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(54) **BASE STATION LOAD BALANCING METHOD AND APPARATUS**

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H04W 28/08	(2023.01)
H04W 28/086	(2023.01)

(52) **U.S. Cl.**

CPC ***H04W 28/0942*** (2020.05); ***H04W 24/02*** (2013.01); ***H04W 28/0861*** (2023.05)

(58) **Field of Classification Search**

CPC H04W 28/0861; H04W 24/02

USPC 370/329, 400, 403

See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

8,688,120	B2	4/2014	Song et al.
10,271,242	B2	4/2019	Lee et al.
2015/0289158	A1	10/2015	Shim et al.
2019/0279082	A1	9/2019	Moloney et al.

FOREIGN PATENT DOCUMENTS

KR	10-2015-0031067	3/2015	
KR	10-2020-0097623	8/2020	
WO	WO-201116674 A1 *	9/2011	.... H04W 72/0486

OTHER PUBLICATIONS

Md Mehedi Hasan et al., "Adaptive Mobility Load Balancing Algorithm for LTE Small-Cell Networks," IEEE Transactions on Wireless Communications, Jan. 12, 2018 (Current Version Apr. 8, 2018), pp. 2205-2217, vol. 17, No. 4, IEEE.

(Continued)

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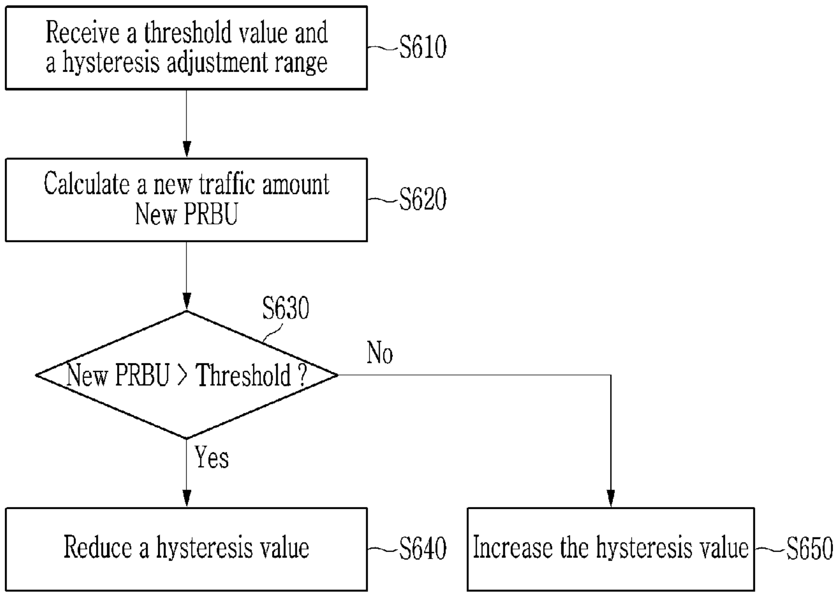
(57) **ABSTRACT**

A method for load balancing in a base station is provided. The base station updates a traffic amount of a current time by reflecting a predicted traffic amount of a future time in the traffic amount of the current time, and determines parameters necessary for load balancing of the base station by comparing the updated traffic amount of the current time with a predetermined threshold.

17 Claims, 7 Drawing Sheets


Receive a threshold value and a hysteresis adjustment range
S610
Calculate a new traffic amount New PRBU
S620
S630
New PRBU > Threshold ?
No
Yes
Reduce a hysteresis value
S640
Increase the hysteresis value
S650

(56) **References Cited**

OTHER PUBLICATIONS

Ghada Alsuhli et al., “Mobility Load Management in Cellular Networks: A Deep Reinforcement Learning Approach,” IEEE Transactions on Mobile Computing, Aug. 30, 2021 (Current Version Feb. 3, 2023), pp. 1581-1598, vol. 22, No. 3, IEEE.
Sangchul Oh et al., “User Mobility Impacts to Mobility Load Balancing for Self-Organizing Network over LTE System,” 2018 14th International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (TCSET), Feb. 20-24, 2018, pp. 1082-1086, IEEE.

* cited by examiner

FIG. 1

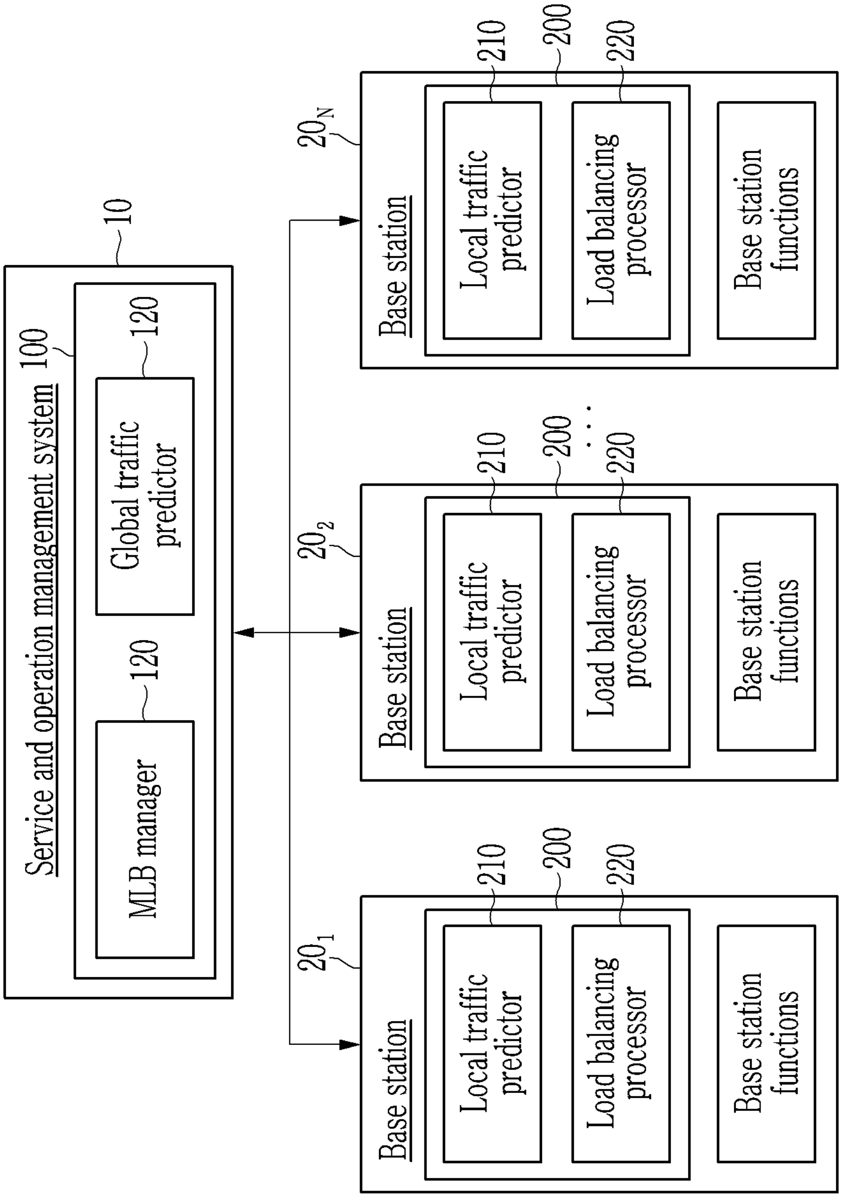

10
Service and operation management system
100
MLB manager
120
Global traffic predictor
120
20_1
20_2
20_N
Base station
Local traffic predictor
Load balancing processor
Base station functions
210
200
220
Base station
Local traffic predictor
Load balancing processor
Base station functions
210
200
220
Base station
Local traffic predictor
Load balancing processor
Base station functions
210
200
220

