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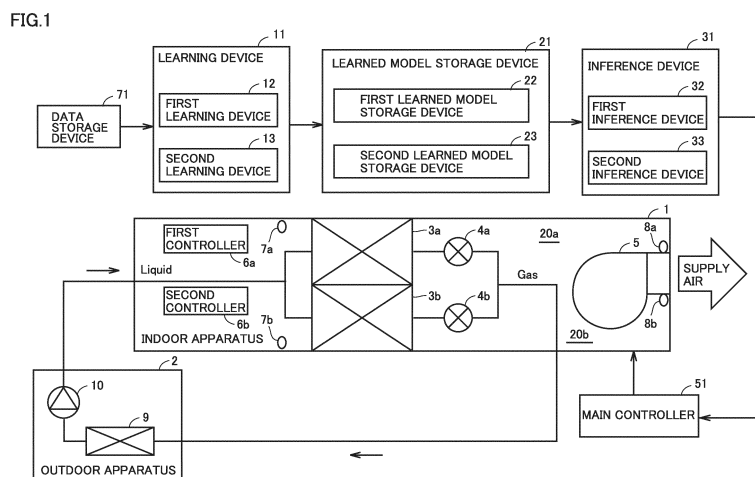
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(54) **AIR CONDITIONING DEVICE, AND LEARNING DEVICE OF AIR CONDITIONING DEVICE**

(57) An indoor unit (20a, 20b) includes a controller (6a, 6b), an indoor heat exchanger (3a, 3b), an electronic expansion valve (4a, 4b), an intake thermistor (7a, 7b) that detects a drawn-in air temperature, and a discharge thermistor (8a, 8b) that detects a discharged air temperature, and performs a thermo-OFF operation when a temperature detected by the discharge thermistor (8a, 8b) reaches a reference value. An air conditioning device

includes a first inference device (32) to infer, from a factor, whether any of a plurality of indoor units (20a, 20b) performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by a plurality of intake thermistors (7a, 7b), and temperatures detected by a plurality of discharge thermistors (8a, 8b) during a past period of time.



Description

TECHNICAL FIELD

5 **[0001]** The present disclosure relates to an air conditioning device and a learning device of an air conditioning device.

BACKGROUND ART

10 **[0002]** An air conditioning device is known which includes multiple indoor units and allows each indoor unit to perform a thermo-OFF operation.

[0003] For example, the air conditioning device disclosed in PTL 1 has a refrigerant circuit in which multiple indoor units individually having an indoor heat exchanger and an indoor expansion valve and an outdoor unit having an outdoor expansion valve are connected by a liquid refrigerant communication tube and a gas refrigerant communication tube. The indoor units perform the thermo-OFF operations independent of each other.

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CITATION LIST

PATENT LITERATURE

20 **[0004]** PTL 1: Japanese Patent Laying-Open No. 2020-169809

SUMMARY OF INVENTION

TECHNICAL PROBLEM

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[0005] In the air conditioning device disclosed in PTL 1, it is determined, for each indoor unit, whether the indoor unit performs the thermo-OFF operation. Since each indoor unit performs the thermo-OFF operation autonomously, if a certain indoor unit performs the thermo-OFF operation, the outdoor apparatus needs to reduce the circulation volume of the refrigerant for that indoor unit in order to keep the high pressure and the low pressure of the compressor within an operating range. As a result, the circulation volume of the refrigerant of the entire air conditioning device rapidly decreases, ending up with perturbation of the temperature of the drawn-in air.

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[0006] Therefore, an object of the present disclosure is to provide an air conditioning device which includes multiple indoor units capable of a thermo-OFF operation and allows stabilized temperature of the drawn-in air, and a learning device of an air conditioning device.

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SOLUTION TO PROBLEM

[0007] The present disclosure is an air conditioning device which includes an indoor apparatus and an outdoor apparatus. The outdoor apparatus includes a compressor and an outdoor heat exchanger. The indoor apparatus includes a plurality of indoor units and a fan. Each indoor unit includes a controller, an indoor heat exchanger, an electronic expansion valve, an intake thermistor for detecting a drawn-in air temperature, and a discharge thermistor for detecting a discharged air temperature, and performs a thermo-OFF operation when the temperature detected by the discharge thermistor reaches a reference value. The air conditioning device further includes a first inference device to infer whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, from a factor including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors during a past period of time.

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[0008] The present disclosure is a learning device of an air conditioning device which includes an indoor apparatus and an outdoor apparatus. The outdoor apparatus includes a compressor and an outdoor heat exchanger. The indoor apparatus includes a plurality of indoor units and a fan. Each indoor unit includes a controller, an indoor heat exchanger, an electronic expansion valve, an intake thermistor that detects a drawn-in air temperature, and a discharge thermistor that detects a discharged air temperature, and the indoor unit performs a thermo-OFF operation when the temperature detected by the discharge thermistor reaches a reference value. The learning device of the air conditioning device includes: a first data acquisition unit to obtain first learning data including (i) factor data including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors during a first time period, and (ii) predictive data indicating whether any of the plurality of indoor units performs a thermo-OFF operation during a second time period later in time than the first time period; and a first model generator to generate, using the first learning data, a first learned model for outputting a prediction as to whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time from a factor including a set temperature,

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temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors during a past period of time.

ADVANTAGEOUS EFFECTS OF INVENTION

[0009] According to the present disclosure, the temperature of the drawn-in air can be stabilized in the air conditioning device which includes multiple indoor units capable of the thermo-OFF operation.

BRIEF DESCRIPTION OF DRAWINGS

[0010]

Fig. 1 is a diagram depicting a configuration of an air conditioning device according to an embodiment.

Fig. 2 is a diagram depicting an example of a thermo-OFF operation when the air conditioning device is in a cooling operation.

Fig. 3 is a diagram depicting an example of the thermo-OFF operation when the air conditioning device is in a heating operation.

Fig. 4 is a diagram depicting a configuration of a learning device 11.

Fig. 5 is a diagram for illustrating a first learned model according to Embodiment 1.

Fig. 6 is a diagram for illustrating a second learned model according to Embodiment 1.

Fig. 7 is a diagram for illustrating an example of acquisition of first learning data when the air conditioning device is in the cooling operation.

Fig. 8 is a diagram for illustrating an example of acquisition of the first learning data when the air conditioning device is in the heating operation.

Fig. 9 is a diagram depicting a configuration of a neural network.

Fig. 10 is a flowchart depicting a first learning procedure performed by a first learning device 12.

Fig. 11 is a flowchart depicting a second learning procedure performed by a second learning device 13.

Fig. 12 is a diagram depicting a configuration of an inference device 31.

Fig. 13 is a flowchart depicting a first inferring procedure performed by a first inference device 32.

Fig. 14 is a flowchart depicting a second inferring procedure performed by a second inference device 33.

Fig. 15 is a diagram depicting an example of a first inference, a second inference, and an air-conditioning control when the air conditioning device is in the cooling operation.

Fig. 16 is a diagram depicting an example of the first inference, the second inference, and the air-conditioning control when the air conditioning device is in the heating operation.

Fig. 17 is a diagram for illustrating a first learned model according to Embodiment 2.

Fig. 18 is a diagram for illustrating a second learned model according to Embodiment 2.

Fig. 19 is a diagram for illustrating a first learned model according to Embodiment 3.

Fig. 20 is a diagram for illustrating a second learned model according to Embodiment 3.

Fig. 21 is a diagram depicting a hardware configuration of a learning device 11, an inference device 31, or a main controller 51.

DESCRIPTION OF EMBODIMENTS

Embodiment 1

[0011] Fig. 1 is a diagram depicting a configuration of an air conditioning device according to an embodiment.

[0012] An air conditioning device includes an outdoor apparatus 2, an indoor apparatus 1, a learning device 11, a learned model storage device 21, an inference device 31, a data storage device 71, and a main controller 51.

[0013] The outdoor apparatus 2 includes a compressor 10 and an outdoor heat exchanger 9.

[0014] The indoor apparatus 1 includes a first indoor unit 20a, a second indoor unit 20b, and a fan 5.

[0015] The first indoor unit 20a includes a first controller 6a, a first indoor heat exchanger 3a, a first electronic expansion valve 4a, a first intake thermistor 7a for detecting a drawn-in air temperature into the first indoor unit 20a, and a first discharge thermistor 8a for detecting a discharged air temperature from the first indoor unit 20a. The first controller 6a is connected to the first indoor heat exchanger 3a, the first electronic expansion valve 4a, the first intake thermistor 7a, the first discharge thermistor 8a, and the fan 5.

[0016] The second indoor unit 20b includes a second controller 6b, a second indoor heat exchanger 3b, a second electronic expansion valve 4b, a second intake thermistor 7b for detecting a drawn-in air temperature into the second indoor unit 20b, and a second discharge thermistor 8b for detecting a discharged air temperature from the second indoor

unit 20b. The second controller 6b is connected to the second indoor heat exchanger 3b, the second electronic expansion valve 4b, the second intake thermistor 7b, the second discharge thermistor 8b, and the fan 5.

[0017] Fig. 1 shows a flow of a refrigerant when the air conditioning device is in a cooling operation.

[0018] As the temperature detected by the first discharge thermistor 8a reaches a reference value, the first indoor unit 20a performs a thermo-OFF operation. In the thermo-OFF operation, the first controller 6a, for example, sets the first electronic expansion valve 4a fully closed and notifies the outdoor apparatus 2 that the operation of the first indoor unit 20a is switched to the thermo-OFF operation. The outdoor apparatus 2 lowers the upper limit for the frequency of the compressor 10 and lowers the actual operation frequency of the compressor 10.

[0019] As the temperature detected by the second discharge thermistor 8b reaches a reference value, the second indoor unit 20b performs a thermo-OFF operation. In the thermo-OFF operation, the second controller 6b, for example, sets the second electronic expansion valve 4b fully closed, stops the fan 5, and notifies the outdoor apparatus 2 that the operation of the second indoor unit 20b is switched to the thermo-OFF operation. The outdoor apparatus 2 lowers the upper limit for the frequency of the compressor 10 and lowers the actual operation frequency of the compressor 10.

[0020] Fig. 2 is a diagram depicting an example of the thermo-OFF operation when the air conditioning device is in the cooling operation.

