ELEVATOR TRAFFIC DEMAND PREDICTION APPARATUS

CROSS-REFERENCE TO RELATED APPLICATIONS

This application is based upon and claims the benefit of priority from Japanese Patent Application No. 2013-046937, filed March 8, 2013, the entire contents of which are incorporated herein by reference.

FIELD

Embodiments described herein relate generally to an elevator traffic demand prediction apparatus.

BACKGROUND

An elevator apparatus including a plurality of elevator cars includes a group management control device which performs centralized control of these elevator cars. The group management control device assigns an elevator car in response to a hall call in accordance with a control method. The group management control device changes the control method in accordance with the day of the week and the time zones on the assumption that the traffic demand in a building changes depending on the day of the week and the time zones.

However, the feature of an actual traffic demand changes from building to building in which an elevator apparatus is located. Further, the traffic demand changes from hour to hour. Therefore, the group management control device mentioned above may assign an elevator car in accordance with a control method optimized for a traffic demand different from the actual traffic demand. In this

case, the service performance of the elevator apparatus may be lowered; for example, the waiting time of the user may increase and the traffic volume may be lowered. Therefore, to assign the elevator car in accordance with a control method optimized for the actual traffic demand in order to improve the service performance, accurate prediction of a traffic demand is important.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 is a block diagram schematically showing an elevator apparatus including a traffic demand prediction apparatus according to the first embodiment;

FIG. 2 is a diagram showing an example of an origin destination (OD) table;

FIG. 3 is a flowchart showing procedures to calculate the feature amount of the traffic demand by a feature amount calculation unit shown in FIG. 1;

FIG. 4 is a graph showing an example of getting-on ratios and getting-off ratios for the respective moving directions and the respective floors;

FIG. 5 is a graph showing another example of getting-on ratios and getting-off ratios for the respective moving directions and the respective floors;

FIG. 6 is a diagram showing an example of a method of calculating the feature amount of the number of users by the feature amount calculation unit shown in FIG. 1;

FIG. 7 is a diagram showing an example of data stored by a feature amount database shown in FIG. 1;

FIG. 8 is a diagram showing an example of data stored by a prediction parameter database shown in FIG. 1;

FIG. 9 is a flowchart showing an example of the operation of the traffic demand prediction apparatus shown in FIG. 1;

FIG. 10 is a diagram showing an example of a control method list held by a control method selector shown in FIG. 1;

FIG. 11 is a block diagram schematically showing an elevator apparatus including a traffic demand prediction apparatus according to the second embodiment;

FIG. 12 is a diagram showing an example of expert prediction result data stored by a prediction parameter database shown in FIG. 11;

FIG. 13 is a diagram showing an example of the design of an expert according to the second embodiment;

FIG. 14 is a flowchart showing an example of a method of predicting the traffic demand by the traffic demand prediction apparatus shown in FIG. 11;

FIG. 15 is a flowchart showing an example of a method of creating an expert list in step S1402 of FIG. 14;

FIG. 16 is a flowchart showing an example of a method of predicting the feature amount of the traffic demand by a traffic demand predictor shown in FIG. 11;

FIG. 17 is a block diagram schematically showing an elevator apparatus including a traffic demand prediction apparatus according to the third embodiment;

FIG. 18 is a diagram showing an example of attribute information according to the third embodiment;

FIG. 19 is a diagram showing an example of a screen for inputting working system information by an information input unit shown in FIG. 17; and

FIG. 20 is a diagram showing an example of an input screen for setting a reliability calculation target period by the information input unit shown in FIG. 17.

DETAILED DESCRIPTION

According to one embodiment, there is provided an elevator traffic demand prediction apparatus applied to up/down button group control to assign an elevator car in response to a hall call. The elevator traffic demand prediction apparatus includes an acquisition unit, a calculation unit, a feature amount database, a predictor, and selector. The acquisition unit is configured to acquire an elevator control result including getting-on loads and getting-off loads for respective moving directions and respective floors. The calculation unit is configured to calculate a feature amount of a traffic demand based on the elevator control result, the feature amount including a category feature amount representing a category of the traffic demand. The feature amount database is configured to store the calculated feature amount in association with attribute information and time information. The predictor is configured to predict a traffic demand by referring to the feature amount database,

the predictor comprising a plurality of experts configured to predict a category of a traffic demand by referring to different data items included in the feature amount database to generate predicted values, and the prediction unit outputting, as a prediction result, one of the predicted values. The selector is configured to select a control method complying with the prediction result from a plurality of predetermined control methods.

Various embodiments will hereinafter be described with reference to the accompanying drawings. The following embodiments are directed to an up/down-button elevator apparatus in which a hall call device for designating a destination direction is installed in each elevator hall and a car call device for designating a destination floor is installed in each elevator car. The elevator apparatus is connected to an elevator traffic demand prediction apparatus which predicts the traffic demand in a building. In traffic demand prediction according to the embodiment, the feature amount of the traffic demand is calculated at regular time intervals, and the traffic demand in the next time zone is predicted by using a database which stores the feature amount of the traffic demand, and the experts of an online algorithm. According to the traffic demand prediction, high-accuracy prediction can be performed even if the traffic demand generation pattern differs between buildings. By assigning an elevator car in accordance with a control method complying with the prediction result, an

elevator operation matching an actual traffic demand can be implemented, improving the service performance.

(First Embodiment)

FIG. 1 schematically shows an elevator apparatus 100 according to the first embodiment. The elevator apparatus 100 is installed in a building (e.g., an office building) having a plurality of floors. The present embodiment assumes that the building has floors one to seven. As shown in FIG. 1, the elevator apparatus 100 includes a group management control device 150 which performs centralized control of a plurality of elevator cars 110A to 110C. The elevator car will be simply called a "car" hereinafter. Although FIG. 1 shows the three cars 110A, 110B, and 110C, the number of cars may be two, or four or more. The group management control device 150 generates operation plans for the cars 110A, 110B, and 110C, and passes them to car controllers 120A, 120B, and 120C which are arranged in correspondence with the cars 110A, 110B, and 110C, respectively. The car controllers 120A, 120B, and 120C control the cars 110A, 110B, and 110C in accordance with the operation plans of the cars 110A, 110B, and 110C, respectively. Each of the car controllers 120A, 120B, and 120C performs various control operations such as car elevating control and door opening/closing control.

Each of the cars 110A, 110B, and 110C includes a car call device 112 for designating a destination floor. When the user designates a destination floor with the car call

device 112, a car movement request (car call) to the designated destination floor is generated. A car call detector 156 detects the car movement request as "generation of a new car call". The car call detector 156 generates car call information regarding the detected car call. The car call information includes a to-be-stopped floor corresponding to the destination floor designated by the user, the identification number of the car, and the generation time of the car call. The car call detector 156 stores the car call information in a car call information storage unit 157. The car call information storage unit 157 stores car call information received from the car call detector 156. After the car stops at a to-be-stopped floor, the car call information storage unit 157 deletes the corresponding car call information.

Further, each of the cars 110A, 110B, and 110C includes an in-car load measurement device 114 which measures an in-car load. The in-car load mainly represents the load (that is, the total body weight) of users in a car. The in-car load is also influenced by the load of the baggage of a user and the like, but is considered to vary in accordance with the number of users. The in-car load measurement device 114 can measure a getting-on load and getting-off load on a floor by detecting variation of the in-car load while the door opens. The getting-on load is the load of users who got on a car on a floor. The getting-off load is the load of users who got off a car on

a floor. Load data including getting-on loads for the respective moving directions and the respective floors, and getting-off loads for the respective moving directions and the respective floors are passed from the cars 110A, 110B, and 110C to an elevator state grasping unit 153 via the car controllers 120A, 120B, and 120C.