FIG. 2

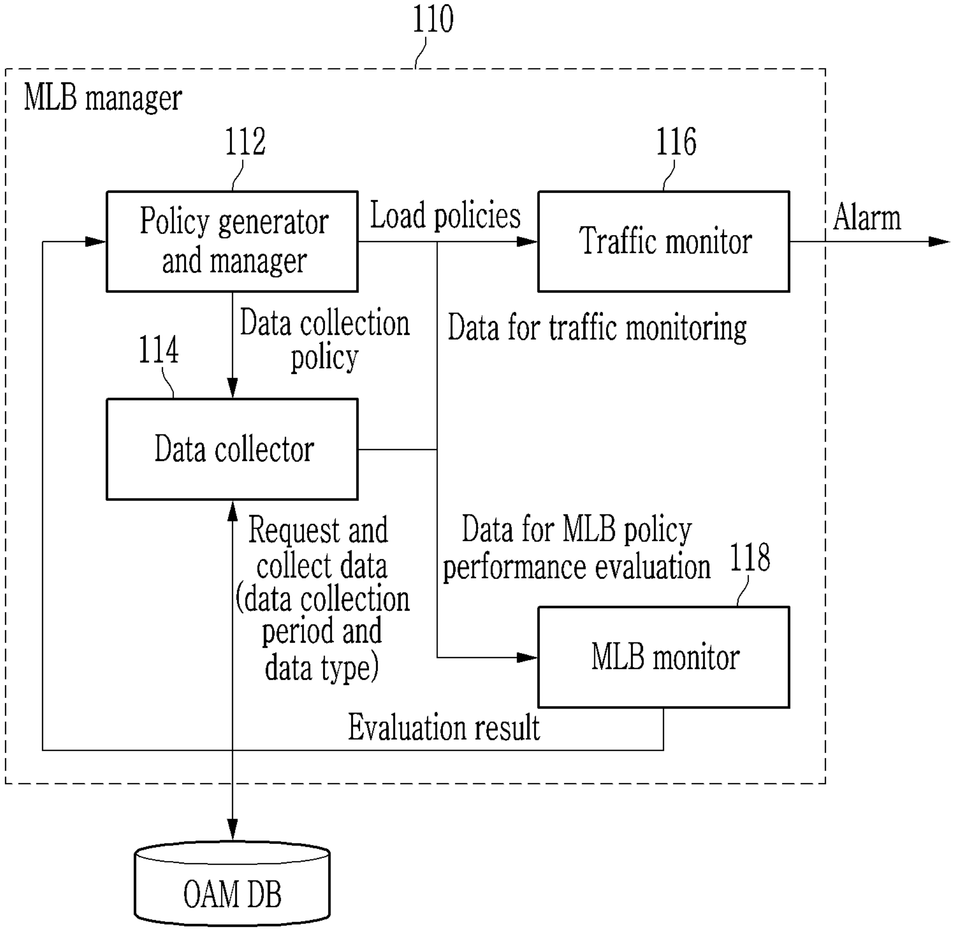

110
MLB manager
112
Policy generator and manager
Load policies
116
Traffic monitor
Alarm
Data collection policy
Data for traffic monitoring
114
Data collector
Request and collect data (data collection period and data type)
Data for MLB policy performance evaluation
118
MLB monitor
Evaluation result
OAM DB

FIG. 3

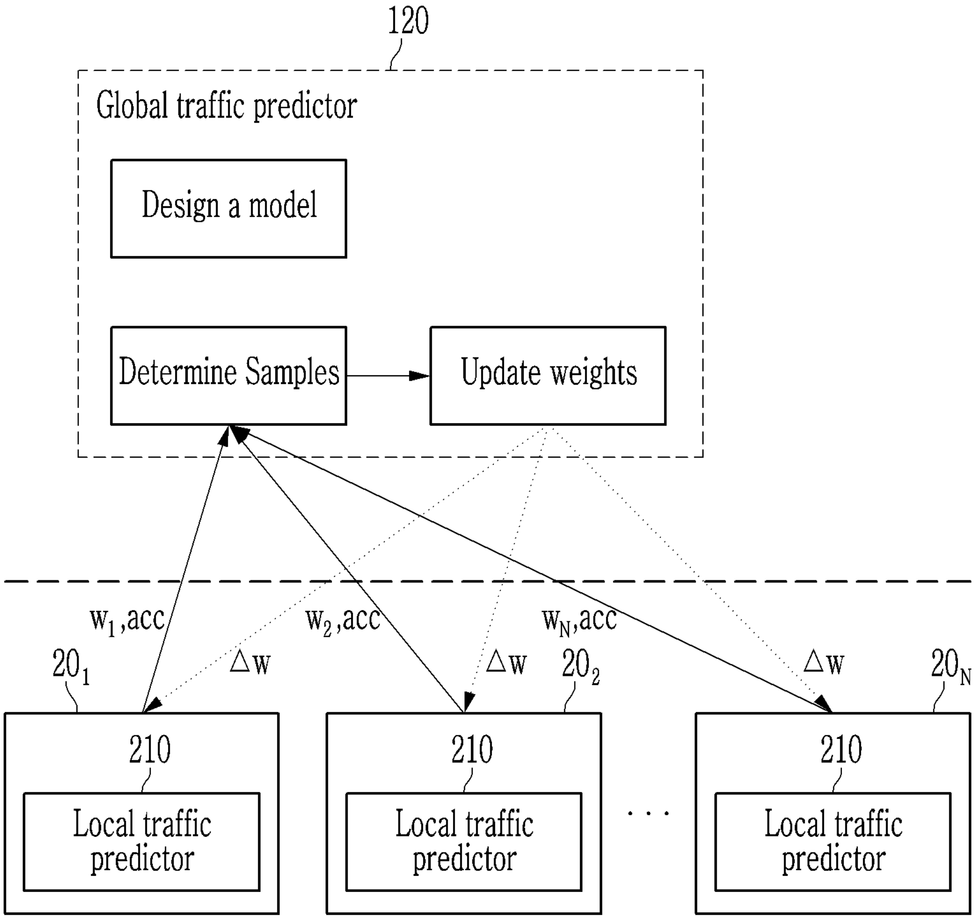
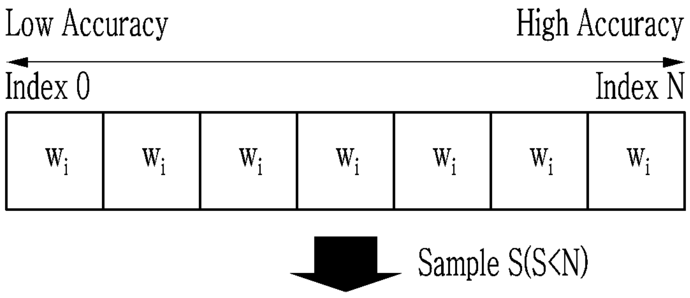

120
Global traffic predictor
Design a model
Determine Samples
Update weights
w_1,acc
w_2,acc
w_N,acc
△w
△w
△w
20_1
20_2
20_N
210
Local traffic predictor
210
Local traffic predictor
. . .
210
Local traffic predictor