[0021] In the cooling operation, the air conditioning device has excess capability for a load. This lowers a discharged temperature discharged from the air conditioning device. As the discharged temperature reaches a lower reference value limit TL, the first indoor unit 20a or the second indoor unit 20b performs the thermo-OFF operation. As a result, the frequency of the compressor 10 is reduced as well in order to prevent a rapid decrease in low pressure. Subsequently, the discharged temperature increases rapidly and hunt, after which it converges to a set temperature set by a remote control.

[0022] Fig. 3 is a diagram depicting an example of the thermo-OFF operation when the air conditioning device is in a heating operation.

[0023] In the heating operation, the air conditioning device has excess capability for a load. This increases a discharged temperature discharged from the air conditioning device. As the discharged temperature reaches an upper reference value limit TH, the first indoor unit 20a or the second indoor unit 20b performs the thermo-OFF operation. Subsequently, the discharged temperature increases rapidly and hunt, after which it converges to the set temperature set by the remote control.

[0024] The data storage device 71 stores data for each time t, the data representing the set temperature, the temperatures detected by the intake thermistors 7a and 7b, the temperatures detected by the discharge thermistors 8a and 8b, and whether one of the indoor units 20a and 20b performs the thermo-OFF operation.

[0025] Fig. 4 is a diagram depicting a configuration of the learning device 11.

[0026] The learning device 11 includes a first learning device 12 and a second learning device 13. The learned model storage device 21 includes a first learned model storage device 22 and a second learned model storage device 23.

[0027] The first learned model storage device 22 stores a first learned model.

[0028] Fig. 5 is a diagram for illustrating the first learned model according to Embodiment 1.

[0029] The first learned model according to Embodiment 1 is a model for outputting a prediction, made from a factor, as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time, the factor including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time.

[0030] The second learned model storage device 23 stores a second learned model.

[0031] Fig. 6 is a diagram for illustrating the second learned model according to Embodiment 1.

[0032] The second learned model according to Embodiment 1 is a model for outputting an action from a state, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, the state including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b.

[0033] The first learning device 12 includes a first data acquisition unit 14 and a first model generator 15.

[0034] Fig. 7 is a diagram for illustrating an example of acquisition of first learning data when the air conditioning device is in the cooling operation. Fig. 8 is a diagram for illustrating an example of acquisition of the first learning data when the air conditioning device is in the heating operation.

[0035] The first data acquisition unit 14 obtains the first learning data from the data storage device 71, the first learning data including (i) factor data including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a first time period (t_1 through $t_1 + \Delta T_x$) and (ii) predictive data as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a second time period ($t_1 + \Delta T_x$ through $t_1 + \Delta T_y$) later in time than the first time period. The first data acquisition unit 14 obtains multiple first learning data items by varying t_1 .

[0036] Using the first learning data obtained by the first data acquisition unit 14, the first model generator 15 generates

a first learned model for outputting a prediction, made from a factor, as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time, the factor including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time. The first model generator 15 stores the first learned model into the first learned model storage device 22.

[0037] The first model generator 15 may use a well-known learning algorithm such as supervised learning, unsupervised learning, or reinforcement learning. By way of example, description is now set forth where a neural network is applied to learning algorithm.

[0038] Fig. 9 is a diagram depicting a configuration of the neural network.

[0039] For example, the first model generator 15 performs what is called supervised learning, in accordance with a neural network model, thereby learning a prediction, made from a factor, as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time, the factor including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time. Here, the supervised learning refers to an approach in which the first learning device 12 is provided with a data set (the first learning data) of input and a result (label), and the first learning device 12 thereby learns features in the first learning data and infers a result from the input.

[0040] The neural network consists of an input layer which includes multiple neurons; an intermediate layer (a hidden layer) which includes multiple neurons; and an output layer which includes multiple neurons. The intermediate layer may be one layer, or two or more layers.

[0041] For example, if the neural network is a three-layer neural network, as multiple inputs are input to input layers (X1 through X3), the values of the inputs are weighed by a weight W1 (w11 through w16) and then input to intermediate layers (Y1 through Y2) where the results are weighed by a weight W2 (w21 through w26), and then output through output layers (Z1 through Z3). The result of this output depends on the values of the weights W1 and W2.

[0042] The neural network generates a first learned model by what is called supervised learning, in accordance with the first learning data obtained by the first data acquisition unit 14. From the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time, the first learned model outputs a prediction as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time.

[0043] In other words, the neural network learns by: providing the input layers with the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time; and adjusting the weights W1 and W2 so that results of outputs from the output layers approach the prediction (a ground truth) as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation within a future period of time.

[0044] The first model generator 15 learns as described above, thereby generating and outputting a learned model to the first learned model storage device 22.

[0045] Fig. 10 is a flowchart depicting a first learning procedure performed by the first learning device 12.

[0046] In step b 1, the first data acquisition unit 14 obtains the first learning data from the data storage device 71. The first learning data includes (i) the factor data including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during the first time period (11 through $t1 + \Delta Tx$), and (ii) the predictive data as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during the second time period ($t1 + \Delta Tx$ through $t1 + \Delta Ty$) later in time than the first time period. The first data acquisition unit 14 obtains multiple first learning data items by varying $t1$.

[0047] In step b2, using the first learning data obtained by the first data acquisition unit 14, the first model generator 15 generates the first learned model for outputting the prediction, made from a factor, as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation within a future period of time, the factor including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time.

[0048] In step b3, the first model generator 15 stores the first learned model into the first learned model storage device 22.

[0049] The second learning device 13 includes a second data acquisition unit 16 and a second model generator 17.

[0050] The second data acquisition unit 16 obtains second learning data including a state and an action in the state, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature.

[0051] Using the second learning data obtained by the second data acquisition unit 16, the second model generator 17 generates a second learned model for outputting an action from a state, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating

temperature, and a target refrigerant condensing temperature, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b. The second model generator 17 stores the second learned model into the second learned model storage device 23.

[0052] The second model generator 17 may use a well-known learning algorithm such as reinforcement learning. By way of example, description is now set forth where the neural network is applied to reinforcement learning. In the reinforcement learning, an agent (actor) within a certain environment observes the current state (parameters of the environment) and determines an action to be taken. The action by the agent dynamically changes the environment, and the agent is provided with a reward in response to the changes in the environment. The agent repeats this process to learn a most rewarded course of action. A representative approach, Q-learning or temporal-difference (TD) learning, can be used. For example, with Q-learning, a general update formula for the action value function $Q(s, a)$ is represented by:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left(r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right) \quad \dots (1)$$

where s_t denotes a state of the environment at the time t , and a_t denotes an action at the time t . The action a_t changes the state to s_{t+1} . A reward that the agent can receive due to the changes in state is represented by r_{t+1} , γ denotes a discount factor, and α denotes a learning coefficient. Note that γ falls in a range of $0 < \gamma \leq 1$, and α falls in a range of $0 < \alpha \leq 1$. The state s_t is the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 20b. The action a_t is the target degree of superheat, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature. With Q-learning, the first learning device 12 learns the best action at in the state s_t at the time t .

[0053] If the value of the action value function Q for an action a yielding a highest Q value at the time $t+1$ is greater than the value of the action value function Q for an action a carried out at the time t , the update formula denoted by Formula (1) yields an increased value of the action value function Q , and, otherwise, yields a reduced value of the action value function Q . Stated differently, the update formula updates the action value function $Q(s, a)$ so that the value of the action value function Q for the action a at the time t approaches a best action value at the time $t+1$. This causes the best action value in a certain environment to sequentially propagate to action values in previous environments.

[0054] As described above, to generate the second learned model by the reinforcement learning, the second model generator 17 includes a reward calculator 18 and a function updater 19.

[0055] The reward calculator 18 calculates a reward, based on an action and a state, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b. The reward calculator 18 calculates a reward r , based on a difference between the set temperature and a discharged air temperature. The discharged air temperature can be one of or an average of the temperatures detected by the discharge thermistors 8a and 8b. For example, the reward calculator 18 increases the reward r (e.g., gives a reward "1") if the difference between the set temperature and the discharged air temperature decreases. The reward calculator 18, on the other hand, reduces the reward r (e.g., gives a reward "-1") if the difference between the set temperature and the discharged air temperature increases.

[0056] In accordance with the reward calculated by the reward calculator 18, the function updater 19 updates a function for determining an action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, and outputs the function to the second learned model storage device 23. With Q-learning, for example, the function updater 19 uses the action value function $Q(s_t, a_t)$ represented by Formula (1), as the function for calculating an action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature.

[0057] The first learning device 12 repeatedly learns as described above. The second learned model storage device 23 stores the action value function $Q(s_t, a_t)$ updated by the function updater 19, that is, the second learned model.

[0058] Fig. 11 is a flowchart depicting the second learning procedure performed by the second learning device 13.

[0059] In step d1, the second data acquisition unit 16 obtains the second learning data which includes a state and an action in the state, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature.

[0060] In step d2, the second model generator 17 calculates a reward, based on the second learning data. Specifically,

the reward calculator 18 determines whether to increase or reduce the reward, based on a difference between the set temperature and the discharged air temperature.

[0061] If the reward calculator 18 determines to increase the reward, the process proceeds to step S103. If the reward calculator 18 determines to reduce the reward, the process proceeds to step S104.

[0062] In step d3, the reward calculator 18 increases the reward.

[0063] In step d4, the reward calculator 18 reduces the reward.

[0064] In step d5, the function updater 19 updates the action value function $Q(st, at)$ represented by Formula (1) and stored in the second learned model storage device 23, based on the reward calculated by the reward calculator 18.

[0065] The second learning device 13 repeats the steps d1 through d5 stated above, and stores a generated action value function $Q(st, at)$ as the second learned model.

[0066] Fig. 12 is a diagram depicting a configuration of the inference device 31.

[0067] The inference device 31 includes a first inference device 32 and a second inference device 33.

[0068] The first inference device 32 includes a first data acquisition unit 34 and a first inference unit 35.

[0069] The first data acquisition unit 34 obtains the factor data including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time. The past period of time can be a time period ($t_0 - \Delta T_x$ through t_0), where the current time is t_0 .

[0070] The first inference unit 35 inputs the factor data obtained by the first data acquisition unit 34 to the first learned model stored in the first learned model storage device 22, and outputs the prediction as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time.