In the elevator hall of each floor, a hall call device 130 for designating a destination direction (up or down direction) is installed. In the example of FIG. 1, one hall call device 130 is provided on each floor. A user on a floor operates the hall call device 130 on the floor to input a destination direction of his choice. More specifically, the hall call device 130 includes up and down buttons, and the user presses a button (up or down button) corresponding to a destination direction of his choice. When the user designates a destination direction with the hall call device 130, a car dispatch request (hall call) is generated. The "car dispatch" means dispatching a car in response to a hall call. A hall call detector 151 detects the car dispatch request as "generation of a new hall call". The hall call detector 151 generates hall call information regarding the detected hall call. The hall call information includes the generation time, generation floor, and destination direction (up or down direction) of the hall call. The hall call detector 151 stores the hall call information in a hall call information storage unit 152. Further, the hall call detector 151 passes the hall

call information to a car assignment unit 154 via the elevator state grasping unit 153.

The hall call information storage unit 152 stores hall call information regarding an unresponded hall call. The unresponded hall call is a hall call for which car dispatch has not been completed yet. The hall call information storage unit 152 stores the generation time, generation floor, and destination direction of each unresponded hall call. Hall call information regarding an unresponded hall call is deleted from the hall call information storage unit 152 upon completion of car dispatch.

The elevator state grasping unit 153 acquires hall call information stored in the hall call information storage unit 152, and car call information stored in the car call information storage unit 157. Further, the elevator state grasping unit 153 receives car operation information from the car controllers 120A, 120B, and 120C. The car operation information includes information about the position, moving direction (up or down direction), speed, and door state (door opening or door closing) of a car, together with load data. The elevator state grasping unit 153 generates aggregated operation information by aggregating the hall call information, car call information, and car operation information. Load data included in the aggregated operation information will be called aggregated load data. The aggregated load data is the aggregation of load data measured for the respective

cars. The elevator state grasping unit 153 provides the aggregated operation information to the car assignment unit 154 and a traffic demand prediction apparatus 160.

The car assignment unit 154 receives information of a newly generated hall call from the hall call detector 151. The car assignment unit 154 selects, from the cars 110A, 110B, and 110C in accordance with a control method decided by the traffic demand prediction apparatus 160, a car which is to respond to a hall call. That is, the car assignment unit 154 decides a car to be assigned to the hall call. As the method of assigning a car to a hall call, for example, a method disclosed in Japanese Patent No. 4454979 is usable. A car operation controller 155 makes the operation plans of the cars 110A, 110B, and 110C while reflecting the assignment result of the car assignment unit 154. The car controllers 120A, 120B, and 120C operate the cars 110A, 110B, and 110C in accordance with the operation plans made by the car operation controller 155, respectively.

The traffic demand prediction apparatus 160 predicts the traffic demand in the building based on aggregated operation information received from the elevator state grasping unit 153 and decides, based on the prediction result, a control method to be used by the car assignment unit 154. The traffic demand prediction apparatus 160 performs prediction of the traffic demand and decision of the control method at regular time intervals (e.g., at intervals of 5 minutes). The traffic demand prediction

apparatus 160 includes an elevator control result acquisition unit 161, feature amount calculation unit 162, feature amount database (DB) 163, prediction parameter database (DB) 164, traffic demand predictor 165, and control method selector 166.

The elevator control result acquisition unit 161 acquires an elevator control result from aggregated operation information generated by the elevator state grasping unit 153. The feature amount calculation unit 162 calculates the feature amount of the traffic demand based on the elevator control result. The feature amount DB 163 stores the feature amount of the traffic demand in association with attribute information and time information. The prediction parameter DB 164 stores parameters used for prediction of the traffic demand in association with the attribute information and time information. The traffic demand predictor 165 predicts the traffic demand by referring to the feature amount DB 163 and prediction parameter DB 164. The control method selector 166 selects a control method complying with the prediction result of the traffic demand predictor 165 from a plurality of predetermined control methods. The control method selected by the control method selector 166 is sent to the car assignment unit 154.

The elevator apparatus 100 including the above-described arrangement periodically predicts the traffic demand in the building, and assigns cars in

accordance with a control method complying with the prediction result. Cars can therefore be assigned in correspondence with an actual traffic demand, improving the service performance.

The group management control device 150 shown in FIG. 1 includes the hall call detector 151, hall call information storage unit 152, elevator state grasping unit 153, car assignment unit 154, car operation controller 155, car call detector 156, car call information storage unit 157, and traffic demand prediction apparatus 160. Note that the traffic demand prediction apparatus 160 is not limited to an example in which it is contained in the group management control device 150, but may be implemented as an independent apparatus.

In the up/down button elevator apparatus as in the embodiment, a user in an elevator hall presses a button corresponding to a direction in which he wants to move. At this time, the elevator apparatus can monitor the operation of the hall call device, but cannot know the number of waiting users for the generated hall call and the destination floor of each user. Measurable data are, e.g., getting-on loads and getting-off loads for the respective moving directions and the respective floors. The getting-on loads and getting-off loads will be explained with reference to FIG. 2.

FIG. 2 shows an example of an origin destination (OD) table expressing the traffic demand in the building. The

OD table can be represented by a matrix, in which the row represents an elevator hall floor, and the column represents a destination floor. Each matrix element represents the number of users who moved from a given elevator hall floor to a given destination floor. The OD table in FIG. 2 shows data obtained by measuring 360 users in a predetermined time. However, strict OD as shown in FIG. 2 can be measured only when pieces of information about respective users are collected.

The up/down button elevator apparatus can obtain getting-on loads and getting-off loads specific to each moving direction and each floor, but cannot obtain strict OD as shown in FIG. 2 from this information. The up/down button elevator apparatus can obtain the total load of users who got on an upward moving car from the second floor, i.e., the total load of users who moved from the second floor to the third and upper floors. This total load corresponds to a value obtained by multiplying the sum "5" of second-row elements of an upper triangular matrix in FIG. 2 by the average weight (e.g., 65 kg) of the human. Similarly, the up/down button elevator apparatus can obtain the total load of users who got on a downward moving car from the fifth floor. This total load corresponds to a value obtained by multiplying the sum "57" of fifth-row elements of a lower triangular matrix in FIG. 2 by the average weight. As for the getting-off load, the total load of users who got off an upward moving car on the third

floor, i.e., the total load of users who got on the upward moving car from the first floor and got off on the third floor, and those who got on from the second floor and got off on the third floor is obtained. This total load corresponds to a value obtained by multiplying the sum "2" of third-row elements of the upper triangular matrix in FIG. 2 by the average weight.

Next, the traffic demand prediction apparatus 160 will be explained in more detail.