FIG. 4



$E = \min(1, \delta \times \text{standard deviation of Accuracy}), 0 \leq \delta < 1$

```
If Random(0,1) < E
    S = Random Index choice
Else
    S = High Accuracy Index choice
```

$$\text{Average Weight} = \frac{1}{S}\sum_{i=1}^{S}(w_i)$$

FIG. 5

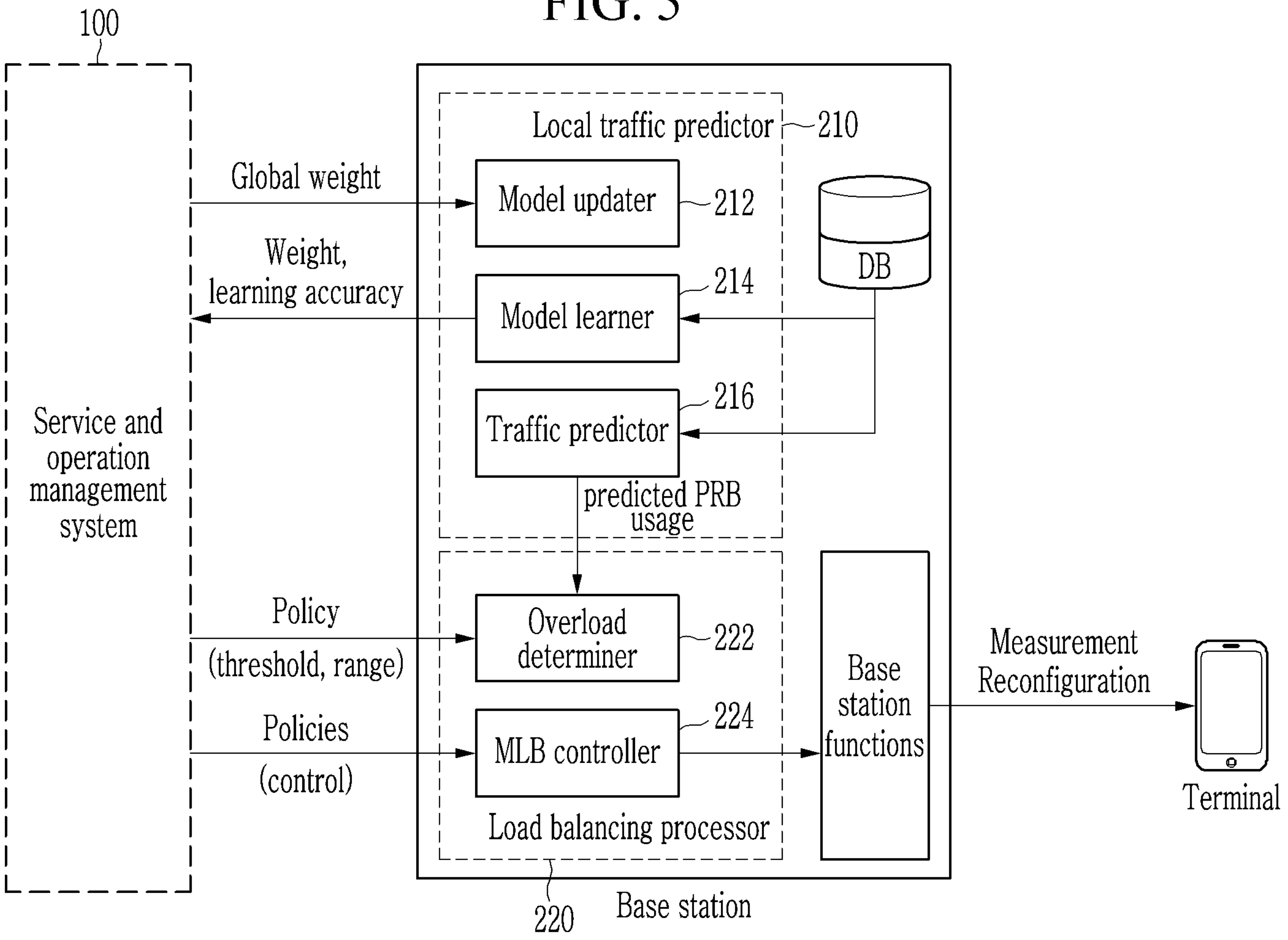

100
Service and operation management system
Global weight
Weight, learning accuracy
Policy
(threshold, range)
Policies
(control)
Local traffic predictor
210
Model updater
212
Model learner
214
Traffic predictor
216
DB
predicted PRB usage
Overload determiner
222
MLB controller
224
Load balancing processor
220
Base station functions
Base station
Measurement Reconfiguration
Terminal

FIG. 6

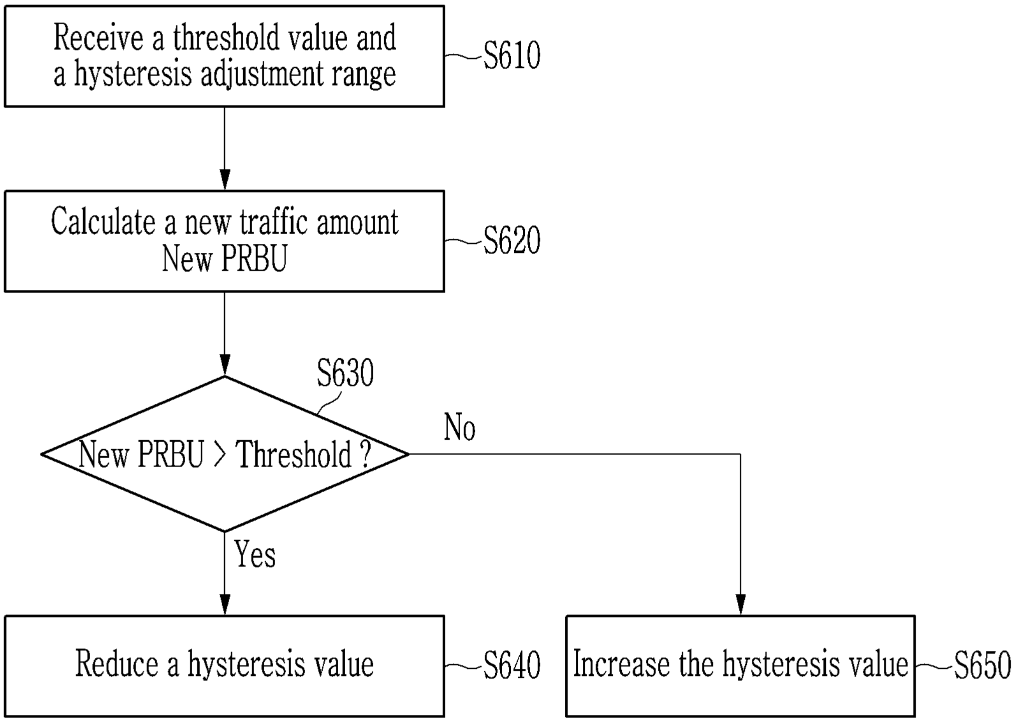
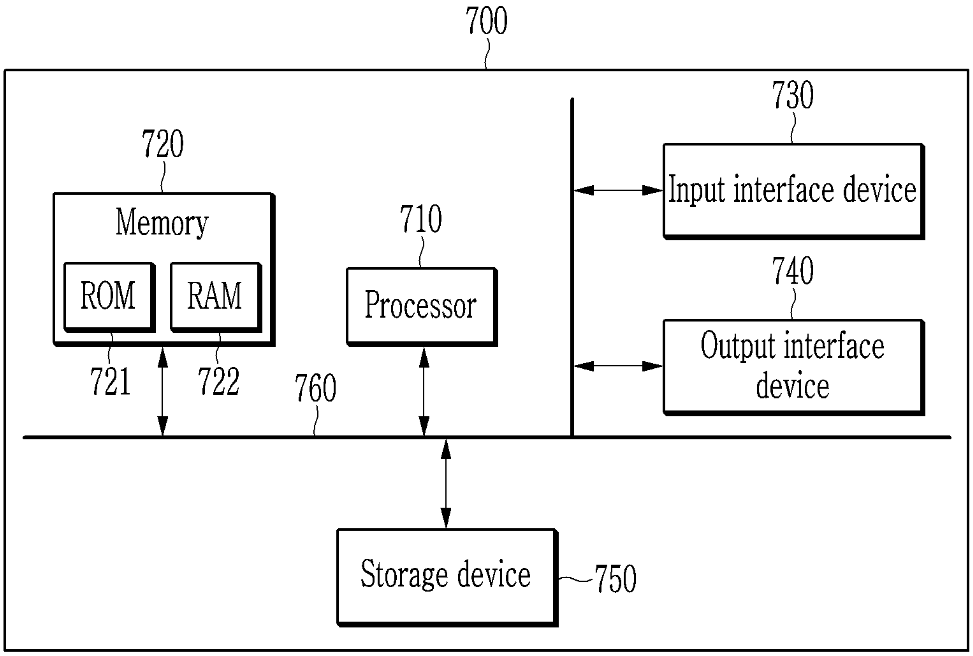