[0071] Fig. 13 is a flowchart depicting the first inferring procedure performed by the first inference device 32.

[0072] In step c1, the first data acquisition unit 34 obtains the factor data including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time.

[0073] In steps c2 and c3, the first inference unit 35 inputs the factor data obtained by the first data acquisition unit 34 to the first learned model stored in the first learned model storage device 22, and outputs the prediction as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time.

[0074] In step c4, if one of the indoor units 20a and 20b is predicted to perform the thermo-OFF operation during a future period of time, the process proceeds to step c5. The process ends if none of the indoor units 20a and 20b is predicted to perform the thermo-OFF operation during a future period of time.

[0075] In step c5, the second inference device 33 performs an inference process, which is described next.

[0076] The second inference device 33 includes a second data acquisition unit 36 and a second inference unit 37.

[0077] The second data acquisition unit 36 obtains a state including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b.

[0078] Using the second learned model stored in the second learned model storage device 23, the second inference unit 37 infers an action from the state obtained by the second data acquisition unit 36, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature.

[0079] For example, the second inference unit 37 reads the action value function $Q(st, at)$ from the second learned model storage device 23, as a second learned model. The second inference unit 37 obtains an action at in response to a state st , based on the action value function $Q(s, a)$, the action at including the target degree of superheat, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature, the state st including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b.

[0080] The main controller 51 controls the air conditioning device, based on the action at including the target degree of superheat output from the second inference unit 37, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature.

[0081] For example, when the air conditioning device is in the cooling operation, the main controller 51 controls the electronic expansion valves 4a and 4b so that the degree of superheat of the liquid refrigerant immediately after passing through the indoor heat exchangers 3a and 3b results in the target degree of superheat. For example, when the air conditioning device is in the heating operation, the main controller 51 controls the electronic expansion valves 4a and 4b so that the degree of supercooling of the liquid refrigerant immediately after passing through the indoor heat exchangers 3a and 3b results in the target degree of supercooling.

[0082] Fig. 14 is a flowchart depicting a second inferring procedure performed by the second inference device 33.

[0083] In step e1, the second data acquisition unit 36 obtains a state including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b.

[0084] In step e2, using the second learned model stored in the second learned model storage device 23, the second inference unit 37 infers an action from the state obtained by the second data acquisition unit 36, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant

evaporating temperature, and a target refrigerant condensing temperature.

[0085] In step e3, the second inference unit 37 outputs the target degree of superheat, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature to the main controller 51.

[0086] In step e4, the main controller 51 controls the air conditioning device, based on the target degree of superheat, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature.

[0087] Fig. 15 is a diagram depicting an example of a first inference, a second inference, and an air-conditioning control when the air conditioning device is in the cooling operation. Fig. 16 is a diagram depicting an example of the first inference, the second inference, and the air-conditioning control when the air conditioning device is in the heating operation.

[0088] The first inference device 32, at a time t_a , inputs the factor data during a past period of time ($t_a - \Delta T_x$ through t_a) to the first learned model, thereby predicting that one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time (t_a through $t_a + \Delta T_x$).

[0089] Using the second learned model stored in the second learned model storage device 23, the second inference device, at and after the time t_a , infers an action from a state, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b.

[0090] The main controller 51 controls the air conditioning device, based on the target degree of superheat, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature. This prevents the discharged temperature from reaching the lower reference value limit TL when the air conditioning device is in the cooling operation. Thus, the discharged temperature reaches the set temperature, without the first indoor unit 20a or the second indoor unit 20b performing the thermo-OFF operation. Since the discharged temperature does not reach the upper reference value limit TH when the air conditioning device is in the heating operation, the discharged temperature reaches the set temperature, without the first indoor unit 20a or the second indoor unit 20b performing the thermo-OFF operation.

[0091] As described above, the air conditioning device according to the present embodiment outputs the prediction, made from a factor, as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time, the factor including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time. This allows predicting that each indoor unit performs the thermo-OFF operation in the air conditioning device which includes multiple indoor units capable of the thermo-OFF operation.

[0092] The air conditioning device according to the present embodiment further outputs an action from a state, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b. This allows the air conditioning device to control each indoor unit so that the discharged air temperature is stabilized at the set temperature, without requiring the indoor unit to perform the thermo-OFF operation.

Embodiment 2

[0093] Fig. 17 is a diagram for illustrating a first learned model according to Embodiment 2.

[0094] The first learned model according to Embodiment 2 is a model for outputting a prediction, made from a factor, as to whether one of indoor units 20a and 20b performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by intake thermistors 7a and 7b, and temperatures detected by discharge thermistors 8a and 8b during a past period of time and a forecast of the outdoor air temperature and a forecast of weather conditions during a future period of time. The forecast of the outdoor air temperature and the forecast of weather conditions during a future period of time can be, for example, forecasts for a period of time, such as within ten minutes or within an hour from the present time, which are obtained through the Internet, for example.

[0095] Fig. 18 is a diagram for illustrating a second learned model according to Embodiment 2.

[0096] The second learned model according to Embodiment 2 is a model for outputting an action from a state, the action including a target degree of superheat, a target degree of supercooling, a set frequency of a compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, the state including a set temperature, temperatures detected by intake thermistors 7a and 7b, and temperatures detected by discharge thermistors 8a and 8b.

[0097] A first learning device 12 is now described.

[0098] A first data acquisition unit 14 obtains first learning data, which includes (i) factor data including the set tem-

perature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a first time period (t_1 through $t_1 + \Delta T_x$) and a forecast of the outdoor air temperature and a forecast of weather conditions during a second time period ($t_1 + \Delta T_x$ through $t_1 + \Delta T_y$) later in time than the first time period, and (ii) predictive data as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during the second time period ($t_1 + \Delta T_x$ through $t_1 + \Delta T_y$). The first data acquisition unit 14 obtains multiple first learning data items by varying t_1 .

[0099] Using the first learning data obtained by the first data acquisition unit 14, a first model generator 15 generates the first learned model for outputting the prediction, made from a factor, as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation within a future period of time, the factor including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time and a forecast of the outdoor air temperature and a forecast of weather conditions during a future period of time. The first model generator 15 stores the first learned model into a first learned model storage device 22.

[0100] A second learning device 13 is now described.

[0101] A second data acquisition unit 16 obtains second learning data which includes a state and an action in the state, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature.

[0102] Using the second learning data obtained by the second data acquisition unit 16, a second model generator 17 generates the second learned model for outputting an action from a state, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b.

[0103] A reward calculator 18 calculates a reward, based on the action including the target degree of superheat, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature, and the state including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b. The reward calculator 18 calculates a reward r , based on a difference between the set temperature and the discharged air temperature.

[0104] In accordance with the reward calculated by the reward calculator 18, a function updater 19 updates a function for determining an action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, and outputs the function to the second learned model storage device 23.

[0105] A first inference device 32 is now described.

[0106] A first data acquisition unit 34 obtains factor data including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time and a forecast of the outdoor air temperature and a forecast of weather conditions during a future period of time.

[0107] A first inference unit 35 inputs the factor data obtained by the first data acquisition unit 34 to the first learned model stored in the first learned model storage device 22, and outputs a prediction as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time.

[0108] A second inference device 33 is now described.

[0109] A second data acquisition unit 36 obtains a state including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b.

[0110] Using the second learned model stored in the second learned model storage device 23, a second inference unit 37 infers an action from the state obtained by the second data acquisition unit 36, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature.

[0111] For example, the second inference unit 37 reads an action value function $Q(s_t, a_t)$ from the second learned model storage device 23 as the second learned model. In response to a state s_t including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b, the second inference unit 37 obtains an action a_t based on the action value function $Q(s, a)$, the action a_t including the target degree of superheat, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature.

[0112] Similarly to Embodiment 1, a main controller 51 controls an air conditioning device, based on the target degree of superheat, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature.

[0113] According to the present embodiment, the discharged air temperature can be stabilized, without being subject

to the weather.

Embodiment 3

[0114] Fig. 19 is a diagram for illustrating a first learned model according to Embodiment 3.

[0115] The first learned model according to Embodiment 3 is a model for outputting a prediction, made from a factor, as to whether one of indoor units 20a and 20b performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by intake thermistors 7a and 7b, and temperatures detected by discharge thermistors 8a and 8b during a past period of time and a forecast of the outdoor air temperature, a forecast of the outdoor air humidity, and a forecast of weather conditions during a future period of time. The forecast of the outdoor air temperature, the forecast of the outdoor air humidity, and the forecast of weather conditions during a future period of time can be, for example, forecasts for a period of time, such as within ten minutes or within an hour from the present time, which are obtained through the Internet, for example.

[0116] Fig. 20 is a diagram for illustrating a second learned model according to Embodiment 3.

[0117] The second learned model according to Embodiment 3 is a model for outputting an action from a state, the action including a target degree of superheat, a set frequency of a compressor 10, a target refrigerant evaporating temperature, and a target humidity, the state including a set temperature, temperatures detected by intake thermistors 7a and 7b, and temperatures detected by discharge thermistors 8a and 8b.

[0118] A first learning device 12 is now described.

[0119] A first data acquisition unit 14 obtains first learning data which includes (i) factor data including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a first time period (t_1 through $t_1 + \Delta T_x$) and a forecast of the outdoor air temperature, a forecast of the outdoor air humidity, and a forecast of weather conditions during a second time period ($t_1 + \Delta T_x$ through $t_1 + \Delta T_y$) later in time than the first time period, and (ii) predictive data as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during the second time period ($t_1 + \Delta T_x$ through $t_1 + \Delta T_y$). The first data acquisition unit 14 obtains multiple first learning data items by varying t_1 .

[0120] Using the first learning data obtained by the first data acquisition unit 14, a first model generator 15 generates the first learned model for outputting the prediction, made from a factor, as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation within a future period of time, the factor including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time and a forecast of the outdoor air temperature, a forecast of the outdoor air humidity, and a forecast of weather conditions during a future period of time. The first model generator 15 stores the first learned model into a first learned model storage device 22.

[0121] A second learning device 13 is now described.

[0122] A second data acquisition unit 16 obtains second learning data which includes a state and an action in the state, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b, the action including a target degree of superheat, a set frequency of the compressor 10 of an outdoor apparatus 2, a target refrigerant evaporating temperature, and a target humidity.

