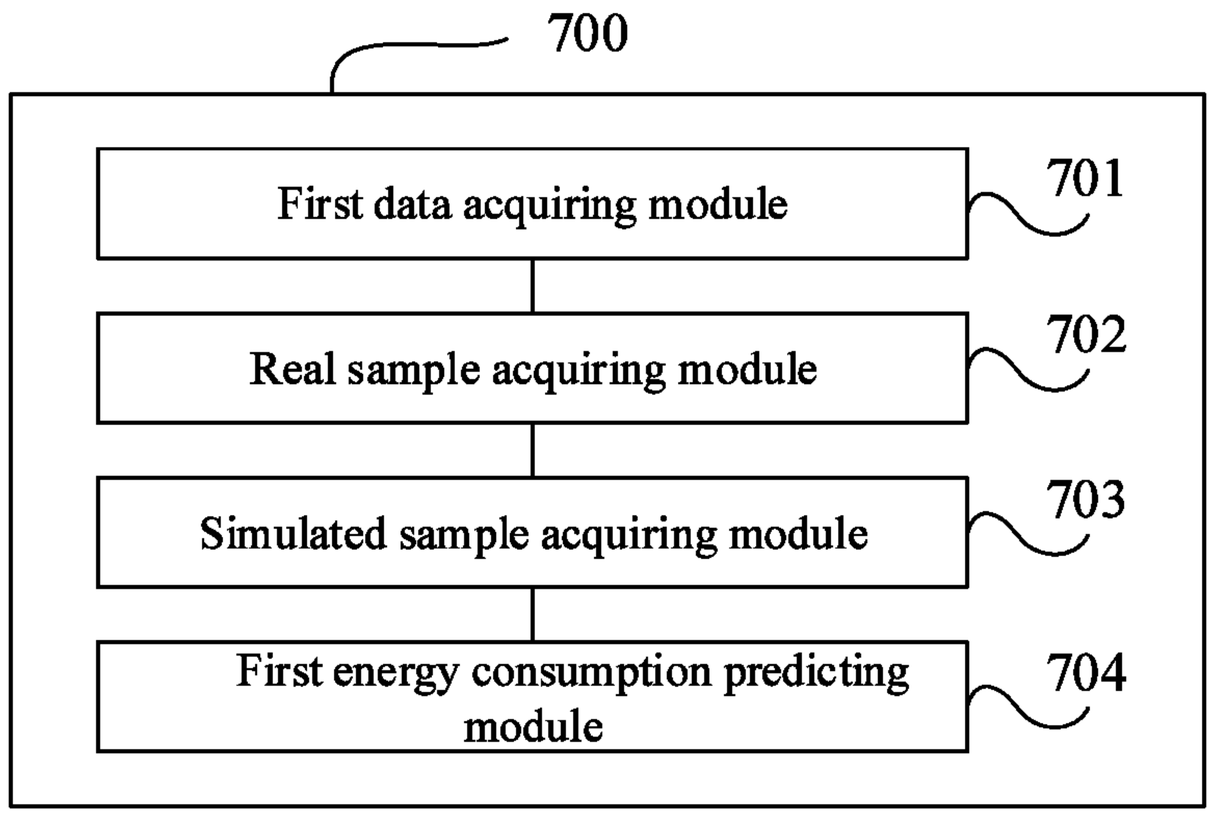

700
First data acquiring module
701
Real sample acquiring module
702
Simulated sample acquiring module
703
First energy consumption predicting module
704

FIG. 7

700
First data acquiring module
701
Real sample acquiring module
702
Candidate sample generating module
705
Authenticity calculating module
706
Simulated sample determining module
707
Simulated sample acquiring module
703
First energy consumption predicting module
704
Second vector acquiring module
708
Neural network constructing module
709
Neural network training module
710
Second data acquiring module
711
Prediction model training module
712
Model parameter fine-adjusting module
713