Receive a threshold value and a hysteresis adjustment range
S610
Calculate a new traffic amount New PRBU
S620
S630
New PRBU > Threshold ?
No
Yes
Reduce a hysteresis value
S640
Increase the hysteresis value
S650

FIG. 7


700
720
Memory
ROM
RAM
721
722
710
Processor
760
730
Input interface device
740
Output interface device
Storage device
750

BASE STATION LOAD BALANCING METHOD AND APPARATUS

CROSS-REFERENCE TO RELATED APPLICATION

This application claims priority to and the benefit of Korean Patent Application No. 10-2021-0147009 filed in the Korean Intellectual Property Office on Oct. 29, 2021, the entire contents of which are incorporated herein by reference.

BACKGROUND OF THE INVENTION

(a) Field of the Invention

The present invention relates to a base station load balancing method and apparatus, and more particularly, to a base station load balancing method and apparatus capable of effectively monitoring an overload state of a base station and distributing a load.

(b) Description of the Related Art

Recently, with the advent of the 5G mobile communication era, the demand for services such as remote robot control, vehicle autonomous driving, drone control, unmanned aerial vehicle (UAV), and augmented reality (AR)/virtual reality (VR) requiring large data is increasing.

With the development of various terminals and the exponential increase in services based on large-capacity content, the traffic that base stations have to process is greatly increasing.

Mobile communication base stations using high frequency are developing into structures that can provide high-capacity data services, but in order to satisfy all user needs, it is necessary to construct high-density base stations, and it is becoming increasingly difficult for an operator to manage the high-density base stations due to cost and complexity.

SUMMARY OF THE INVENTION

The present invention has been made in an effort to a base station load balancing method and apparatus capable of effectively controlling the overload of the base station while minimizing intervention of the operator.

According to an exemplary embodiment, a base station load balancing method in a base station is provided. The base station load balancing method includes: updating a traffic amount of a current time by reflecting a predicted traffic amount of a future time in the traffic amount of the current time; and determining parameters necessary for load balancing of the base station by comparing the updated traffic amount of the current time with a predetermined threshold.

The updating may include predicting the traffic amount of the future time from the traffic amount of the current time using a prediction model, and the weight value of the prediction model may be determined through federated learning between a service and operation management system and a plurality of base stations.

The base station load balancing method may further include: learning a machine learning model using learning data; updating the machine learning model; and repeating the learning of the machine learning model and updating of the machine learning model to use the machine learning model as the predictive model.

The updating of the machine learning model may include: transmitting a weight value and learning accuracy according to the learning result of the machine learning model to the service and operation management system; receiving a global weight value determined by the service and operation management system based on the weight values and learning accuracy received from the plurality of base stations; and updating a weight value of the machine learning model with the global weight value.

The global weight value may be an average value of part of the weight values received from the plurality of base stations, and the part of the weight values may be randomly selected according to a standard deviation for learning accuracy provided by the plurality of base stations, or are selected in the order of high learning accuracy.

The updating may include calculating the traffic amount at the current time by applying a first weight value and a second weight value to downlink physical resource block (PRB) usage and uplink PRB usage, respectively, and the first weight value and the second weight value may be determined according to a ratio of PRBs allocated to downlink and uplink in the entire PRB.

The updating may include applying a first weight value to the traffic amount of the current time and applying a second weight value to the predicted traffic amount of the future time, and the first weight value may be set to be greater than the second weight value.

The determining may include adjusting handover-related parameters so that the terminals at the edge of the base station move to another base station earlier if the updated traffic amount at the current time is greater than the threshold value.

According to another embodiment, a base station load balancing method for balancing load of a plurality of base stations in a base station load control apparatus is provided. The base station load balancing method includes: generating and managing policies necessary for the load balancing operation; modifying the policies using a load balancing result of an overloaded base station; and determining a weight value of a machine learning model used for predicting traffic of a future time in the plurality of base stations by performing federated learning with the plurality of base stations.

The determining may include: receiving a weight value and learning accuracy according to a learning result of the machine learning model from the plurality of base stations, respectively; calculating a global weight value based on the weight values and learning accuracy received from the plurality of base stations; and transmitting the global weight value to the plurality of base stations so that the plurality of base stations update the weight values of the machine learning model with the global weight value.

The calculating may include: selecting weight values of part of the weight values received from the plurality of base stations according to the standard deviation for the learning accuracy provided by the plurality of base stations; and calculating an average of the selected weight values of the part as the global weight value.

The selecting may include: randomly selecting the weight values of the part if a random value between 0 and 1 is less than a value corresponding to the standard deviation; and selecting the weight values of the part in order of high learning accuracy if the random value is equal to or greater than a value calculated based on the standard deviation.

According to yet another embodiment, a base station load balancing apparatus for load balancing by interworking with a service and operation management system in a base station is provided. The base station load balancing apparatus includes: a local traffic predictor that predicts a traffic amount in a future time using a prediction model; and a load balancing processor that updates a traffic amount of a current time by reflecting the predicted traffic amount of the future time in the traffic amount of the current time, and determines parameters necessary for load balancing of the base station by comparing the updated traffic amount of the current time with a predetermined threshold.

The local traffic predictor may include: a model updater for updating a machine learning model with a global weight value determined by the service and operation management system through federated learning between a plurality of base stations and the service and operation management system; and a model learner for learning the updated machine learning model, and the prediction mode may be finally generated through repetition of the learning the machine learning model and updating the machine learning model.

The model learner may transmit a weight value and learning accuracy according to a learning result of the machine learning model to the service and operation management system, and the global weight value may be determined by the service and operation management system based on the weight values and learning accuracy received from the plurality of base stations.

The global weight value may be an average value of part of the weight values received from the plurality of base stations, and the part of the weight values may be randomly selected according to a standard deviation for learning accuracy provided by the plurality of base stations, or are selected in the order of high learning accuracy.

The load balancing processor may include an overload determiner for calculating the updated traffic amount of the current time by applying a first weight value to the traffic amount of the current time and applying a second weight to the predicted traffic amount of the future time, and the first weight value may be set to be greater than the second weight value.

The load balancing processor may include a mobility load balancing (MLB) controller for adjusting handover-related parameters so that the terminals at the edge of the base station move to another base station earlier if the updated traffic amount at the current time is greater than the threshold value.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a diagram for explaining load balancing of base stations according to an embodiment of the present invention.

FIG. **2** is a diagram illustrating the MLB manager shown in FIG. **1**.

FIG. **3** is a diagram for explaining a method of optimizing a weight value of a machine learning model by interworking between the global traffic predictor and the local traffic predictor of each base station shown in FIG. **1**.