[0123] Using the second learning data obtained by the second data acquisition unit 16, a second model generator 17 generates the second learned model for outputting an action from a state, the action including a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target humidity, the state including a set temperature, temperatures detected by the intake thermistors 7a and 7b, and temperatures detected by the discharge thermistors 8a and 8b.

[0124] A reward calculator 18 calculates a reward, based on the action including the target degree of superheat, the target degree of supercooling, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target refrigerant condensing temperature, and the state including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b. The reward calculator 18 calculates a reward r , based on a difference between the set temperature and the discharged air temperature.

[0125] In accordance with the reward calculated by the reward calculator 18, a function updater 19 updates a function for determining an action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, and outputs the function to the second learned model storage device 23.

[0126] A first inference device 32 is now described.

[0127] A first data acquisition unit 34 obtains factor data including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b during a past period of time and a forecast of the outdoor air temperature and a forecast of weather conditions during a future period of time.

[0128] A first inference unit 35 inputs the factor data obtained by the first data acquisition unit 34 to the first learned

model stored in the first learned model storage device 22, and outputs a prediction as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time.

[0129] A second inference device 33 is now described.

[0130] A second data acquisition unit 36 obtains a state including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b.

[0131] Using the second learned model stored in the second learned model storage device 23, a second inference unit 37 infers an action from the state obtained by the second data acquisition unit 36, the action including a target degree of superheat, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target humidity.

[0132] For example, the second inference unit 37 reads an action value function $Q(st, at)$ from the second learned model storage device 23 as the second learned model. In response to a state st including the set temperature, the temperatures detected by the intake thermistors 7a and 7b, and the temperatures detected by the discharge thermistors 8a and 8b, the second inference unit 37 obtains an action at based on the action value function $Q(s, a)$, the action at including the target degree of superheat, the set frequency of the compressor 10, the target refrigerant evaporating temperature, and the target humidity.

[0133] Similarly to Embodiment 1, a main controller 51 controls an air conditioning device, based on the target degree of superheat, the set frequency of the compressor 10, and the target refrigerant evaporating temperature. The main controller 51 also controls the cooling operation or the dehumidification operation so that the indoor humidity reaches the target humidity.

[0134] According to the present embodiment, the operation of the air conditioning device can be automatically switched to the dehumidification operation when the humidity is increased, such as when the weather forecast indicates the chance of rain.

Variations

[0135]

(1) While the learning device 11 and the inference device 31 are provided inside the air conditioning device, the learning device 11 and the inference device 31 may be separate from the air conditioning device and connected to the air conditioning device through a network. Furthermore, the learning device 11 and the inference device 31 may reside on a cloud server.

(2) Fig. 21 is a diagram depicting a hardware configuration of the learning device 11, the inference device 31, or the main controller 51.

Operations corresponding to the operations of the learning device 11, the inference device 31, and the main controller 51 can be configured in hardware or software for digital circuits. If the functions of the learning device 11, the inference device 31, and the main controller 51 are implemented using software, the learning device 11, the inference device 31, and the main controller 51 can include, for example, a processor 5002 and a memory 5001 that are connected together by a bus 5003 as shown in Fig. 21, and the processor 5002 can execute programs stored in the memory 5001.

(3) While the embodiments have been described with reference to the supervised learning being applied to the learning algorithm for use by the first model generator 15, the present disclosure is not limited thereto. Besides the supervised learning, reinforcement learning, unsupervised learning, or semi-supervised learning, etc. is also applicable to the learning algorithm. While the embodiments have been described with reference to the reinforcement learning being applied to the learning algorithm for use by the second model generator 17, the present disclosure is not limited thereto. Besides the reinforcement learning, supervised learning, unsupervised learning, or semi-supervised learning, etc. is also applicable to the learning algorithm.

(4) The first model generator 15 and the second model generator 17 may generate the first learned model and the second learned model in accordance with the first learning data and the second learning data, respectively, created at multiple air conditioning devices. The first model generator 15 and the second model generator 17 may obtain the first learning data and the second learning data from multiple air conditioning devices that are used in a same area, or obtain the first learning data and the second learning data from multiple air conditioning devices operating independently in different areas. The air conditioning device that collects the first learning data and the second learning data can be added to or excluded from a target. Furthermore, the first learning data and the second learning data of a certain air conditioning device may be used to generate a first learned model and a second learned model, and the first learned model and the second learned model may be updated (re-learned) using first learning data and a second learned model of a different air conditioning device.

(5) Deep learning that learns extraction of features themselves can be used as the learning algorithms that use the first model generator 15 and the second model generator 17, and the machine learning may be performed in

accordance with other well-known method, for example, genetic programming, functional and logic programming, or a support vector machine.

(6) In the embodiment, the first inference unit 35 uses the first learned model to output the prediction, made from the factor data obtained by the first data acquisition unit 34, as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time. However, the present disclosure is not limited thereto. For example, the first inference unit 35 may output the prediction as to whether one of the indoor units 20a and 20b performs the thermo-OFF operation during a future period of time, from the factor data obtained by the first data acquisition unit 34, based on a rule-based inference or an incident-based inference.

The second inference unit 37 according to Embodiment 1 uses the second learned model to infer an action from the state obtained by the second data acquisition unit 36, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature. However, the present disclosure is not limited thereto. For example, the second inference unit 37 may infer, from the state obtained by the second data acquisition unit 36 based on the rule-based inference or the incident-based inference, an action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor 10, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature. The same is true for Embodiments 2 and 3.

(7) While the factor of the first learned model according to the embodiments described above includes a set temperature during a past period of time, the present disclosure is not limited thereto. A factor of the first learned model may be a difference between the set temperature during a past period of time and each of the temperatures detected by multiple discharge thermistors during a past period of time. While the state of the second learned model according to the embodiments described above includes a set temperature, the present disclosure is not limited thereto. A factor of the second learned model may be a difference between the set temperature and each of the temperatures detected by multiple discharge thermistors.

(8) While the embodiments described above include two indoor units, the present disclosure is not limited thereto. There may be three or more indoor units.

[0136] The presently disclosed embodiments above should be considered illustrative in all aspects and do not limit the present disclosure. The scope of the present disclosure is defined by the appended claims, rather than by the above description. All changes which come within the meaning and range of equivalency of the appended claims are intended to be embraced within their scope.

REFERENCE SIGNS LIST

[0137] 1 indoor apparatus; 2 outdoor apparatus; 3a first indoor heat exchanger; 3b second indoor heat exchanger; 4a first electronic expansion valve; 4b second electronic expansion valve; 5 fan; 6a first controller; 6b second controller; 7a first intake thermistor; 7b second intake thermistor; 8a first discharge thermistor; 8b second discharge thermistor; 9 outdoor heat exchanger; 10 compressor; 11 learning device; 12 first learning device; 13 second learning device; 14, 34 first data acquisition unit; 15 first model generator; 16, 36 second data acquisition unit; 17 second model generator; 18 reward calculator; 19 function updater; 20a first indoor unit; 20b second indoor unit; 21 learned model storage device; 22 first learned model storage device; 23 second learned model storage device; 31 inference device; 32 first inference device; 33 second inference device; 35 first inference unit; 37 second inference unit; 51 main controller; 71 data storage device; 5001 memory; 5002 processor; and 5003 bus.

Claims

1. An air conditioning device, comprising an indoor apparatus and an outdoor apparatus,

the outdoor apparatus including a compressor and an outdoor heat exchanger,
the indoor apparatus including a plurality of indoor units and a fan, wherein
each indoor unit, among the plurality of indoor units, includes a controller, an indoor heat exchanger, an electronic expansion valve, an intake thermistor for detecting a drawn-in air temperature, and a discharge thermistor for detecting a discharged air temperature, wherein the indoor unit performs a thermo-OFF operation when a temperature detected by the discharge thermistor reaches a reference value,

the air conditioning device further comprising
a first inference device to infer, from a factor, whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by a plurality of the intake thermistors, and temperatures detected by a plurality of the discharge thermistors during

a past period of time.

2. The air conditioning device according to claim 1, wherein the first inference device includes:

a first data acquisition unit that obtains factor data including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors during a past period of time; and

a first inference unit that inputs the factor data obtained by the first data acquisition unit to a first learned model and outputs a prediction as to whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the first learned model being a learned model for outputting a prediction, made from a factor, as to whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors during a past period of time.

3. The air conditioning device according to claim 2, wherein

the first data acquisition unit obtains the factor data further including a forecast of an outdoor air temperature and a forecast of weather conditions during a future period of time, and

the first inference unit inputs the factor data obtained by the first data acquisition unit to a first learned model, and outputs a prediction as to whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the first learned model being a learned model for outputting a prediction, made from a factor, as to whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors during a past period of time and a forecast of an outdoor air temperature and a forecast of weather conditions during a future period of time.

4. The air conditioning device according to claim 2, wherein

the first data acquisition unit obtains the factor data further including a forecast of an outdoor air temperature, a forecast of an outdoor air humidity, and a forecast of weather conditions during a future period of time, and the first inference unit inputs the factor data obtained by the first data acquisition unit to a first learned model, and outputs a prediction as to whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the first learned model being a learned model for inferring, from a factor, whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors during a past period of time and a forecast of an outdoor air temperature, a forecast of an outdoor air humidity, and a forecast of weather conditions during a future period of time.

5. The air conditioning device according to claim 1, comprising:

a second inference device to infer, when a prediction is output that one of the plurality of indoor units performs a thermo-OFF operation during a future period of time, a target degree of superheat, a target degree of supercooling, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature from a state including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors; and a main controller to control the air conditioning device, based on a result of inference by the second inference device.

6. The air conditioning device according to claim 5, wherein the second inference device includes:

a second data acquisition unit that obtains a state including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors; and a second inference unit that infers, using a second learned model, an action from the state obtained by the second data acquisition unit, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target refrigerant con-

densing temperature, the second learned model being a learned model for inferring an action from a state, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, the state including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors.

7. The air conditioning device according to claim 1, comprising:

a second inference device to infer, when a prediction is output that any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, a target degree of superheat, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target humidity from a state including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors; and
a main controller to control the air conditioning device, based on a result of inference by the second inference device.