The elevator control result acquisition unit 161 receives aggregated operation information from the elevator state grasping unit 153, and acquires an elevator control result from the aggregated operation information. The elevator control result includes measurement data used when calculating the feature amount of the traffic demand. The measurement data includes aggregated load data representing getting-on loads and getting-off loads for the respective moving directions and the respective floors. In the embodiment, the getting-on loads and getting-off loads for the respective moving directions and the respective floors are represented by vectors. The aggregated load data includes an upward getting-on load vector, upward getting-off load vector, downward getting-on load vector, and downward getting-off load vector. Each of these vectors has N elements when the building has N floors. For a seven-story building as in the embodiment, the upward getting-on load vector is a vector in which the first to

seventh elements indicate the loads of users who got on an upward moving car from the first to seventh floors, respectively. The upward getting-off load vector is a vector in which the first to seventh elements indicate the loads of users who got off an upward moving car on the first to seventh floors, respectively. The downward getting-on load vector is a vector in which the first to seventh elements indicate the loads of users who got on a downward moving car from the first to seventh floors, respectively. The downward getting-off load vector is a vector in which the first to seventh elements indicate the loads of users who got off a downward moving car on the first to seventh floors, respectively. Measurement data is acquired at a predetermined time interval. In the embodiment, the elevator control result acquisition unit 161 acquires measurement data at intervals 5 minutes. Note that the time interval (to be also referred to as the measurement period) to acquire measurement data is not limited to the 5-minute interval and can be arbitrarily set.

Measurement data may further include the no-response time. The no-response time is a time interval until a car responds to a hall call after the hall call is generated. The no-response time can be acquired for each floor and each moving direction. The elevator control result acquisition unit 161 can calculate an average no-response time from no-response times for the respective floors and

the respective moving direction.

The feature amount calculation unit 162 calculates the feature amount of the traffic demand based on aggregated load data included in the elevator control result. The feature amount of the traffic demand includes the feature amount of the upward getting-on ratio, the feature amount of the upward getting-off ratio, the feature amount of the downward getting-on ratio, the feature amount of the downward getting-off ratio, the feature amount of the number of users, and the category feature amount. These feature amounts will be described later. A method of calculating the feature amount of the traffic demand will be explained with reference to FIG. 3.

In step S301 of FIG. 3, the feature amount calculation unit 162 calculates, from aggregated load data in the time zone t-1, getting-on ratios and getting-off ratios for the respective moving directions and the respective floors, and the estimated value of the number of users. The time zone t-1 is a period from time t-2 to time t-1. The getting-on ratio is obtained by dividing a getting-on load by the sum of getting-on loads. The sum of getting-on loads is a total of getting-on loads for the respective moving directions and the respective floors. Hence, the sum of getting-on ratios calculated for the respective moving directions and the respective floors is 1. The getting-off ratio is obtained by dividing a getting-off load by the sum of getting-off loads. The sum of getting-off loads is a

total of getting-off loads for the respective moving directions and the respective floors. Therefore, the sum of getting-off ratios calculated for the respective moving directions and the respective floors is 1.

In the embodiment, getting-on loads and getting-off loads for the respective moving directions and the respective floors are represented by four vectors (upward getting-on load vector, upward getting-off load vector, downward getting-on load vector, and downward getting-off load vector). For this reason, getting-on ratios and getting-off ratios for the respective moving directions and the respective floors are also represented by four vectors (upward getting-on ratio vector, upward getting-off ratio vector, downward getting-on ratio vector, and downward getting-off ratio vector). The upward getting-on ratio vector is obtained by dividing an upward getting-on load vector by the sum of getting-on loads. The upward getting-off ratio vector is obtained by dividing an upward getting-off load vector by the sum of getting-off loads. The downward getting-on ratio vector is obtained by dividing a downward getting-on load vector by the sum of getting-on loads. The downward getting-off ratio vector is obtained by dividing a downward getting-off load vector by the sum of getting-off loads. FIG. 4 is a graph showing an example of getting-on ratios and getting-off ratios calculated for the respective moving directions and the respective floors. The example of FIG. 4 corresponds to a

traffic demand in which most users move from the first floor having an entrance to respective floors, as observed at the start of office hours. FIG. 5 is a graph showing another example of getting-on ratios and getting-off ratios calculated for the respective moving directions and the respective floors. The example of FIG. 5 corresponds to a traffic demand in which most users move from respective floors to the first floor having an entrance, as observed in the quitting time zone.

Subsequently, the feature amount calculation unit 162 obtains the estimated value of the number of getting-on persons during the measurement period by dividing the sum of getting-on loads by the average weight (e.g., 65 kg) of a human, and sets the estimated value of the number of getting-on persons as the estimated value of the number of users. Note that the feature amount calculation unit 162 may set, as the estimated value of the number of users, the estimated value of the number of getting-off persons obtained by dividing the sum of getting-off loads by the average weight of a human. Alternatively, the estimated value of the number of users may be obtained by dividing the average of the sum of getting-on loads and the sum of getting-off loads by the average weight of a human.

In step S302 of FIG. 3, the feature amount calculation unit 162 calculates the feature amount of the upward getting-on ratio, the feature amount of the upward getting-off ratio, the feature amount of the downward

getting-on ratio, and the feature amount of the downward getting-off ratio from the upward getting-on ratio vector, upward getting-off ratio vector, downward getting-on ratio vector, and downward getting-off ratio vector calculated in step S301. In addition, the feature amount calculation unit 162 calculates the feature amount of the number of users from the estimated value of the number of users that has been calculated in step S301. In the embodiment, each of the feature amount of the upward getting-on ratio, the feature amount of the upward getting-off ratio, the feature amount of the downward getting-on ratio, and the feature amount of the downward getting-off ratio is also represented by an N-dimensional vector having N elements. As described above, N is the number of floors of a building. These vectors will be called the feature amount vector of the upward getting-on ratio, the feature amount vector of the upward getting-off ratio, the feature amount vector of the downward getting-on ratio, and the feature amount vector of the downward getting-off ratio.

More specifically, first, the feature amount calculation unit 162 sets, as the feature amount of the number of users, a value obtained by discretizing the estimated value of the number of users, that is, performing threshold processing for the estimated value of the number of users. By discretizing the estimated value of the number of users, the data amount can be reduced when saving data in an embedded system, compared to recording data of

continuous values. The threshold processing will be explained in brief. For example, assume that the measurement period is an interval of 5 minutes, and the estimated value of the number of users is calculated to be N^{up}. When the number of users per hour is discretized by ΔN (for example, 100), $N^{up}/\Delta N/(300/3600)$ is calculated, and the quotient is used as the feature amount of the number of users. For example, FIG. 6 shows a conversion table for converting the estimated value of the number of users into the feature amount of the number of users when the measurement period is an interval of 5 minutes. In the example of FIG. 6, $\Delta N = 300$. As shown in FIG. 6, when the estimated value N^{up} of the number of users is 0 (inclusive) to 25 (exclusive), 0 is obtained as the feature amount of the number of users. When the estimated value N^{up} of the number of users is 25 (inclusive) to 50 (exclusive), the feature amount of the number of users becomes 1. A larger value of the feature amount of the number of users means that a larger number of users used an elevator during that period.

Then, the feature amount calculation unit 162 discretizes the upward getting-on ratio vector, upward getting-off ratio vector, downward getting-on ratio vector, and downward getting-off ratio vector by threshold processing, thereby obtaining the feature amount vector of the upward getting-on ratio, feature amount vector of the upward getting-off ratio, feature amount vector of the

downward getting-on ratio, and feature amount vector of the downward getting-off ratio. The threshold processing is processing to return 1 when an element exceeds a threshold ω, and 0 when an element is equal to or smaller than the threshold ω. Therefore, each element has a value of 0 or 1.