FIG. **4** is a diagram for explaining a method of determining a weight value in the global traffic predictor shown in FIG. **3**.

FIG. **5** is a diagram illustrating a detailed configuration of a base station load balancing apparatus in the base station shown in FIG. **1**.

FIG. **6** is a diagram for explaining a method of optimizing parameters in the load balancing processor shown in FIG. **5**.

FIG. **7** is a diagram illustrating a base station load balancing apparatus according to another embodiment.

DETAILED DESCRIPTION OF THE EMBODIMENTS

Hereinafter, embodiments of the disclosure will be described in detail with reference to the attached drawings so that a person of ordinary skill in the art may easily implement the disclosure. As those skilled in the art would realize, the described embodiments may be modified in various different ways, all without departing from the spirit or scope of the disclosure. The drawings and description are to be regarded as illustrative in nature and not restrictive. Like reference numerals designate like elements throughout the specification.

Throughout the specification and claims, when a part is referred to "include" a certain element, it means that it may further include other elements rather than exclude other elements, unless specifically indicated otherwise.

Furthermore, in this specification, each of the phrases such as "A or B", "at least one of A and B", "at least one of A or B", "A, B, or C", "at least one of A, B, and C", and "at least one of A, B, or C" may include any one of the items listed together in the corresponding one of the phrases, or all possible combinations thereof.

Now, a base station load balancing method and apparatus according to an embodiment will be described in detail with reference to the drawings.

FIG. **1** is a diagram for explaining load balancing of base stations according to an embodiment of the present invention.

Referring to FIG. **1**, the service and operation management system **10** includes a base station load balancing apparatus **100** that monitors a plurality of base stations **20_1** to **20_N** managed by an operator and predicts load states of the base station **20_1** to **20_N**.

The base station load balancing apparatus **100** includes a mobility load balancing (MLB) manager **110** and a global traffic predictor **120**.

The MLB manager **110** monitors the traffic state (overload state) for all the base stations **20_1** to **20_N** operated by the network operator, and generates and manages policies necessary for the MLB optimization operation. In addition, the MLB manager **110** evaluates the MLB execution result executed by the policies, and supplements the policies through the MLB evaluation.

The global traffic predictor **120** optimizes the traffic prediction in the local traffic predictor **210** of each base station **20_1** to **20_N** while exchanging and updating information necessary for machine learning by interworking with the local traffic predictor **210** of each base station **20_1** to **20_N**.

Each of the base stations **20_1** to **20_N** includes a base station load balancing apparatus **200** that performs traffic prediction and load balancing.

The base station load balancing apparatus **200** includes a local traffic predictor **210** and a load balancing processor **220**.

The local traffic predictor **210** calculates new traffic reflecting the traffic of the future time from the current time. The local traffic predictor **210** collects traffic at the current time, and predicts traffic at a future time using a machine learning model from the traffic at the current time.

The load balancing processor **220** calculates a new traffic amount reflecting the traffic of the future time at the current time using the traffic usage of the current time and the traffic information of the future time predicted by the local traffic predictor **210**, and determines the parameters necessary for load balancing of the base station based on the calculated new traffic amount.

The determined parameters are transferred to the relevant base station functions.

Related base station functions update base station configuration information by reflecting the parameters determined by the load balancing processor **220**, and transmit measurement configuration information to the terminal based on the updated base station configuration information. The terminal performs measurement based on the measurement configuration information.

FIG. **2** is a diagram illustrating the MLB manager shown in FIG. **1**.

Referring to FIG. **2**, the MLB manager **110** may include a policy generator and manager **112**, a data collector **114**, a traffic monitor **116**, and an MLB monitor **118**.

The policy generator and manager **112** generates and manages policies necessary for MLB optimization operation. The policy generator and manager **112** may generate load policies that set criteria for determining overload of the traffic monitor **116**. For example, the load policies may include a threshold for determining whether or not an overload is present. The policy generator and manager **112** may generate a data collection policy indicating a performance measurement (PM) data type and a data collection period.

The policy generator and manager **112** may supplement the policies using the MLB performance result evaluated by the MLB monitor **118**. The policy generator and manager **112** may delete, modify, and generate the policies based on evaluation result information obtained by evaluating the load balancing performance result of the overloaded base station.

The data collector **114** collects PM data collected from each base station based on the data collection policy transmitted from the policy generator and manager **112**. The PM data collected by each base station may be stored in an operation administration maintenance (OAM) DB. Furthermore, the data collector **114** transmits data for traffic monitoring and data for MLB policy performance evaluation among the collected PM data to the traffic monitor **116** and the MLB monitor **118**, respectively.

Table 1 shows data for traffic monitoring and MLB policy performance evaluation.

TABLE 1

	Mandatory	Optional (Enrichment)
Traffic monitoring	Downlink (DL)/Uplink (UP) PRB (Physical resource block) Usage DL/UL PRB used for data traffic DL/UL total available PRB	RRC connection number related Information Number of Active UEs related Information
MLB policy performance evaluation	Failed Handover related Information Measurement related Information to MRO (Too Early, Too Late, To Wrong)	Ping-Pong related Information UE throughput
Learning data	DL/UL PRB Usage Number of Active UEs	PM data generated by the base station

As defined in Table 1, in addition to mandatory data, optional data may be transmitted to the traffic monitor **116** and the MLB monitor **118** for more effective monitoring and evaluation. In addition, the data shown in Table 1 is an example, and other information not mentioned in Table 1 may be used for traffic monitoring and MLB policy performance evaluation.

The traffic monitor **116** recognizes an overload state for all base stations **20**$_1$ to **20**$_N$ operated by a network operator based on the load policies provided by the policy generator and manager **112** and performs a function of alarming the overload state.

A determination criterion that satisfies the alarm condition in the traffic monitor **116** may be defined as Equation 1. The traffic monitor **116** calculates the amount of traffic at the current time of the corresponding base station based on the downlink PRB usage and the uplink PRB usage of the base station corresponding to the cell identifier Cellio as shown in Equation 1, determines that the corresponding base station is in an overload state if the amount of traffic at the current time is greater than the threshold for the load policy, and may transmit an alarm to the base station in the overload state. That is, the traffic monitor **116** calculates the traffic of the base station based on Equation 1 and informs an overload state to the base station in the overload state.

$$(\alpha \cdot PRBU[cell\_ID]_{DL}{}^{T}+\beta \cdot PRBU[cell_{ID}]_{UL}{}^{T})>Threshold\ \alpha+\beta=1 \quad \text{(Equation 1)}$$

Here, $PRBU[cell\_ID]_{DL}{}^{T}$ denotes downlink PRB usage, and $PRBU[cell\_ID]_{DL}{}^{T}$ denotes uplink PRB usage. α and β are variables that determine the weights of the downlink PRB usage and the uplink PRB usage, and may be determined according to the PRB ratio allocated to the downlink and the uplink in the entire PRB. Threshold indicates a threshold value for the load policy generated by the policy generator and manager **112**, and the unit is %.

The MLB monitor **118** evaluates the result performed by the overloaded base station for load balancing using the MLB algorithm and transmits the evaluation result to the policy generator and manager **112**, and the policy generator and manager **112** may modify the policies in case of a wrong result.

For MLB policy performance evaluation, the MLB monitor **118** periodically collects data for MLB policy performance evaluation shown in Table 1 and performs MLB policy performance evaluation. The performance evaluation method compares the statistics before and after MLB operation, including the number of handover attempts that have failed, mobility robust optimization (MRO) related statistical information, the number of ping-pongs, and other additional information. Next, if the comparison result is out of a certain ratio defined by the operator, the MLB monitor **118** may instruct to the policy generator and manager **112** to modify the policies related to MLB operation.