8. The air conditioning device according to claim 7, wherein the second inference device includes:

a second data acquisition unit that obtains a state including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors; and
a second inference unit that infers, using a second learned model, an action from the state obtained by the second data acquisition unit, the action including a target degree of superheat, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target humidity, the second learned model being a learned model for inferring an action from a state, the action including a target degree of superheat, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target humidity, the state including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors.

9. A learning device of an air conditioning device which includes an indoor apparatus and an outdoor apparatus,

the outdoor apparatus including a compressor and an outdoor heat exchanger, the indoor apparatus including a plurality of indoor units and a fan, wherein each indoor unit, among the plurality of indoor units, includes a controller, an indoor heat exchanger, an electronic expansion valve, an intake thermistor for detecting a drawn-in air temperature, and a discharge thermistor for detecting a discharged air temperature, wherein the indoor unit performs a thermo-OFF operation when a temperature detected by the discharge thermistor reaches a reference value, the learning device, comprising:

a first data acquisition unit to obtain first learning data including (i) factor data including a set temperature, temperatures detected by a plurality of the intake thermistors, and temperatures detected by a plurality of the discharge thermistors during a first time period, and (ii) predictive data as to whether any of the plurality of indoor units performs a thermo-OFF operation during a second time period later in time than the first time period; and

a first model generator to generate, using the first learning data, a first learned model for outputting a prediction, made from a factor, as to whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors during a past period of time.

10. The learning device of the air conditioning device according to claim 9, wherein

the first data acquisition unit obtains first learning data including the predictive data and the factor data further including a forecast of an outdoor air temperature and a forecast of weather conditions during a future period of time, and

using the first learning data, the first model generator generates a first learned model for outputting a prediction, made from a factor, as to whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by the plurality of intake

thermistors, and temperatures detected by the plurality of discharge thermistors during a past period of time and a forecast of an outdoor air temperature and a forecast of weather conditions during a future period of time.

11. The learning device of the air conditioning device according to claim 9, wherein

the first data acquisition unit obtains first learning data including the predictive data and the factor data further including a forecast of an outdoor air temperature, a forecast of an outdoor air humidity, and a forecast of weather conditions during a future period of time, and
using the first learning data, the first model generator generates a first learned model for outputting a prediction, made from a factor, as to whether any of the plurality of indoor units performs a thermo-OFF operation during a future period of time, the factor including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors during a past period of time and a forecast of an outdoor air temperature, a forecast of an outdoor air humidity, and a forecast of weather conditions during a future period of time.

12. The learning device of the air conditioning device according to claim 9, comprising:

a second data acquisition unit to obtain second learning data including a state and an action in the state, the state including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature; and
a second model generator to generate, using the second learning data, a second learned model for outputting an action from a state, the action including a target degree of superheat, a target degree of supercooling, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target refrigerant condensing temperature, the state including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors.

13. The learning device of the air conditioning device according to claim 9, comprising:

a second data acquisition unit to obtain second learning data including a state and an action in the state, the state including a set temperature, temperatures detected by the plurality of intake thermistors, and temperatures detected by the plurality of discharge thermistors, the action including a target degree of superheat, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target humidity; and
a second model generator to generate, using the second learning data, a second learned model for outputting an action from a state, the action including a target degree of superheat, a set frequency of the compressor, a target refrigerant evaporating temperature, and a target humidity, the state including a set temperature, the temperatures detected by the plurality of intake thermistors, and the temperatures detected by the plurality of discharge thermistors.

14. The learning device of the air conditioning device according to any one of claims 9 to 13, wherein the second model generator generates the second learned model by Q-learning.

15. The learning device of the air conditioning device according to claim 14, wherein

the second model generator increases a reward when a difference between the set temperature and a discharged air temperature decreases, and reduces a reward when a difference between the set temperature and the discharged air temperature increases.