FIG. 8

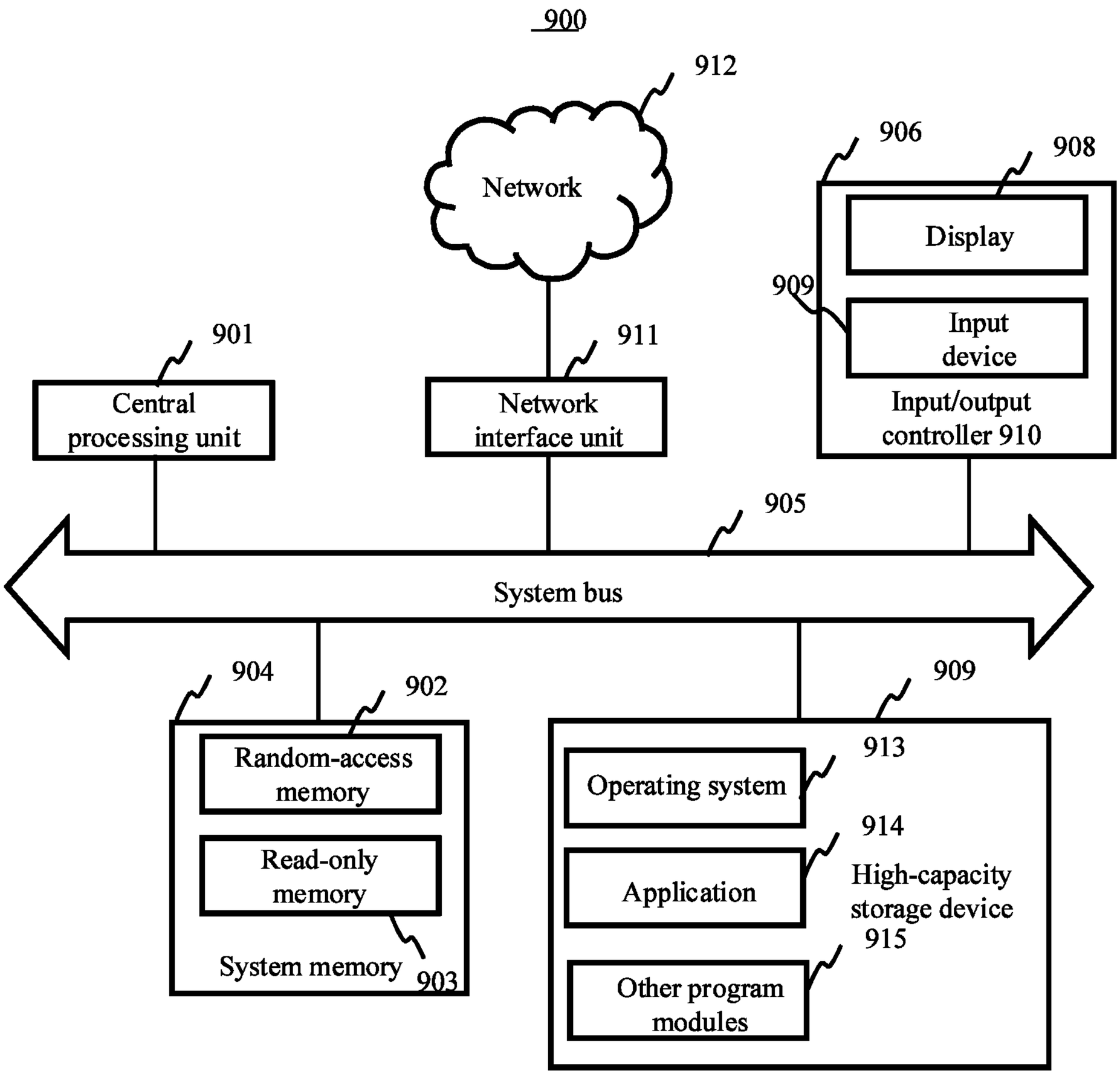

900
912
Network
906
908
Display
909
Input device
Input/output controller 910
901
Central processing unit
911
Network interface unit
905
System bus
904
902
Random-access memory
Read-only memory
System memory
903
909
913
Operating system
914
Application
High-capacity storage device
915
Other program modules

FIG. 9

INTERNATIONAL SEARCH REPORT

International application No.
PCT/SG2020/050775

A. CLASSIFICATION OF SUBJECT MATTER

G06N 3/02 (2006.01) ***G06Q 10/04 (2012.01)*** *G06Q 50/06 (2012.01)*

According to International Patent Classification (IPC)

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

G06N, G06Q

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

Databases: FAMPAT, CNKI, IEEE

Keywords: electrical energy, power, prediction, forecasting, expansion, extrapolation, interpolation, synthesis, estimation, noise vector, GAN, 电能, 电力, 预言, 预报, 扩张, 外推, 插补, 合成, 估算, 噪声矢量 and other related terms

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	ZHANG C. ET. AL., Generative Adversarial Network for Synthetic Time Series Data Generation in Smart Grids. *2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, 27 December 2018, pages 1-6 [Retrieved on 2021-04-05] <DOI: 10.1109/SMARTGRIDCOMM.2018.8587464> sections I, III, III.A, III.B, IV.A, IV.C.2, V.A.1, figure 3, 4b	1-10
X	GU Y. ET. AL., GAN-based Model for Residential Load Generation Considering Typical Consumption Patterns. *2019 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, 8 August 2019, pages 1-5 [Retrieved on 2021-04-05] <DOI: 10.1109/ISGT.2019.8791575> sections I, II.A, III.B.2, IV.A, IV.B, V	1, 3-10

☒ Further documents are listed in the continuation of Box C. ☐ See patent family annex.

*Special categories of cited documents:

"A" document defining the general state of the art which is not considered to be of particular relevance

"D" document cited by the applicant in the international application

"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
14/04/2021 *(day/month/year)*	*15/04/2021* *(day/month/year)*
Name and mailing address of the ISA/SG **Intellectual Property Office of Singapore** 1 Paya Lebar Link, #11-03 PLQ 1, Paya Lebar Quarter Singapore 408533 Email: pct@ipos.gov.sg	Authorized officer Danny Yap Ming Ann (Mr) IPOS Customer Service Tel. No.: (+65) 6339 8616

INTERNATIONAL SEARCH REPORT

International application No.
PCT/SG2020/050775

C (Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	WANG F. ET. AL., Generative adversarial networks and convolutional neural networks based weather classification model for day ahead short-term photovoltaic power forecasting. *Energy Conversion and Management*, 1 February 2019, Vol. 181, pages 443-462 [Retrieved on 2021-04-05] <DOI: 10.1016/J.ENCONMAN.2018.11.074> the whole document especially section 2.1.1	