FIG. **3** is a diagram for explaining a method of optimizing a weight value of a machine learning model by interworking between the global traffic predictor and the local traffic predictor of each base station shown in FIG. **1**.

Referring to FIG. **3**, by extending a federated learning technique of machine learning, the global traffic predictor **120** and the local traffic predictor **210** of each base station **20**$_1$ to **20**$_N$ share weight values of the machine learning model with each other, and update weight values of the machine learning model by interacting with each other.

The global traffic predictor **120** designs an initial machine learning model. Then, the unlearned initial machine learning model is transferred to the local traffic predictor **210** of each base station **20**$_1$ to **20**$_N$.

The local traffic predictor **210** of each base station **20**$_1$ to **20**$_N$ performs learning on the machine learning model based on the PM data collected by each base station $\mathbf{20}_1$ to $\mathbf{20}_N$. After learning the machine learning model for one predetermined learning cycle, the local traffic predictor **210** of each base station $\mathbf{20}_1$ to $\mathbf{20}_N$ transmits weights W_1 to W_N and learning accuracy (acc) according to the learning result to the global traffic predictor **120**. Here, the unit of learning accuracy varies depending on the machine learning model, and in the case of a classification model, it may be a percentage. In the case of a regression model, learning accuracy means an error value due to a loss function such as mean squared error (MSE), mean of absolute scaled errors (MASE), and root mean squared error (RMSE).

The global traffic predictor **120** performs sample determination using the weights W_1 to W_N and the learning accuracy acc received from the local traffic predictor **210** of each base station $\mathbf{20}_1$ to $\mathbf{20}_N$. The global traffic predictor **120** determines a weight value Δw of the machine learning model using a specific number of weights selected through sample determination, and transmits the weight value Δw to the local traffic predictor **210** of each base station $\mathbf{20}_1$ to $\mathbf{20}_N$. The local traffic predictor **210** of each base station $\mathbf{20}_1$ to $\mathbf{20}_N$ updates the weight value W_1 to W_N of the machine learning model as the weight value Δw, respectively.

A method of determining the weight value Δw of the machine learning model in the global traffic predictor **120** will be described with reference to FIG. **4**.

FIG. **4** is a diagram for explaining a method of determining a weight value in the global traffic predictor shown in FIG. **3**.

Referring to FIG. **4**, the global traffic predictor **120** selects a specific number of weights from among the weights W_1 to W_N received from the local traffic predictor **210** of each base station $\mathbf{20}_1$ to $\mathbf{20}_N$, and may determine an average of the selected weights as the weight value Δw of the machine learning model to be updated.

The global traffic predictor **120** first sorts the weights W_1 to W_N received from the local traffic predictor **210** of each base station $\mathbf{20}_1$ to $\mathbf{20}_N$ in order of accuracy. In the regression model, a smaller learning accuracy value means higher accuracy. It is difficult to reflect the characteristics of the base stations $\mathbf{20}_1$ to $\mathbf{20}_N$ and the convergence of learning may be delayed if the average is calculated average with all weights W_1 to W_N of the base stations $\mathbf{20}_1$ to $\mathbf{20}_N$. Accordingly, the global traffic predictor **120** samples S weights from among the N weights W_1 to W_N and calculates an average of the S weights. Here, since the effect on learning is different depending on the sampling method, an effective sampling method of the global traffic predictor **120** is proposed.

The global traffic predictor **120** may randomly sample and select S weights by sampling, but if only the weights that do not learn well are selected, the learning effect may be reduced. Therefore, the global traffic predictor **120** uses a method of randomly selecting S weights at the beginning of learning, exploring the weights of all base stations, and selecting only the weights of base stations with high accuracy whenever the number of times of learning increases. The global traffic predictor **120** randomly selects S weights from among N weights W_1 to W_N if the random value between 0 and 1 is less than the value E of Equation 2, and selects S weights from among the N weights W_1 to W_N in the order of learning accuracy if the random value between 0 and 1 is equal to or greater than the value E of Equation 2, using a characteristic that the standard deviation of the weights W_1 to W_N provided by each base station $\mathbf{20}_1$ to $\mathbf{20}_N$ becomes smaller as the number of times of learning increases.

$$E=\min(1,\delta\times\mathrm{Std}),0\leq\delta<1 \qquad \text{(Equation 2)}$$

Here, δ can be defined by the operator and has a value between 0 and 1, and Std represents the standard deviation of the learning accuracy acc provided by each base station $\mathbf{20}_1$ to $\mathbf{20}_N$.

After selecting the S weights, the global traffic predictor **120** calculates an average weight of the S weights as shown in Equation 3.

$$\text{Average Weight}=\frac{1}{S}\sum\nolimits_{i=1}^{S}(w_i) \qquad \text{(Equation 3)}$$

The global traffic predictor **120** determines the calculated average weight as a weight value of the machine learning model to be updated, and transmits the average weight to the local traffic predictor **210** of each base station $\mathbf{20}_1$ to $\mathbf{20}_N$.

The local traffic predictor **210** of each base station $\mathbf{20}_1$ to $\mathbf{20}_N$ updates the weight value of the machine learning model to the received average weight, and performs learning on the machine learning model based on the collected PM data.

FIG. **5** is a diagram illustrating a detailed configuration of a base station load balancing apparatus in the base station shown in FIG. **1**.

Referring to FIG. **5**, the local traffic predictor **210** includes a model updater **212**, a model learner **214**, and a traffic predictor **216**.

The model updater **212** updates the machine learning model. The model updater **212** may receive the global weight from the global traffic predictor **120** and update the weight value of the machine learning model to the global weight. The global weight means an average weight calculated by the global traffic predictor **120**.

The model learner **214** learns the updated machine learning model. The model learner **214** may learn the machine learning model by using the learning data stored in the DB. When the learning of the machine learning model is completed, the model learner **214** stores the weight w and the learning accuracy acc of the machine learning model, and transmits the weight w and the learning accuracy acc to the global traffic predictor **120**.

The machine learning model update of the model updater **212** and the machine learning model of the model learner **214** are repeated until the learning is finally completed, and the finally learned machine learning model is used as a prediction model to predict traffic in the traffic predictor **216**.

The traffic predictor **216** predicts the amount of traffic in the future time after a predetermined time from data input in real time by using the prediction model, and transmits the predicted amount of traffic of the future time to the load balancing processor **220**.

The load balancing processor **220** includes an overload determiner **222** and an MLB controller **224**.

The overload determiner **222** receives policies required for MLB optimization operation from the MLB manager **110** of the service and operation management system **100**. The overload determiner **222** receives the predicted traffic amount from the local traffic predictor **210**, and generates a new traffic amount New PRBU reflecting the traffic amount $\mathrm{PRBU}_{Predicted}$ of the future time from the current time, using the predicted traffic amount $\mathrm{PRBU}_{Predicted}$ and the traffic usage $\mathrm{PRBU}_{Current}$ of the current time as in Equation 4.

$$\text{New } PRBU=\frac{w_1\times PRBU_{Current},+w_{12}\times PRBU_{Predicted}}{w_1+w_2} \qquad \text{(Equation 4)}$$

$$w_1>w_2$$

Here, W_1 and W_2 are weight values r applied to the traffic amount of the current time and the traffic amount of the future time, respectively, and W_1 has a greater value than W_2. $PRBU_{Current}$ indicates the downlink and uplink PRB usage at the current time as shown in Equation 1. $PRBU_{Predicted}$ indicates the amount of traffic in the future time predicted by the traffic predictor **216**.

The overload determiner **222** determines the overload by using the threshold determined by the policy and the new traffic amount New PRBU.