FIG.1

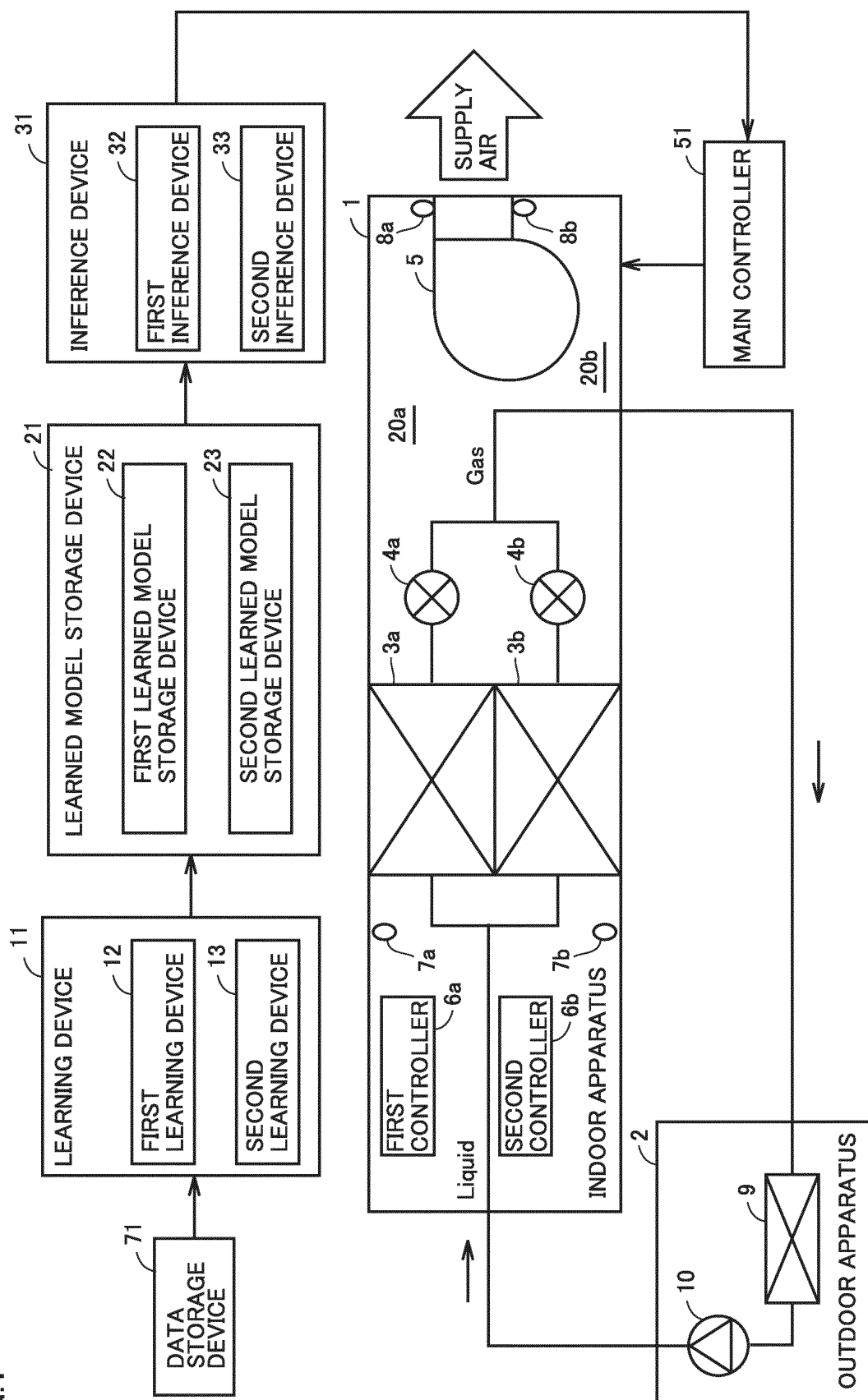


FIG.2

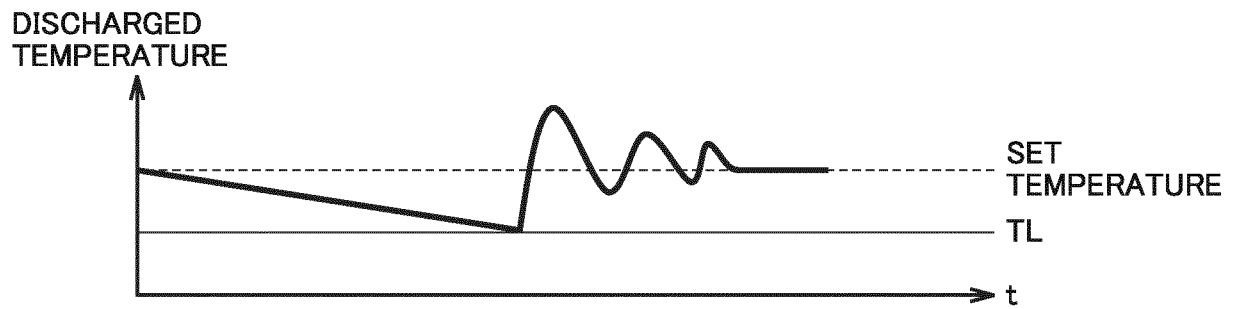


FIG.3

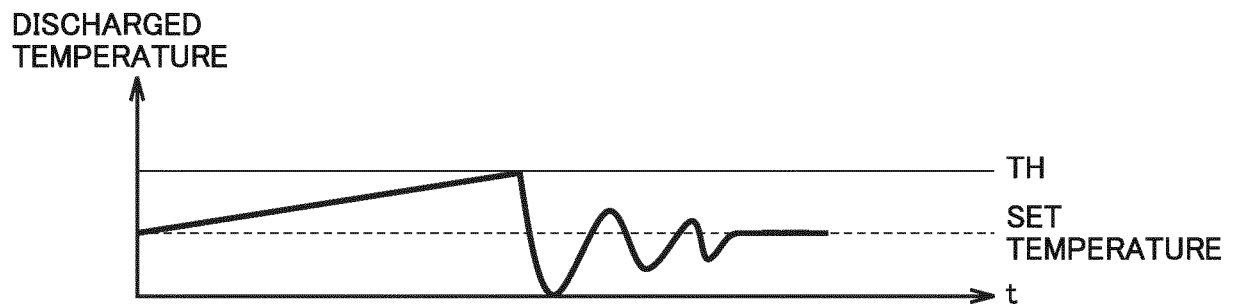


FIG.4

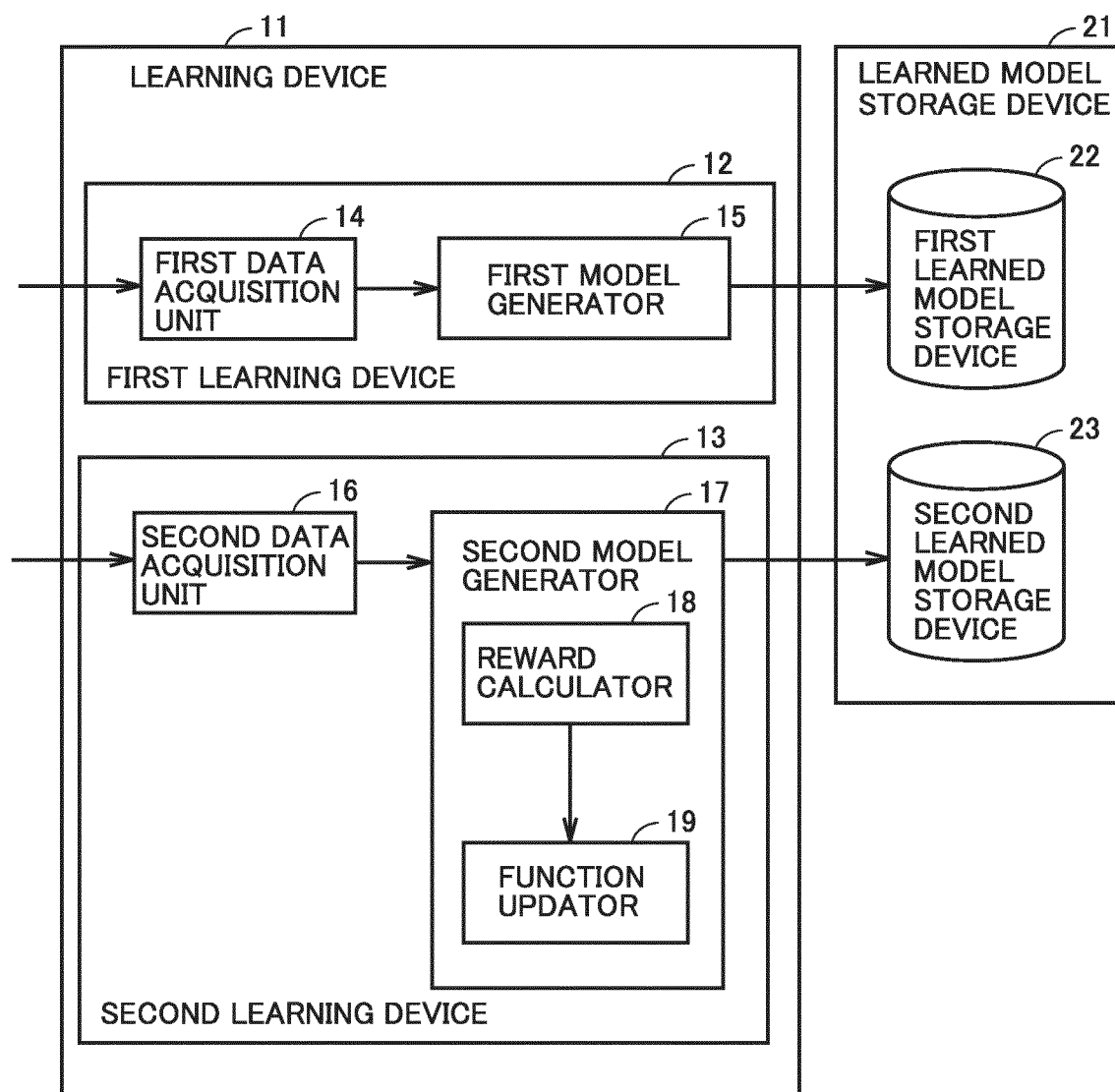


FIG.5

FACTOR	PREDICTION
SET TEMPERATURE DURING PAST PERIOD OF TIME TEMPERATURES DETECTED BY INTAKE THERMISTORS DURING PAST PERIOD OF TIME TEMPERATURES DETECTED BY DISCHARGE THERMISTORS DURING PAST PERIOD OF TIME	WHETHER ANY OF INDOOR UNITS PERFORMS THERMO-OFF OPERATION DURING FUTURE PERIOD OF TIME

FIG.6

STATE	ACTION
SET TEMPERATURE TEMPERATURES DETECTED BY INTAKE THERMISTORS TEMPERATURES DETECTED BY DISCHARGE THERMISTORS	TARGET DEGREE OF SUPERHEAT TARGET DEGREE OF SUPERCOOLING SET FREQUENCY OF COMPRESSOR TARGET REFRIGERANT EVAPORATING TEMPERATURE TARGET REFRIGERANT CONDENSING TEMPERATURE