For example, when the threshold ω is 0.25, the feature amount vectors are obtained as follows from data shown in FIG. 4:

feature amount vector of upward getting-on ratio: (1, 0, 0, 0, 0, 0, 0)

feature amount vector of upward getting-off ratio: (0, 0, 0, 0, 0, 0, 0)

feature amount vector of downward getting-on ratio: (0, 0, 0, 0, 0, 0, 0)

feature amount vector of downward getting-off ratio: (0, 0, 0, 0, 0, 0, 0)

For example, when the threshold ω is 0.25, the feature amount vectors are obtained as follows from data shown in FIG. 5:

feature amount vector of upward getting-on ratio: (0, 0, 0, 0, 0, 0, 0)

feature amount vector of upward getting-off ratio: (0, 0, 0, 0, 0, 0, 0)

feature amount vector of downward getting-on ratio: (0, 0, 0, 0, 0, 0, 0)

feature amount vector of downward getting-off ratio:

(1, 0, 0, 0, 0, 0, 0)

In step S303 of FIG. 3, the feature amount calculation unit 162 calculates a category feature amount from the four feature amount vectors calculated in step S302. The category feature amount represents the category (classification) of the traffic demand. In the embodiment, the category feature amount is represented by a four-dimensional vector (to be referred to as a category feature amount vector hereinafter) having four elements. The first element of the category feature amount vector is 1 when 1 exists in at least one of elements of the feature amount vector of the upward getting-on ratio, and 0 when 1 does not exist. The second element is 1 when 1 exists in at least one of elements of the feature amount vector of the upward getting-off ratio, and 0 when 1 does not exist. The third element is 1 when 1 exists in at least one of elements of the feature amount vector of the downward getting-on ratio, and 0 when 1 does not exist. The fourth element is 1 when 1 exists in at least one of elements of the feature amount vector of the downward getting-off ratio, and 0 when 1 does not exist. In the example of FIG. 4, (1, 0, 0, 0) is obtained as the category feature amount vector. In the example of FIG. 5, (0, 0, 0, 1) is obtained as the category feature amount vector.

The number of elements of the category feature amount vector is always 4 regardless of the number of floors of a building, and this representation can be used for a

building having an arbitrary number of floors. In the embodiment, each of the four elements of the category feature amount vector has a value of 0 or 1. That is, traffic demands are classified into 16 categories.

Note that the above-described method of calculating the feature amount of the traffic demand is merely an example, and the feature amount of the traffic demand may be calculated by another method. For example, the vector representation may not be used.

The feature amount of the traffic demand calculated by the feature amount calculation unit 162 in steps S301 to S303 is recorded in the feature amount DB 163. In the following description, the feature amount of the traffic demand calculated by the feature amount calculation unit 162 is sometimes called the measured value of the feature amount of the traffic demand or simply the measured value. FIG. 7 shows an example of data stored in the feature amount DB 163. The feature amount DB 163 stores the feature amount of the traffic demand in association with attribute information and time information. The attribute information in the embodiment includes information about the number of elapsed days indicating the number of days elapsed after the operation start day (or data collection start day) of the traffic demand prediction apparatus 160, the date, and the day of the week. Note that the attribute information is not limited to an example in which it includes all the number of elapsed days, the date, and the

day of the week. It suffices if the attribute information includes the number of elapsed days, the date, or the same kind of information. For example, when the attribute information includes date information, the number of elapsed days can be calculated from the date and a known operation start day, and the day of the week can be specified from the date and the calendar function of the traffic demand prediction apparatus 160.

Next, a method of predicting the traffic demand by the traffic demand predictor 165 will be explained. The traffic demand prediction is an issue of predicting the feature amount of a traffic demand in the time zone t for the number d of elapsed days from measured value data of the feature amount of the traffic demand acquired until the time t-1 for the number d of elapsed days. In the embodiment, the expert federation model of an online learning algorithm is used as a basic algorithm for traffic demand prediction.

The issue of prediction of the traffic demand can be formularized as follows as a repeated game periodically performed between a plurality of (for example, N_E) experts which output predicted values, an algorithm (learner) which aggregates the predicted values of these experts to output the predicted value of the learner, and an environment where a true result is presented.

Assume that Y is a set of measured values, Y' is a set of predicted values, and a loss function $L: Y \times Y' \rightarrow [0, \infty]$

for evaluating the accuracy of prediction is given. A series of operations at each time t when viewed from the learner (elevator learning function) is as follows:

1. The learner receives a predicted value $x_{t,i}'$ ($\in$ Y') from each expert i ($i = \{1, 2, \ldots, N_E\}$).

2. The learner aggregates the predicted values of all the experts to output a predicted value y_t' ($\in$ Y').

3. The learner receives a measured value y_t ($\in$ Y) from the environment.

4. The learner and each expert i suffer the losses $L(y_t, y_t')$ and $L(y_t, x_{t,i}')$, respectively.

When the above process is performed until time T, the cumulative loss L^T_A of the learner and the cumulative loss L^T_i of each expert i are given by equations (1) and (2), respectively:

$$L_A^T = \sum_{t=1}^{T} L(y_t, y_t') \qquad (1)$$

$$L_i^T = \sum_{t=1}^{T} L(y_t, x_{t,i}') \qquad (2)$$

The purpose of the learner is to minimize a difference R^T_A, given by equation (3) below, between the cumulative loss of the learner and the cumulative loss of an optimum expert. This is called the regret of the learner.

$$R_A^T = L_A^T - \min_{1 \le i \le N_E} L_i^T \qquad (3)$$

Vovk has proposed a learner's strategic scheme called an aggregating algorithm (to be referred to as AA

hereinafter). Vovk shows that the AA performs optimum prediction on a given mild assumption in an arbitrary game. The AA assigns a weight $v_{t,i}$ given by equation (4) below to the expert i at time t:

$$v_{t,i} = \frac{v_{1,i} e^{-\beta L_i^{t-1}}}{\sum_{j=1}^{N_E} v_{1,j} e^{-\beta L_j^{t-1}}} \qquad (4)$$

$$L_i^{t-1} = \sum_{q=1}^{t-1} L\left(y_q, x'_{q,i}\right) \qquad (5)$$

where L^{t-1}_i given by equation (5) is the cumulative loss of the expert i at time t-1, and β is a parameter called a learning coefficient or learning constant, in which $0 < \beta < 1$. As is apparent from equation (4), a smaller weight is assigned to an expert having a larger cumulative loss, i.e., an expert which makes a larger number of mistakes. The initial value $v_{1,i}$ of the weight can be arbitrarily set for each expert i. Typically, the initial value $v_{1,i}$ of the weight is set to $1/N_E$.

In practice, to maintain the relationship in the above equation, when the loss $L(y_t, x_{t,i}')$ of each expert i at time t is clarified, the weight $v_{t,i}$ calculated according to equation (4) is updated according to equation (6):

$$v_{t,i} = \frac{v_{t,i} e^{-\beta L\left(y_t, x'_{t,i}\right)}}{\sum_{j=1}^{N_E} v_{t,j} e^{-\beta L\left(y_t, x'_{t,j}\right)}} \qquad (6)$$

where $v_{t,i}$ on the left-hand side is the updated weight.

Next, prediction by the learner will be explained. The learner performs prediction based on a function F(·) satisfying equation (7) below by using the prediction and weights of the experts:

$$y' = F(\vec{v}, \vec{x}) \qquad (7)$$

$$\vec{x} = (x_{t,1}, x_{t,2}, \ldots, x_{t,N_E})$$
$$\vec{v} = (v_{t,1}, v_{t,2}, \ldots, v_{t,N_E})$$

Although a traffic demand pattern is to be predicted originally, it is difficult to accurately predict a subdivided traffic demand. Thus, the embodiment adopts the following strategy:

1. The category of the traffic demand is predicted.

2. The getting-on ratios and getting-off ratios for the respective moving direction, and the feature amount of the number of users are predicted by using the prediction of an expert having a largest weight.