MLB hands over the terminals at the edge to distribute the load of the overloaded base station. In all communication technologies (4G, LTE, and 5G), handover is determined by the base station based on the measurement report of the terminal.

3GPP proposes a set of measurement reporting mechanisms to be performed by the terminal in order to minimize unnecessary handover, and this is called an event. The event type to be reported by the terminal is indicated by the RRC signaling message transmitted from the base station. 3GPP TS 38.331 defines eight event types in 5G NR. As shown in Table 2, all events have an offset called hysteresis.

TABLE 2

Event	Parameter	Range		Value	
A1, A2, A4, A5, B1	RSRP Threshold	0	127	−156 dBm	−31 dBm
	RSRQ Threshold	0	127	−40 dB	20 dB
	SINR Threshold	0	127	−23 dB	40 dB
All	Hysteresis	0	30	0 dB	15 dB
A3, A6	Offset	−30	30	−15 dB	+15 dB
A3, A4, A5, A6, B1, B2	Cell Specific Offset (CIO)			−24 dB	+24 dB
B1, B2	LTE RSRP	0	97	−140 dBm	−44 dBm
	LTE RSRQ	0	34	−19.5 dB	−3 dBm
	LTE SINR	23	40	−23 dB	40 dB

When the overload is determined by the overload determiner **222**, the MLB controller **224** optimizes handover-related measurement configuration parameters so that terminals connected to its own base station can be moved to another base station.

The MLB controller **224** adjusts the terminal to handover earlier or the terminal to stay in its base station for a longer period according to the load state of the base station by optimizing the hysteresis values.

The MLB controller **224** transmits the optimized measurement configuration parameters to the related base station function. The MLB controller **224** may delete or cancel the measurement configuration parameters according to the policies received from the MLB manager of the service and operation management system **100**.

FIG. **6** is a diagram for explaining a method of optimizing parameters in the load balancing processor shown in FIG. **5**.

Referring to FIG. **6**, the overload determiner **222** calculates the amount of traffic at the current time by collecting the traffic (uplink and downlink PRB usage) of the base station at the current time. The amount of traffic at the current time may be calculated based on the downlink PRB usage and the uplink PRB usage of the base station as shown in Equation 1.

The overload determiner **222** receives a threshold value and a hysteresis adjustment range for the A**3** event among the policies generated by the MLB manager of the service and operation management system **100** (S**610**). The initial hysteresis value and the threshold value are determined by the policies, and the values are transmitted to the base station as an initial set value when operating the base station. In the embodiment, it is shown that the middle value (7 dB) of the hysteresis range is used as the initial hysteresis value for effective operation, as shown in Table 2.

The overload determiner **222** receives the predicted traffic amount of the future time from the local traffic predictor.

The overload determiner **222** calculates a new traffic amount New PRBU reflecting the traffic amount of the future time at the current time by using the predicted traffic amount of the future time and the calculated traffic amount of the current time (S**620**).

The overload determiner **222** determines the overload by comparing the new traffic amount New PRBU of the current time with the threshold (S**630**).

When the new traffic amount New PRBU is greater than the threshold value, the MLB controller **224** reduces a hysteresis value by a predetermined dB (S**640**), so that the terminals can move to another base station earlier.

On the other hand, when the new traffic amount New PRBU is less than or equal to the threshold value, the MLB controller **224** increases the hysteresis value by a predetermined dB (S**650**), so that the terminals can access the currently connected base station for a longer period of time.

By applying the method for optimizing the parameters described in the embodiment, offsets of eight events can be optimized.

FIG. **7** is a diagram illustrating a base station load balancing apparatus according to another embodiment.

Referring to FIG. **7**, the base station load balancing apparatus **700** may represent a computing device in which the method for load balancing of a base station is implemented.

The base station load balancing apparatus **700** may be implemented in the base station. Alternatively, the base station load balancing apparatus **700** may be implemented in a service and operation management system **100**.

The base station load balancing apparatus **700** may include at least one of a processor **710**, a memory **720**, an input interface device **730**, an output interface device **740**, and a storage device **750**. Each of the components may be connected by a common bus **760** to communicate with each other. In addition, each of the components may be connected through an individual interface or a separate bus centering on the processor **710** instead of the common bus **760**.

The processor **710** may be implemented as various types such as an application processor (AP), a central processing unit (CPU), a graphics processing unit (GPU), etc., and may be any semiconductor device that executes a command stored in the memory **720** or the storage device **750**. The processor **710** may execute program commands stored in at least one of the memory **720** and the storage device **750**.

In the case of the base station load balancing apparatus **700** implemented in the base station, the processor **710** stores program commands for implementing at least some functions of the local traffic predictor **210** and the load balancing processor **220** in the memory **720**, and may control to perform the operation described with reference to FIGS. **1** to **6**.

In addition, in the case of the base station load balancing apparatus **700** implemented in the service and operation management system **100**, the processor **710** stores program commands for implementing at least some functions of the MLB manager **110** and the global traffic predictor **120** in the memory **720**, and may control to perform the operation described with reference to FIGS. **1** to **6**.

The memory **720** and the storage device **750** may include various types of volatile or non-volatile storage media. For example, the memory **720** may include a read-only memory (ROM) **721** and a random access memory (RAM) **722**. The memory **720** may be located inside or outside the processor **710**, and the memory **720** may be connected to the processor **710** through various known means.

The input interface device **730** is configured to provide data to the processor **710**.

The output interface device **740** is configured to output data from the processor **710**.

At least some of the method for load balancing of a base station according to an embodiment may be implemented as a program or software executed in a computing device, and the program or software may be stored in a computer-readable medium.

In addition, at least some of the method for load balancing of a base station according to an embodiment may be implemented as hardware that can be electrically connected to the computing device.

According to an embodiment, when constructing a high-density base station, overload of base stations can be automatically solved without operator intervention, and more accurate load balancing can be performed at the present time by predicting traffic of the near future time.

In addition, by updating the machine learning model using advanced federated learning technology to obtain fast and effective learning results, more accurate traffic prediction becomes possible.