FIG.7

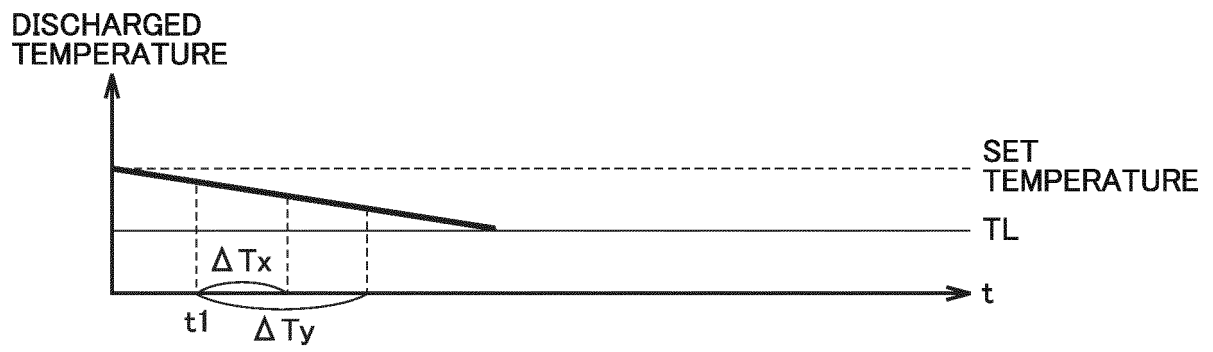


FIG.8

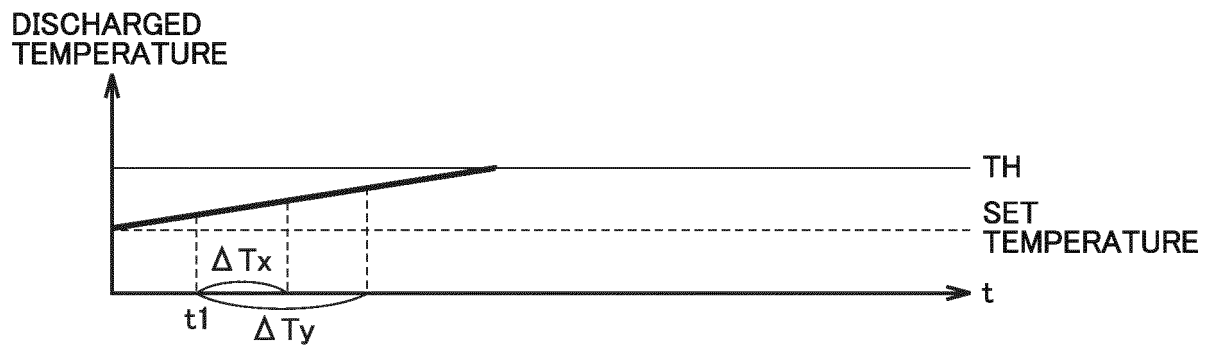


FIG.9

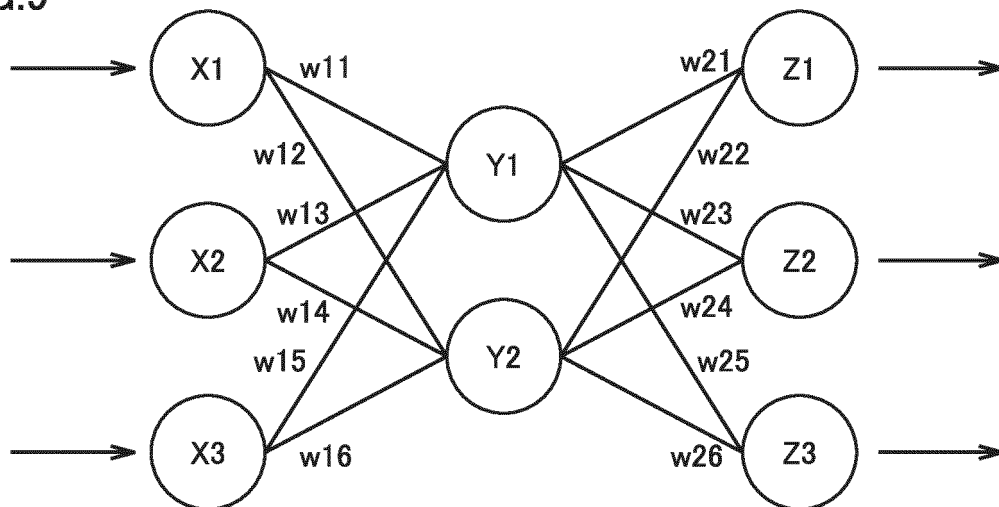


FIG.10

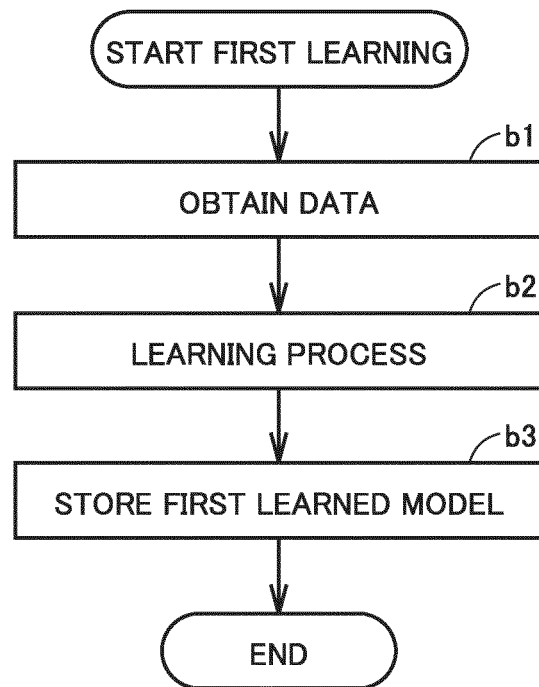


FIG.11

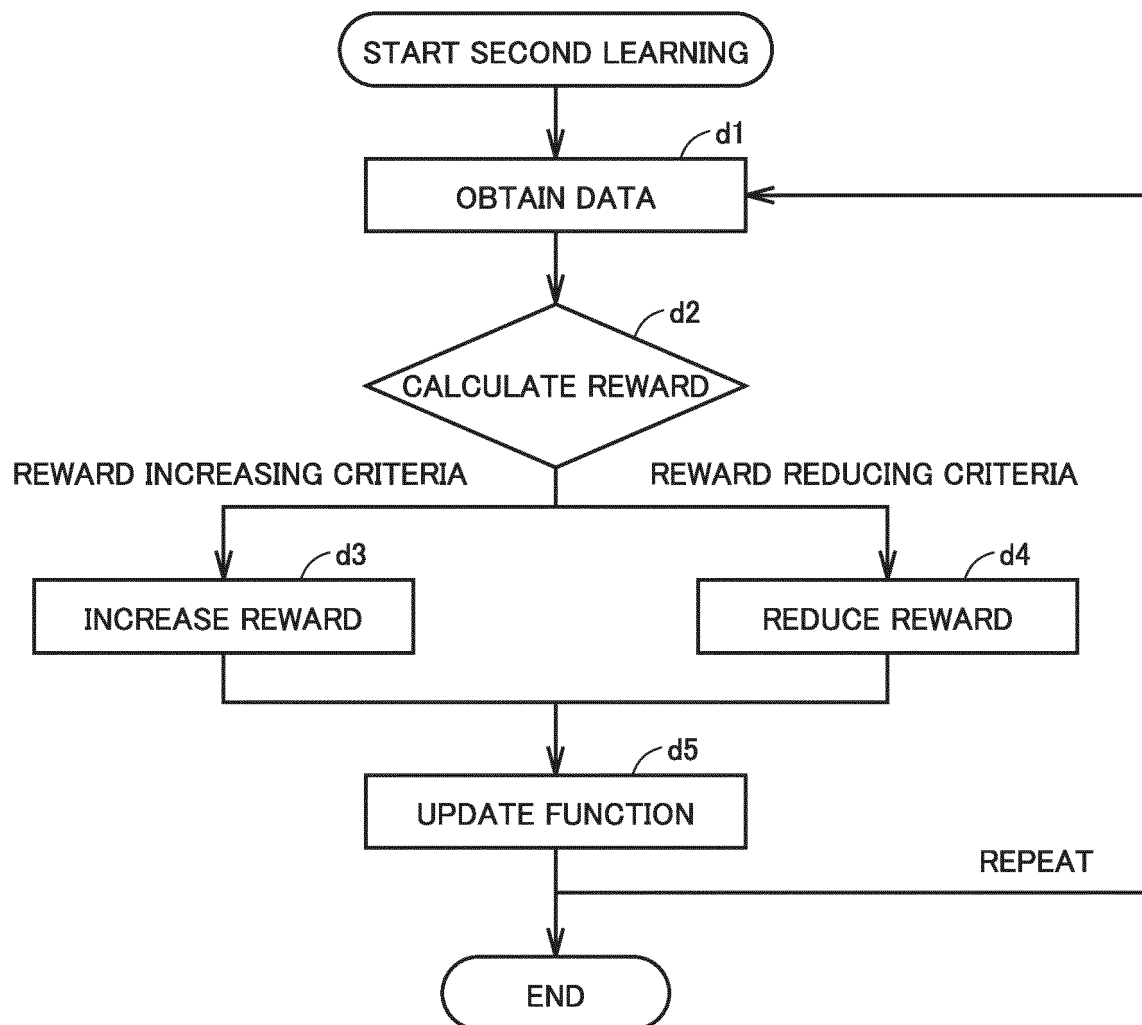


FIG.12

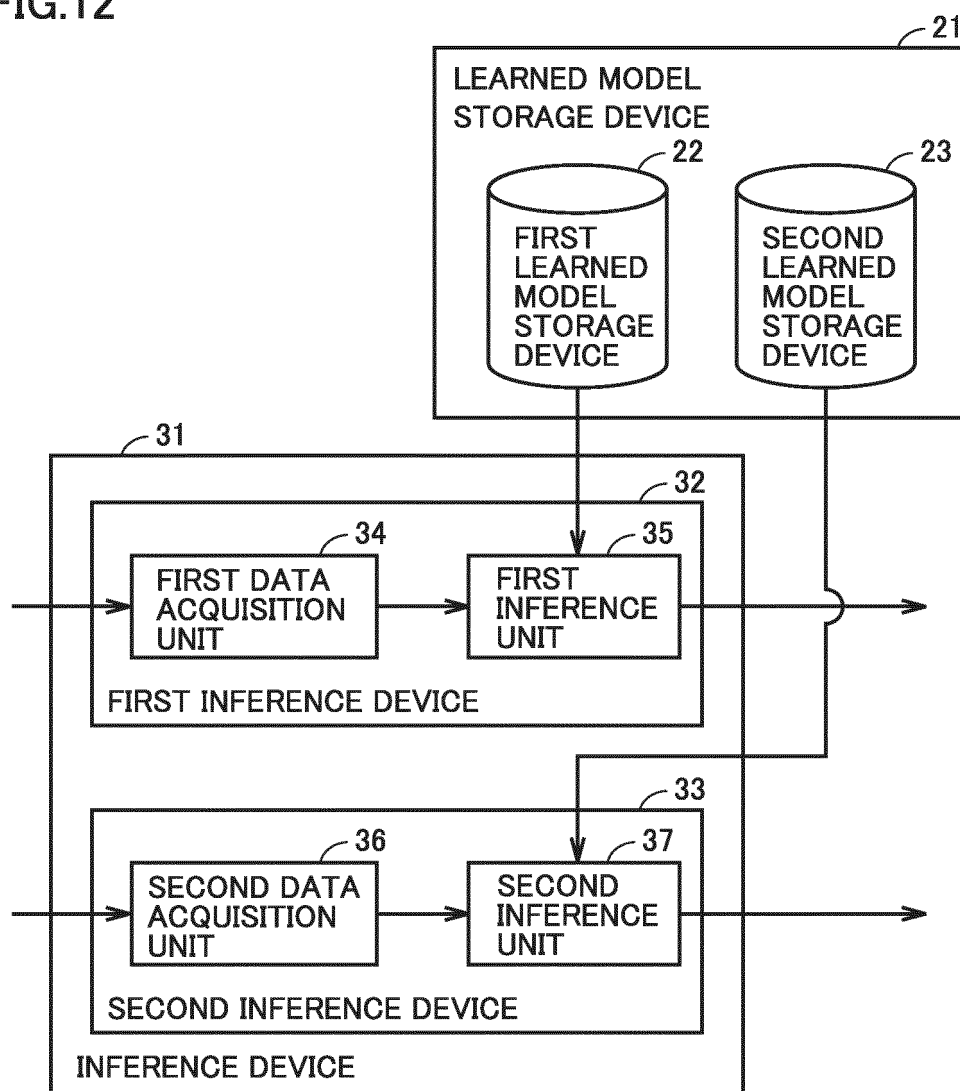


FIG.13

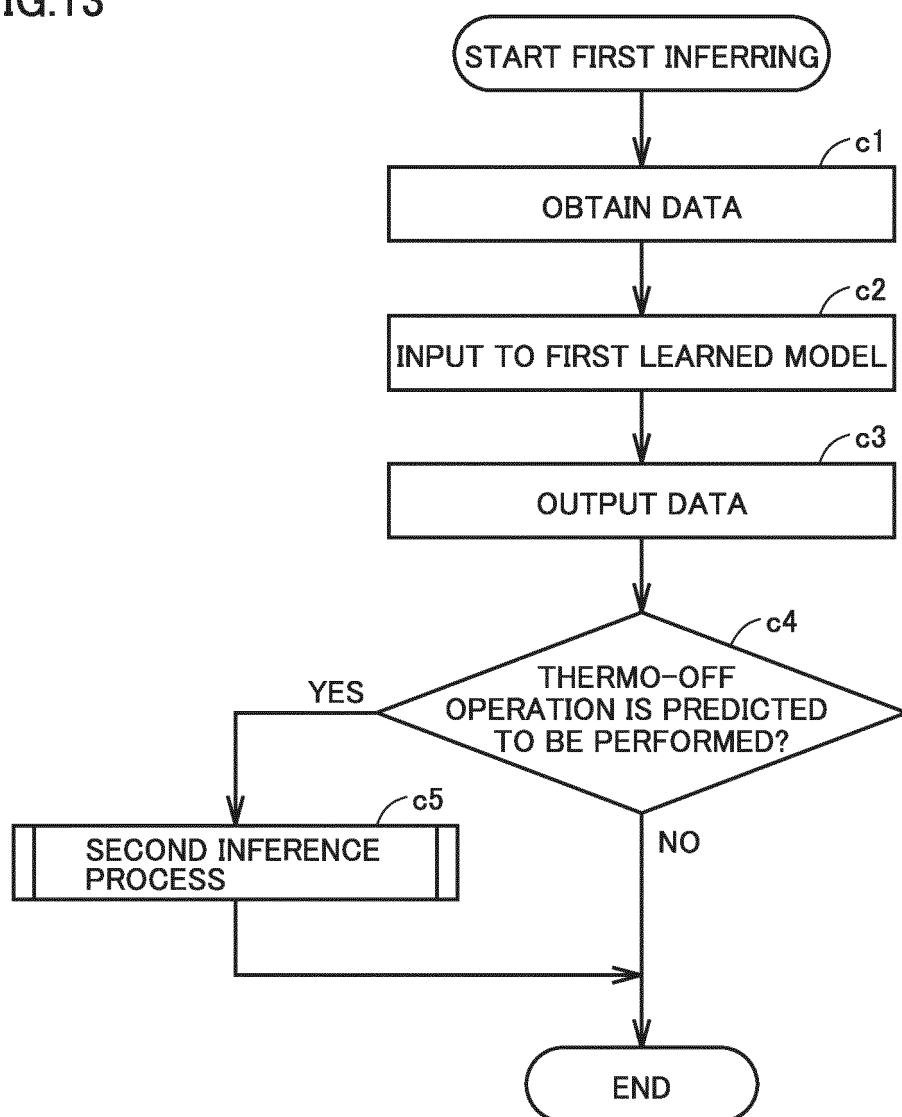


FIG.14

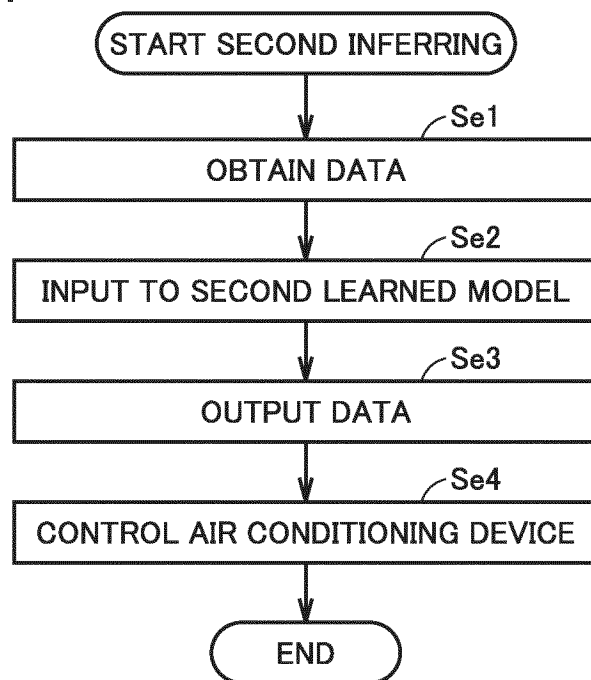


FIG.15

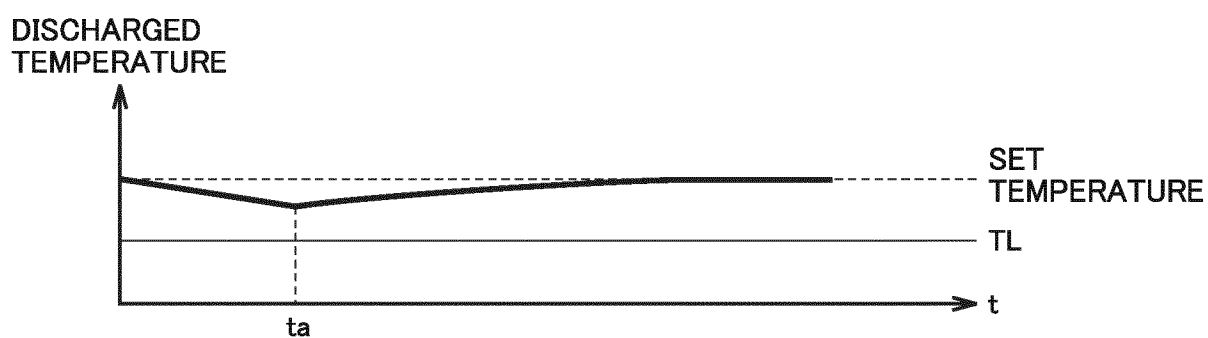


FIG.16

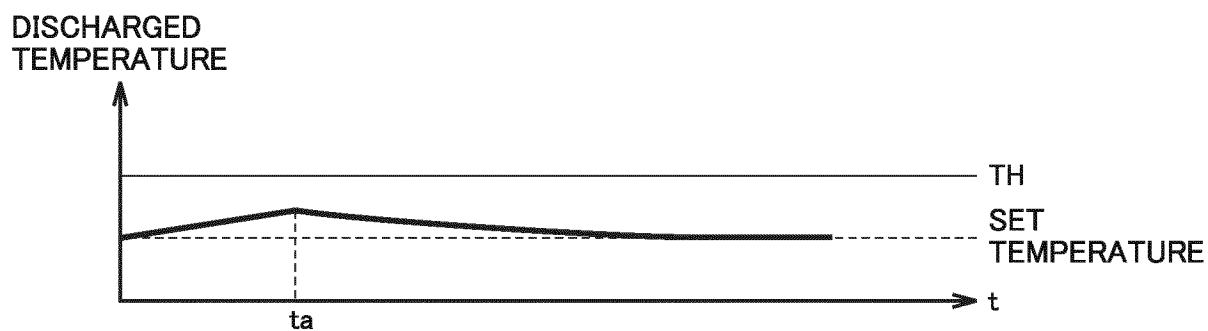


FIG.17

FACTOR	PREDICTION
SET TEMPERATURE DURING PAST PERIOD OF TIME TEMPERATURES DETECTED BY INTAKE THERMISTORS DURING PAST PERIOD OF TIME TEMPERATURES DETECTED BY DISCHARGE THERMISTORS DURING PAST PERIOD OF TIME FORECAST OF OUTDOOR AIR TEMPERATURE DURING FUTURE PERIOD OF TIME FORECAST OF WEATHER CONDITIONS DURING FUTURE PERIOD OF TIME	WHETHER ANY OF INDOOR UNITS PERFORMS THERMO-OFF OPERATION DURING FUTURE PERIOD OF TIME

FIG.18

STATE	ACTION
SET TEMPERATURE TEMPERATURES DETECTED BY INTAKE THERMISTORS TEMPERATURES DETECTED BY DISCHARGE THERMISTORS	TARGET DEGREE OF SUPERHEAT TARGET DEGREE OF SUPERCOOLING SET FREQUENCY OF COMPRESSOR TARGET REFRIGERANT EVAPORATING TEMPERATURE TARGET REFRIGERANT CONDENSING TEMPERATURE

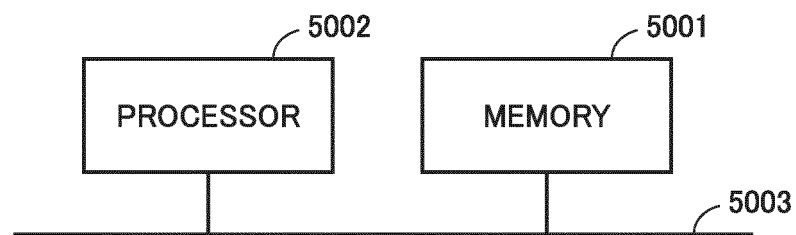
FIG.19

FACTOR	PREDICTION
SET TEMPERATURE DURING PAST PERIOD OF TIME TEMPERATURES DETECTED BY INTAKE THERMISTORS DURING PAST PERIOD OF TIME TEMPERATURES DETECTED BY DISCHARGE THERMISTORS DURING PAST PERIOD OF TIME FORECAST OF OUTDOOR AIR TEMPERATURE DURING FUTURE PERIOD OF TIME FORECAST OF OUTDOOR AIR HUMIDITY DURING FUTURE PERIOD OF TIME FORECAST OF WEATHER CONDITIONS DURING FUTURE PERIOD OF TIME	WHETHER ANY OF INDOOR UNITS PERFORMS THERMO-OFF OPERATION DURING FUTURE PERIOD OF TIME

FIG.20

STATE	ACTION
SET TEMPERATURE TEMPERATURES DETECTED BY INTAKE THERMISTORS TEMPERATURES DETECTED BY DISCHARGE THERMISTORS	TARGET DEGREE OF SUPERHEAT SET FREQUENCY OF COMPRESSOR TARGET REFRIGERANT EVAPORATING TEMPERATURE TARGET HUMIDITY

FIG.21



INTERNATIONAL SEARCH REPORT

International application No.

PCT/JP2020/041935

A. CLASSIFICATION OF SUBJECT MATTER

F24F 11/64(2018.01)i; F24F 110/10(2018.01)n; F24F 130/10(2018.01)n