The category of the traffic demand is predicted because the control method selector 166 to be described later sets one or more control method candidates (e.g., zoning, multiple-car assignment, pullback, and distributed standby) for each traffic demand category. As conditions to select a control method to be actually used from control method candidates, the feature amounts of getting-on ratios and getting-off ratios for the respective moving direction and the feature amount of the number of users are used.

Next, a method of performing prediction by the expert will be explained. Each expert refers to data at a

specific portion of the feature amount DB 163, and outputs a prediction result from the data. To simplify the description, an example in which the traffic demand predictor 165 includes three experts will be explained. For example, when predicting the category of a traffic demand in the time zone t for the number d of elapsed days, the three experts are set as follows:

expert 1: to perform prediction from data in the time zones t-3, t-2, and t-1 for the number d of elapsed days.

expert 2: to perform prediction from data in the time zone t+1 for the numbers d-3, d-2, and d-1 of elapsed days.

expert 3: to perform prediction from data in the time zone t for the numbers d-21, d-14, and d-7 of elapsed days.

Expert 1 generates a predicted value by using data acquired immediately before prediction. For example, when predicting a traffic demand in a time zone of 8:00 to 8:05, expert 1 acquires three category feature amount vectors by referring to data in time zones of 7:45 to 7:50, 7:50 to 7:55, and 7:55 to 8:00 on the same day. Then, expert 1 makes majority determination based on the three acquired category feature amount vectors, generating a predicted value. Prediction using data in a past time zone, like expert 1, will be called past time zone prediction.

Expert 2 generates a predicted value by using data acquired in the time zone t+1 one day before, two days before, and three days before. For example, when predicting a traffic demand in a time zone of 8:00 to 8:05

on April 28, expert 2 acquires three category feature amount vectors by referring to data in a time zone of 8:05 to 8:10 on April 27, April 26, and April 25. Then, expert 2 makes majority determination based on the three acquired category feature amount vectors, generating a predicted value. Prediction using data in a future time zone, like expert 2, will be called future time zone prediction.

Expert 3 generates a predicted value by using data acquired in the time zone t one week before, two weeks before, and three weeks before. For example, when predicting a traffic demand in a time zone of 8:00 to 8:05 on April 28, expert 3 acquires three category feature amount vectors by referring to data in a time zone of 8:00 to 8:05 on April 21, April 14, and April 7 in the feature amount DB 163. Then, expert 3 makes majority determination by using the three acquired category feature amount vectors, thereby generating a predicted value. Prediction using data in the same time zone, like expert 3, will be called current time zone prediction.

When a category feature amount vector acquired from the feature amount DB 163 includes two or more identical category feature amount vectors, each expert generates the category feature amount vector as a predicted value. When three category feature amounts differ from each other, the expert suspends prediction, that is, does not generate a predicted value. A model which allows an expert to suspend prediction is called a specialist model in the online

learning algorithm.

In a general Vovk algorithm, the predicted value of the learner is output as the weighted sum of the predicted values of experts. However, when predicting a discrete pattern, as in the embodiment, the Vovk algorithm cannot be directly applied. In the embodiment, the learner employs the predicted value of an expert having a largest weight. This model is called an expert federation model, and theoretical studies have been made widely.

In the embodiment, the loss function $L(y_t, x_{t,i})$ of the expert i at time t is defined by equation (8):

$$L(y_t, x_{t,i}) = \begin{cases} 0 & (y_t = x_{t,i}) \\ 1 & (y_t \neq x_{t,i}) \end{cases} \qquad (8)$$

This loss function is generally called the 0-1 loss function. When a predicted value and measured value are different, it is considered that a loss has been generated. By using this loss function, the weight update equation of the specialist federation model is given by equation (9):

$$\nu_{t,i} = \frac{\nu_{t,i} e^{-\beta L(y_t, x_{t,i}) \cdot (1-u_{t,i}) - \gamma(u_{t,i})}}{\sum_{j=1}^{N_E} \nu_{t,j} e^{-\beta L(y_t, x_{t,j}) \cdot (1-u_{t,j}) - \gamma(u_{t,j})}} \qquad (9)$$

where γ is the loss factor in suspension, in which $0 < \gamma < 1$, and $u_{t,i}$ is a variable representing whether the expert i has suspended prediction at time t, as represented by equation (10):

$$u_{t,i} = \begin{cases} 0 \ (suspend) \\ 1 \ (not\ suspend) \end{cases} \qquad (10)$$

This variable (to be referred to as a suspension variable hereinafter) may be changed every time the expert i performs prediction. According to equation (9), the weight of each expert is updated to be relatively large when the prediction is correct (that is, the predicted value and measured value are equal), and relatively small when the prediction is incorrect (that is, the predicted value and measured value are different).

The weight of the expert is recorded in the prediction parameter DB 164 in association with additional information and time information (time zone). FIG. 8 shows an example of weight data recorded in the prediction parameter DB 164. FIG. 8 shows an example in which the weights of four experts are recorded in association with the day of the week and time information. For example, when predicting a traffic demand in a time zone of 8:00 to 8:05 on 2011/4/28 (Thursday), the traffic demand predictor 165 selects an expert having a largest weight by referring to the weights of the respective experts in the time zone of 8:00 to 8:05 on Thursday. After that, the feature amount calculation unit 162 calculates a measured value in the time zone of 8:00 to 8:05 on 2011/4/28 (Thursday). Then, the traffic demand predictor 165 updates the weight of each expert based on the predicted value of each expert and the measured value in this time zone, as represented by, e.g.,

equation (9).

Note that weight data is not limited to an example in which the weight is recorded in association with the day of the week and time information, as shown in FIG. 8. The weight may be recorded by including calendar information such as weekdays and holidays in additional information. However, the embodiment assumes that the weight is recorded in association with the day of the week and time information for descriptive convenience. In this case, the weight in a given time zone on a given day of the week is updated once a week. If weekdays and holidays are included, the weight is updated every time pieces of additional information coincide with each other.

Procedures to update the weight recorded in the prediction parameter DB 164 will be explained in detail with reference to FIG. 9.

Processing in FIG. 9 starts after the traffic demand predictor 165 predicts a traffic demand in the time zone t-1 on ,for example, 2011/4/28 (Thursday). In step S901, the feature amount calculation unit 162 calculates the measured value of the feature amount of the traffic demand from aggregated load data in the time zone t-1 on 2011/4/28 (Thursday). For example, the feature amount calculation unit 162 calculates the measured value of the feature amount of the traffic demand in accordance with the procedures described above with reference to FIG. 3. As a result, the measured value of the feature amount of the

traffic demand in the time zone t-1 on 2011/4/28 (Thursday) is obtained. This measured value is recorded in the feature amount DB 163.

In step S902, the traffic demand predictor 165 updates the weights of the experts in the time zone t-1 on Thursday by using the measured value of the feature amount of the traffic demand in the time zone t-1 on 2011/4/28 (Thursday), and the predicted values of the experts generated at the time of prediction in the time zone t-1 on the same day.

In step S903, the traffic demand predictor 165 predicts a traffic demand in the time zone t on 2011/4/28 (Thursday). More specifically, the traffic demand predictor 165 acquires the weights of the experts in the time zone t on Thursday from the prediction parameter DB 164, and decides the predicted value of an expert having a largest weight as the feature amount of the traffic demand in the time zone t on 2011/4/28 (Thursday). The predicted value and suspension variable of each expert are held until the end of prediction in the next time zone t+1.

In this manner, the weights of the respective experts are updated every time prediction is performed.