The components described in the example embodiments may be implemented by hardware components including, for example, at least one digital signal processor (DSP), a processor, a controller, an application-specific integrated circuit (ASIC), a programmable logic element such as an FPGA, other electronic devices, or combinations thereof. At least some of the functions or the processes described in the example embodiments may be implemented by software, and the software may be recorded on a recording medium. The components, functions, and processes described in the example embodiments may be implemented by a combination of hardware and software. The method according to embodiments may be embodied as a program that is executable by a computer, and may be implemented as various recording media such as a magnetic storage medium, an optical reading medium, and a digital storage medium. Various techniques described herein may be implemented as digital electronic circuitry, or as computer hardware, firmware, software, or combinations thereof. The techniques may be implemented as a computer program product, i.e., a computer program tangibly embodied in an information carrier, e.g., in a machine-readable storage device (for example, a computer-readable medium) or in a propagated signal for processing, or to control an operation of a data processing apparatus, e.g., by a programmable processor, a computer, or multiple computers. A computer program(s) may be written in any form of programming language, including compiled or interpreted languages, and may be deployed in any form including a stand-alone program or a module, a component, a subroutine, or other units suitable for use in a computing environment. A computer program may be deployed to be executed on one computer or on multiple computers at one site or distributed across multiple sites and interconnected by a communication network. Processors suitable for execution of a computer program include, by way of example, both general and special purpose microprocessors, and any one or more processors of any kind of digital computer. Generally, a processor will receive instructions and data from a read-only memory or a random access memory or both. Elements of a computer may include at least one processor to execute instructions and one or more memory devices to store instructions and data. Generally, a computer will also include or be coupled to receive data from, transfer data to, or perform both on one or more mass storage devices to store data, e.g., magnetic or magneto-optical disks, or optical disks. Examples of information carriers suitable for embodying computer program instructions and data include semiconductor memory devices, for example, magnetic media such as a hard disk, a floppy disk, and a magnetic tape, optical media such as a compact disk read-only memory (CD-ROM), a digital video disk (DVD), etc., and magneto-optical media such as a floptical disk and a read-only memory (ROM), a random access memory (RAM), a flash memory, an erasable programmable ROM (EPROM), and an electrically erasable programmable ROM (EEPROM), and any other known computer readable media. A processor and a memory may be supplemented by, or integrated into, a special purpose logic circuit. The processor may run an operating system (OS) and one or more software applications that run on the OS. The processor device may also access, store, manipulate, process, and create data in response to execution of the software. For the purpose of simplicity, the description of a processor device is used as singular; however, one skilled in the art will appreciate that a processor device may include multiple processing elements and/or multiple types of processing elements. For example, a processor device may include multiple processors or a processor and a controller. In addition, different processing configurations are possible, such as parallel processors. Also, non-transitory computer-readable media may be any available media that may be accessed by a computer, and may include both computer storage media and transmission media. The present specification includes details of a number of specific implementations, but it should be understood that the details do not limit any disclosure or what is claimable in the specification but rather describe features of the specific example embodiment. Features described in the specification in the context of individual example embodiments may be implemented as a combination in a single example embodiment. In contrast, various features described in the specification in the context of a single example embodiment may be implemented in multiple example embodiments individually or in an appropriate sub-combination. Furthermore, the features may operate in a specific combination and may be initially described as claimed in the combination, but one or more features may be excluded from the claimed combination in some cases, and the claimed combination may be changed into a sub-combination or a modification of a sub-combination. Similarly, even though operations are described in a specific order in the drawings, it should not be understood as the operations needing to be performed in the specific order or in sequence to obtain desired results or as all the operations needing to be performed. In a specific case, multitasking and parallel processing may be advantageous. In addition, it should not be understood as requiring separation of various apparatus components in the above-described example embodiments in all example embodiments, and it should be understood that the above-described program components and apparatuses may be incorporated into a single software product or may be packaged in multiple software products. It should be understood that the embodiments disclosed herein are merely illustrative and are not intended to limit the scope of the disclosure. It will be apparent to one of ordinary skill in the art that various modifications of the embodiments may be made without departing from the spirit and scope of the claims and their equivalents.

What is claimed is:

1. A base station load balancing method in a base station, the method comprising:

updating a traffic amount of a current time by reflecting a predicted traffic amount of a future time in the traffic amount of the current time; and

determining parameters necessary for load balancing of the base station by comparing the updated traffic amount of the current time with a predetermined threshold,

wherein the updating includes predicting a traffic amount of the future time from the traffic amount of the current time using a prediction model, and

wherein a weight value of the prediction model is determined through federated learning between a service and operation management system and a plurality of base stations.

2. The method of claim **1**, further comprising:

learning a machine learning model using learning data;

updating the machine learning model; and

repeating the learning of a machine learning model and updating of the machine learning model to use the machine learning model as the predictive model.

3. The method of claim **2**, wherein the updating of the machine learning model includes:

transmitting a weight value and learning accuracy according to the learning result of the machine learning model to the service and operation management system;

receiving a global weight value determined by the service and operation management system based on the weight values and learning accuracy received from the plurality of base stations; and

updating a weight value of the machine learning model with the global weight value.

4. The method of claim **3**, wherein the global weight value is an average value of part of the weight values received from the plurality of base stations, and

the part of the weight values is randomly selected according to a standard deviation for learning accuracy provided by the plurality of base stations, or are selected in the order of high learning accuracy.

5. The method of claim **1**, wherein the updating includes calculating the traffic amount at the current time by applying a first weight value and a second weight value to downlink physical resource block (PRB) usage and uplink PRB usage, respectively, and

the first weight value and the second weight value are determined according to a ratio of PRBs allocated to downlink and uplink in the entire PRB.

6. The method of claim **1**, wherein the updating includes applying a first weight value to the traffic amount of the current time and applying a second weight value to the predicted traffic amount of the future time, and

the first weight value is set to be greater than the second weight value.

7. The method of claim **1**, wherein the determining includes adjusting handover-related parameters so that the terminals at the edge of the base station move to another base station earlier if the updated traffic amount at the current time is greater than the threshold value.

8. A base station load balancing method for balancing a load of a plurality of base stations in a base station load control apparatus, the method comprising:

generating and managing policies necessary for a load balancing operation;

modifying the policies using a load balancing result of an overloaded base station; and

determining a weight value of a machine learning model used for predicting traffic of a future time in the plurality of base stations by performing federated learning with the plurality of base stations.

9. The method of claim **8**, wherein the determining includes:

receiving a weight value and learning accuracy according to a learning result of the machine learning model from the plurality of base stations, respectively;

calculating a global weight value based on the weight values and learning accuracy received from the plurality of base stations; and

transmitting the global weight value to the plurality of base stations so that the plurality of base stations update the weight values of the machine learning model with the global weight value.

10. The method of claim **9**, wherein the calculating includes:

selecting weight values of part of the weight values received from the plurality of base stations according to the standard deviation for the learning accuracy provided by the plurality of base stations; and

calculating an average of the selected weight values of the part as the global weight value.

11. The method of claim **10**, wherein the selecting includes:

randomly selecting the weight values of the part if a random value between 0 and 1 is less than a value corresponding to the standard deviation; and

selecting the weight values of the part in order of high learning accuracy if the random value is equal to or greater than a value calculated based on the standard deviation.

12. The method of claim **11**, wherein the value corresponding to the standard deviation is calculated based on Equation 1,

the Equation 1 is

$$E=\min(1,\delta\times\mathrm{Std}),0\leq\delta<1,\text{ and}$$

wherein the δ has a value between 0 and 1, and the Std represents the standard deviation.

13. A base station load balancing apparatus for load balancing by interworking with a service and operation management system in a base station, the apparatus comprising:

a local traffic predictor that predicts a traffic amount in a future time using a prediction model; and

a load balancing processor that updates a traffic amount of a current time by reflecting the predicted traffic amount of the future time in the traffic amount of the current time, and determines parameters necessary for load balancing of the base station by comparing the updated traffic amount of the current time with a predetermined threshold,

wherein the local traffic predictor includes:

a model updater for updating a machine learning model with a global weight value determined by the service and operation management system through federated learning between a plurality of base stations and the service and operation management system; and

a model learner for learning the updated machine learning model, and wherein the prediction model is finally generated through repetition of the learning the machine learning model and updating the machine learning model.

14. The apparatus of claim **13**, wherein the model learner transmits a weight value and learning accuracy according to a learning result of the machine learning model to the service and operation management system, and

the global weight value is determined by the service and operation management system based on the weight values and learning accuracy received from the plurality of base stations.

15. The apparatus of claim **14**, wherein the global weight value is an average value of part of the weight values received from the plurality of base stations, and

the part of the weight values is randomly selected according to a standard deviation for learning accuracy provided by the plurality of base stations, or are selected in the order of high learning accuracy.

16. The apparatus of claim **13**, wherein the load balancing processor includes an overload determiner for calculating the updated traffic amount of the current time by applying a first weight value to the traffic amount of the current time and applying a second weight to the predicted traffic amount of the future time, and

the first weight value is set to be greater than the second weight value.

17. The apparatus of claim **13**, wherein the load balancing processor includes a mobility load balancing (MLB) controller for adjusting handover-related parameters so that the terminals at the edge of the base station move to another base station earlier if the updated traffic amount at the current time is greater than the threshold value.

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