 FI: F24F11/64; F24F110/10; F24F130/10

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

F24F11/64; F24F110/10; F24F130/10

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

Published examined utility model applications of Japan 1922-1996

Published unexamined utility model applications of Japan 1971-2020

Registered utility model specifications of Japan 1996-2020

Published registered utility model applications of Japan 1994-2020

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

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y A	WO 2018/199167 A1 (MITSUBISHI ELECTRIC CORP.) 01 November 2018 (2018-11-01) paragraphs [0015]- [0088], fig. 1-9	1 2-15
Y	WO 2016/016913 A1 (MITSUBISHI ELECTRIC CORP.) 04 February 2016 (2016-02-04) paragraphs [0009]- [0010], [0018], fig. 1	1
Y	JP 2020-56566 A (DAIKIN INDUSTRIES, LTD.) 09 April 2020 (2020-04-09) paragraphs [0030]-[0031], fig. 1	1
A	JP 2011-226767 A (DAIKIN INDUSTRIES, LTD.) 10 November 2011 (2011-11-10) entire text, all drawings	1-15
A	JP 2001-304664 A (SANYO ELECTRIC CO., LTD.) 31 October 2001 (2001-10-31) entire text, all drawings	1-15



Further documents are listed in the continuation of Box C.



See patent family annex.

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"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
15 December 2020 (15.12.2020)

Date of mailing of the international search report
28 December 2020 (28.12.2020)

Name and mailing address of the ISA/
Japan Patent Office
3-4-3, Kasumigaseki, Chiyoda-ku,
Tokyo 100-8915, Japan

Authorized officer

Telephone No.

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No.

PCT/JP2020/041935

Patent Documents referred in the Report	Publication Date	Patent Family	Publication Date
WO 2018/199167 A1	01 Nov. 2018	(Family: none)	
WO 2016/016913 A1	04 Feb. 2016	US 2017/0191686 A1 paragraphs [0016]- [0018], [0027], fig. 1	
JP 2020-56566 A	09 Apr. 2020	GB 2542083 A WO 2020/067428 A1 paragraphs [0030]- [0031], fig. 1	
JP 2011-226767 A	10 Nov. 2011	(Family: none)	
JP 2001-304664 A	31 Oct. 2001	(Family: none)	

REFERENCES CITED IN THE DESCRIPTION

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Patent documents cited in the description

- JP 2020169809 A [0004]