The traffic demand predictor 165 receives the weights of the respective experts from the prediction parameter DB 164, calculates the predicted values of the respective experts by referring to the feature amount DB 163, and decides the predicted value of the learner based on the

weights of the respective experts. The traffic demand predictor 165 outputs the predicted value of the learner as a prediction result. The prediction result includes the category feature amount. The prediction result can further include the feature amounts of getting-on ratios and getting-off ratios for the moving directions and the feature amount of the number of users.

The control method selector 166 receives the prediction result from the traffic demand predictor 165, and selects a control method corresponding to the prediction result from a control method list prepared in advance. FIG. 10 shows an example of the control method list held by the control method selector 166. In the control method list of FIG. 10, control method candidates are set for respective category feature amounts. In the example of FIG. 10, the control method is decided based on a category feature amount and the feature amount of the number of users which are included in the prediction result. For example, when a prediction result in which the category feature amount is (1, 0, 0, 0) and the feature amount of the number of users is equal to or smaller than 2 is obtained, distributed standby is decided as the control method. When a prediction result in which the category feature amount is (1, 0, 0, 0) and the feature amount of the number of users is equal to or larger than 6 is obtained, multiple-car assignment is decided as the control method. In FIG. 10, distributed standby is a control

method of restricting the standby position of a car when the number of users is small. Multiple-car assignment is a control method of dispatching a plurality of cars in response to one hall call. Zoning is a control method of restricting a hall call in order to shorten the round-trip time of a car. In the embodiment, existing methods are used as methods for implementing these control methods, details of which will not be mentioned. In FIG. 10, the control method is uniquely decided based on the prediction result of the traffic demand predictor 165. However, it is also possible to prepare a plurality of control method candidates which can be activated under a given condition, evaluate a plurality of control method candidates based on the result of an actual operation, and narrow them down to one control method candidate to be activated under the condition.

As described above, the elevator apparatus according to the first embodiment includes the traffic demand prediction apparatus which predicts the traffic demand by using the experts of an online algorithm, and can accurately predict the traffic demand. Therefore, assignment matching an actual traffic demand can be performed, improving the service performance.

(Second Embodiment)

The first embodiment has described the method of predicting the feature amount of the traffic demand. In the first embodiment, the weight of each expert is recorded

in the prediction parameter DB 164 in association with the day of the week and the time zone. The weight is updated by using a measured value obtained in the same time zone on the same day of the week. The predicted value of each expert is used to update the weight, but is not used after that and need not be recorded.

In the first embodiment, for example, when a company in a building is replaced and the trend of the traffic demand changes, the prediction result of the traffic demand predictor 165 may become wrong for a specific day of the week and a specific time zone. This is because some period is taken to reflect a change of the performance of the expert in the weight. For example, a given expert exhibits a high percentage of correct answers of prediction in a given time zone on a given day of the week, but after the trend of the traffic demand changes, the percentage of correct answers in this time zone on this day of the week may drop. In this case, in some period after the change of the trend of the traffic demand, the weight of this expert in this time zone on this day of the week is large. For this reason, the predicted value of the expert is employed as the prediction result of the traffic demand predictor 165.

The second embodiment uses reliability representing the percentage of correct answers in a predetermined period, instead of the weight. The second embodiment will be explained in detail with reference to FIGS. 11, 12, 13,

14, 15, and 16.

FIG. 11 schematically shows an elevator apparatus 1100 according to the second embodiment. The elevator apparatus 1100 shown in FIG. 11 includes a reliability calculation unit 1101 and information input unit 1102, in addition to the arrangement of the elevator apparatus 100 shown in FIG. 1. The reliability calculation unit 1101 calculates the reliability of an expert based on the performance of the expert in a predetermined period. The information input unit 1102 includes an input device such as a keyboard or mouse, and receives an input from the operator. In the embodiment, the information input unit 1102 is used to set the number of data items (i.e., the number of prediction results) used when the reliability calculation unit 1101 calculates the reliability. The number of prediction results used to calculate the reliability can be set for each expert.

In the embodiment, a prediction parameter DB 164 stores expert prediction result data which records, in association with attribute information and the time information, whether the predicted value of each expert coincides with a measured value. FIG. 12 shows an example of expert prediction result data. In FIG. 12, a sign "○" in each field represents that the predicted value and measured value coincide with each other (that is, correct), and a sign "×" represents that they do not coincide with each other (that is, incorrect). Suspension of output of

the predicted value by the expert is defined to be incorrect. Further, the expert prediction result data records, in association with attribute information and the time information, the number of a selected expert (also called a final prediction expert) and whether the predicted value of the selected expert coincides with a measured value.

FIG. 13 shows an example of the design of the experts according to the second embodiment. As shown in FIG. 13, data to be referred to in prediction and the reliability calculation target period are designated for each expert. Here, D(t|d) represents data in the time zone t for the number d of elapsed days. For example, expert 1 predicts a traffic demand in the time zone t for the number d of elapsed days by using D(t-3|d), D(t-2|d), and D(t-1|d). The reliability calculation target period represents the number of data items used to calculate the reliability. The reliability calculation target period can be set by using the information input unit 1102. The reliability calculation method will be described later.

Next, a method of predicting the feature amount of the traffic demand according to the second embodiment will be explained with reference to FIG. 14.

In step S1401 of FIG. 14, a feature amount calculation unit 162 calculates the feature amount of the traffic demand in the time zone t-1 based on aggregated load data in the time zone t-1, and records the calculated feature

amount of the traffic demand in a feature amount DB 163. For example, the feature amount calculation unit 162 calculates the feature amount of the traffic demand according to the procedures described above with reference to FIG. 3.

In step S1402, to predict a traffic demand in the time zone t, the reliability calculation unit 1101 calculates the reliabilities of a plurality of experts by referring to the expert prediction result data stored by the prediction parameter DB 164, and creates a list of experts sorted by the reliability. The processing in step S1402 will be explained with reference to FIG. 15.

In step S1501 of FIG. 15, the reliability calculation unit 1101 calculates the reliabilities of experts by referring to the expert prediction result data stored by the prediction parameter DB 164. A method of calculating the reliability of each expert will be described in detail. When performing prediction in a given time zone on a given day of the week, the percentage of correct answers of the expert in this time zone on this day of the week for past P weeks is calculated as reliability. Here, P is a natural number and represents the reliability calculation target period. The percentage of correct answers is a value obtained by dividing the number of correct answers (O) by P. In the example of FIG. 13, the reliability calculation target period P of expert 3 is 3. For example, when performing prediction in a time zone of 7:00 to 7:05 on

2011/4/28 (Thursday), the reliability calculation unit 1101 calculates the reliability of expert 3 by dividing, by 3, the number of correct answers (○) in a time zone of 7:05 to 7:10 on 2011/4/21, 2011/4/14, and 2011/4/7. Note that the reliability is not limited to the above-described example in which the reliability is calculated from data in the same time zone on the same day of the week as the time zone on the day of the week for which prediction is performed. The reliability may be calculated using data in another time zone on another day of the week.

In step S1502, the reliability calculation unit 1101 creates a list of experts sorted in descending order of the reliability. Experts are sorted based on the reliability in order to select an expert having high reliability. More specifically, experts are sorted by using the reliability as the first key. At this time, when there are a plurality of experts having the same reliability, the experts having the same reliability are sorted by using, as the second key, the time (period) taken to acquire data to be used for prediction by each expert. In the example of FIG. 13, the time taken to acquire data to be used for prediction is 15 min for expert 1, 21 days for expert 2, 7 days for expert 3, and 3 days for expert 4.

Referring back to FIG. 14, in step S1403, a traffic demand predictor 165 predicts a traffic demand in the time zone t by using the list created in step S1402. A traffic demand prediction method according to the second embodiment

will be explained with reference to FIG. 16.

In step S1601 of FIG. 16, an index used when referring to the expert list created in step S1402 is initialized. For example, index = 1. In step S1602, the traffic demand predictor 165 predicts the feature amount of the traffic demand by using the index-th expert in the list. As for prediction by the expert, the same method as that described in the first embodiment can be used, and a description thereof will not be repeated.

In step S1603, it is determined whether the index-th expert has suspended prediction. If the index-th expert has not suspended prediction, that is, has generated a predicted value, the traffic demand predictor 165 outputs the predicted value of the expert as the prediction result, and the process ends. However, all experts after the index-th expert need to perform prediction so as to be able to calculate the reliability later.

If it is determined in step S1603 that the index-th expert has suspended prediction, the process advances to step S1604. In step S1604, the index is incremented. In step S1605, it is determined whether the index value has exceeded the number (N_E) of experts. If the index value is equal to or smaller than the number of experts, the process returns to step S1602. If the index value has exceeded the number of experts, that is, all the experts have suspended prediction, the process advances to step S1606. In step S1606, the traffic demand predictor 165 employs, as the

prediction result, a measured value obtained in an immediately preceding time zone ,i.e., in the time zone t-1.

As described above, a traffic demand prediction apparatus 160 according to the second embodiment calculates reliabilities for experts based on the performance in a predetermined period, and selects an expert based on the reliability. Even if an expert having a high percentage of correct answers in a given time zone on a given day of the week changes, the traffic demand prediction apparatus 160 can follow the change in a relatively short time. The traffic demand prediction apparatus 160 employs, as the prediction result, the predicted value of an expert whose recent performance is good, and can accurately predict the traffic demand. Assuming that the reliability calculation target period P is 1, the reliability is obtained from data one week before. In this case, the tracking property to a change becomes highest, but an accidentally correct answer cannot be discriminated.

(Third Embodiment)

The first and second embodiments assume that the traffic demand mainly depends on the day of the week. However, in an actual building, the same traffic demand does not always periodically arise in accordance with merely the day of the week. For example, when attributes are classified into weekdays (Monday, Tuesday, Wednesday, Thursday, and Friday) and weekends (Saturday and Sunday),

traffic demand patterns may be similar between the weekdays and between the weekends in an office building, but the traffic demand on the weekdays and that on the weekends may be different. Even on weekdays, it can be predicted that a generated traffic demand pattern is different between a working day and a day off. The third embodiment considers even information other than the day of the week.

FIG. 17 schematically shows an elevator apparatus 1700 according to the third embodiment. The elevator apparatus 1700 shown in FIG. 17 includes an information input unit 1701, expert creation unit 1702, and reliability calculation unit 1703, in addition to the arrangement of an elevator apparatus 100 shown in FIG. 1. The information input unit 1701 includes an input device such as a keyboard or mouse, and receives an input from the operator. The information input unit 1701 is used to input working system information about a company in a building. The expert creation unit 1702 creates experts based on the working system information acquired by the information input unit 1701. The reliability calculation unit 1703 performs the same operation as that of the reliability calculation unit 1101 (FIG. 11) in the second embodiment, and a detailed description thereof will not be repeated.

In the third embodiment, attribute information includes information (i.e., calendar information) about a calendar including weekdays, weekends, holidays, and feast days, and information (working system information) about

the working system of each company, including a morning-off day, afternoon-off day, on-time leave day, and a special day off. FIG. 18 shows an example of attribute information. In FIG. 18, "week_num" is a variable representing the day of the week. "weekend" is a variable for discriminating weekdays and weekends. "holiday" is a variable representing a holiday and feast day (holiday/feast day). "working_day" is a variable representing a working system. The variables week_num, weekend, and holiday are uniquely determined from calendar information for a given date "day". week_num values of 1, 2, 3, 4, 5, 6, and 7 represent Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively. A weekend value of 0 represents a weekday (Monday, Tuesday, Wednesday, Thursday, or Friday) and a weekend value of 1 represents a weekend (Saturday or Sunday). A holiday value of 1 represents a holiday/feast day, and a holiday value of 0 represents another day. When the date "day" is 2011/4/29, week_num = 5, weekend = 0, holiday = 1 are uniquely determined.

working_day is information representing the working system of a given company in a building, and needs to be input in advance. The operator inputs working system information by using the information input unit 1701. FIG. 19 shows an example of a screen for inputting working system information to be displayed on the display unit (e.g., a liquid crystal display device) of a personal

computer (PC). The embodiment will explain an example in which working system information is input by using the PC, but the input method is not limited to this example. As shown in FIG. 19, a calendar in a general display form is displayed on the screen. More specifically, information about the Christian Era (or era name) and month is displayed at the upper portion of the screen. At the center of the screen, dates are arranged by setting the day of the week along the abscissa. As for holidays/feast days determined by calendar information, corresponding columns are displayed in color. When the operator locates the cursor at 2011/4/29 on the screen, a working system list appears in a balloon. The operator selects an appropriate item from the list, thereby setting working system information of the day. This description assumes that only one company exists in a building. However, a plurality of companies with different working systems may exist in the building. In this case, working system information is input for each company.

Next, the expert creation unit 1702 will be explained. The expert creation unit 1702 creates experts by using the working system information input from the information input unit 1701.

In the first embodiment, the experts are set as follows:

expert 1: to perform prediction from data in the time zones t-3, t-2, and t-1 for the number d of elapsed days.

expert 2: to perform prediction from data in the time zone t+1 for the numbers d-3, d-2, and d-1 of elapsed days.

expert 3: to perform prediction from data in the time zone t for the numbers d-21, d-14, and d-7 of elapsed days.

These experts can be expressed as follows:

expert 1: Prediction[D(t-3|d), D(t-2|d), D(t-1|d)]

expert 2: Prediction[D(t+1|d-1), D(t+1|d-2), D(t+1|d-3)]

expert 3: Prediction[D(t|d-21), D(t|d-14), D(t|d-7)]

Prediction[D(x1), D(x2), D(x3)] represents that prediction is performed by majority determination using data D(x1), D(x2), and D(x3). The time zone of data used to predict the category of the traffic demand in the time zone t differs between experts 1, 2, and 3:

expert 1: data in the immediately preceding time zones t-3, t-2, and t-1 are used.

expert 2: data in the time zone t+1 for recent three days are used.

expert 3: data in the same time zone t on the same day of the week are used.

Although data in any time zone is usable when performing prediction, it becomes possible to create experts indefinitely. The expert creation unit 1702 creates experts based on three prediction forms, that is, past time zone prediction, future time zone prediction, and current time zone prediction. The expert creation unit 1702 is determined in accordance with a combination of the number d of elapsed days, date "day", weekday/weekend

"weekend", holiday/feast day "holiday", and working system "working_day". Ten combinations are conceivable:

(1) day of the week, holiday/feast day, and working system

(2) weekday/weekend, holiday/feast day, and working system

(3) day of the week, and holiday/feast day

(4) day of the week, and working system

(5) weekday/weekend, and holiday/feast day

(6) weekday/weekend, and working system

(7) holiday/feast day, and working system

(8) day of the week

(9) holiday/feast day

(10) working system

For example, when (1) day of the week, holiday/feast day, and working system is taken into consideration, the expert creation unit 1702 creates the following three experts m1, m2, and m3:

the expert m1 which performs prediction using

data D(t-3|d, week_num, holiday, working_day),

data D(t-2|d, week_num, holiday, working_day), and

data D(t-1|d, week_num, holiday, working_day);

the expert m2 which performs prediction using

data D(t+1|d-7×x_1, week_num, holiday, working_day),

data D(t+1|d-7×x_2, week_num, holiday, working_day), and

data D(t+1|d-7×x_3, week_num, holiday, working_day);

and

the expert m3 which performs prediction using

data D(t|d-7×y_1, week_num, holiday, working_day),

data D(t|d-7×y_2, week_num, holiday, working_day), and

data D(t|d-7×y_3, week_num, holiday, working_day).

x_1, x_2, x_3, y_1, y_2, and y_3 are natural numbers.

In this case, D(t|M) represents data in the time zone t for the attribute M. x_1, x_2, and x_3 in the expert m2 mean that days having the same attribute are x_1 weeks before, x_2 weeks before, and x_3 weeks before. y_1, y_2, and y_3 in the expert m3 mean that days having the same attribute are y_1 weeks before, y_2 weeks before, and y_3 weeks before. Weekday/weekend information is excluded because weekdays and weekends are determined by the day of the week, and consideration of the day of the week includes consideration of weekdays and weekends. However, it should be noted that consideration of weekdays and weekends does not include consideration of the day of the week. The experts m1, m2, and m3 are experts for past time zone prediction, future time zone prediction, and current time zone prediction. However, even for case (1), a plurality of experts can be created. For example, when performing prediction in a time zone of 7:00 to 7:05 on 2011/4/28, an expert using data in time zones of 6:55 to 7:00, 6:50 to 6:55, and 6:45 to 6:50 on 2011/4/28 can be created, and an expert using data in time zones of 6:55 to 7:00, 6:50 to 6:55, and 6:45 to 6:50 on 2011/4/21 can also be created.

In this case, however, creation of an expert is not unique, so no expert can be created automatically. To solve this, an expert is defined to use the latest data when using data of the same attribute. Then, in (1) past time zone prediction, when performing prediction in a time zone of 7:00 to 7:05 on 2011/4/28, an expert using data in time zones of 6:55 to 7:00, 6:50 to 6:55, and 6:45 to 6:50 on 2011/4/28 is used.

In this fashion, for the same attribute, experts can be set uniquely even for attribute groups (1) to (10) by adding the condition to perform prediction by using the latest data for the same attribute.

When no working system information is input with the information input unit, the expert creation unit 1702 creates experts in consideration of (3), (5), (8), and (9), excluding attribute groups including the working system. Experts created by the expert creation unit 1702 are transmitted to a prediction parameter DB 164, registered as experts to be used for prediction, and perform prediction in each time zone. The reliability as described in the second embodiment is used to decide the final prediction result in the third embodiment, and the predicted value of an expert having highest reliability is employed as the prediction result.

Note that a traffic demand predictor 165 can use the weight as described in the first embodiment to decide an expert whose predicted value is employed as the prediction

result. However, the weight is relatively changed between experts. Thus, when there are many experts, a change (increase/decrease) of the weight may become small.

To the contrary, the reliability described in the second embodiment is calculated individually for each expert. For this reason, when there are many experts, it is effective to use the reliability. The reliability calculation target period P is set for each expert created by the expert creation unit 1702. FIG. 20 shows an example of an input screen for setting the reliability calculation target period according to the third embodiment. As shown in FIG. 20, the reliability calculation target period is set for respective attribute combinations (1) to (10) and the three respective prediction forms. The operator inputs and sets a reliability calculation target period in each field by using the information input unit 1701. For example, an initial value of 3 is stored in all fields.

As the reliability calculation method, the same method as that described in the second embodiment can be used. More specifically, the reliability of each expert is calculated from the performance on past days of the same attribute. When the day-of-the-week attribute is taken into account, days of the same attribute appear in every week. In contrast, there are five weekdays in a week and there are two weekends in a week. Thus, when the weekday/weekend attribute is taken into account, the frequency at which days of the same attribute appear

becomes higher than that when the day-of-the-week attribute is taken into account. In this way, the reliability is frequently updated for an attribute which appears frequently, and is rarely updated for an attribute which rarely appears. However, preparing many experts increases the probability of the presence of experts which give correct answers. Further, the predicted value of an expert having high reliability among these experts is employed as the prediction result. Correct prediction can therefore be performed, excluding days of an attribute which rarely appears.

As described above, the traffic demand prediction apparatus according to the third embodiment creates a plurality of experts for various attribute combinations including the working system of a company in a building. Prediction using a larger number of experts can increase the prediction accuracy.

The traffic demand prediction apparatus according to at least one embodiment described above calculates the feature amount of the traffic demand at a predetermined time interval, and predicts a traffic demand in the next time zone by using the database which records the feature amount of the traffic demand, and the experts of the online algorithm. Hence, the traffic demand prediction apparatus can predict the traffic demand in the building accurately.

While certain embodiments have been described, these embodiments have been presented by way of example only, and

are not intended to limit the scope of the inventions. Indeed, the novel embodiments described herein may be embodied in a variety of other forms; furthermore, various omissions, substitutions and changes in the form of the embodiments described herein may be made without departing from the spirit of the inventions. The accompanying claims and their equivalents are intended to cover such forms or modifications as would fall within the scope and spirit of the inventions.

WHAT IS CLAIMED IS:

1. An elevator traffic demand prediction apparatus applied to up/down button group control to assign an elevator car in response to a hall call, the apparatus comprising:

an acquisition unit configured to acquire an elevator control result including getting-on loads and getting-off loads for respective moving directions and respective floors;

a calculation unit configured to calculate a feature amount of a traffic demand based on the elevator control result, the feature amount including a category feature amount representing a category of the traffic demand;

a feature amount database configured to store the calculated feature amount in association with attribute information and time information;

a predictor configured to predict a traffic demand by referring to the feature amount database, the predictor comprising a plurality of experts configured to predict a category of a traffic demand by referring to different data items included in the feature amount database to generate predicted values, and the prediction unit outputting, as a prediction result, one of the predicted values; and

a selector configured to select a control method complying with the prediction result from a plurality of predetermined control methods.

2. The apparatus according to claim 1, wherein

the experts have weights, and every time prediction is performed, a weight of each of the experts is updated to relatively increase the weights when the prediction is correct, and relatively decrease the weights when the prediction is incorrect, and

the predictor outputs, as the prediction result, a predicted value generated by an expert having a largest weight.

3. The apparatus according to claim 2, further comprising a prediction parameter database configured to store the weights of the experts in association with a day of the week and time information.

4. The apparatus according to claim 1, wherein the plurality of experts includes an expert configured to perform past time zone prediction, an expert configured to perform current time zone prediction, and an expert configured to perform future time zone prediction.

5. The apparatus according to claim 1, wherein the attribute information includes at least one of a date and the number of elapsed days representing the number of days elapsed after an operation start day of the elevator traffic demand prediction apparatus.

6. The apparatus according to claim 1, further comprising a reliability calculation unit configured to calculate reliabilities of the experts, the reliabilities each representing a percentage of correct answers of prediction in a predetermined period,

wherein the predictor outputs, as the prediction result, a predicted value generated by an expert having the reliability.

7. The apparatus according to claim 1, further comprising:

an input unit configured to input working system information representing a working system of a company in a building; and

an expert creation unit configured to create the experts based on the working system information,

wherein the attribute information includes the working system information.