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(54) METHOD AND APPARATUS FOR MANAGING NETWORK TRAFFIC VIA UNCERTAINTY

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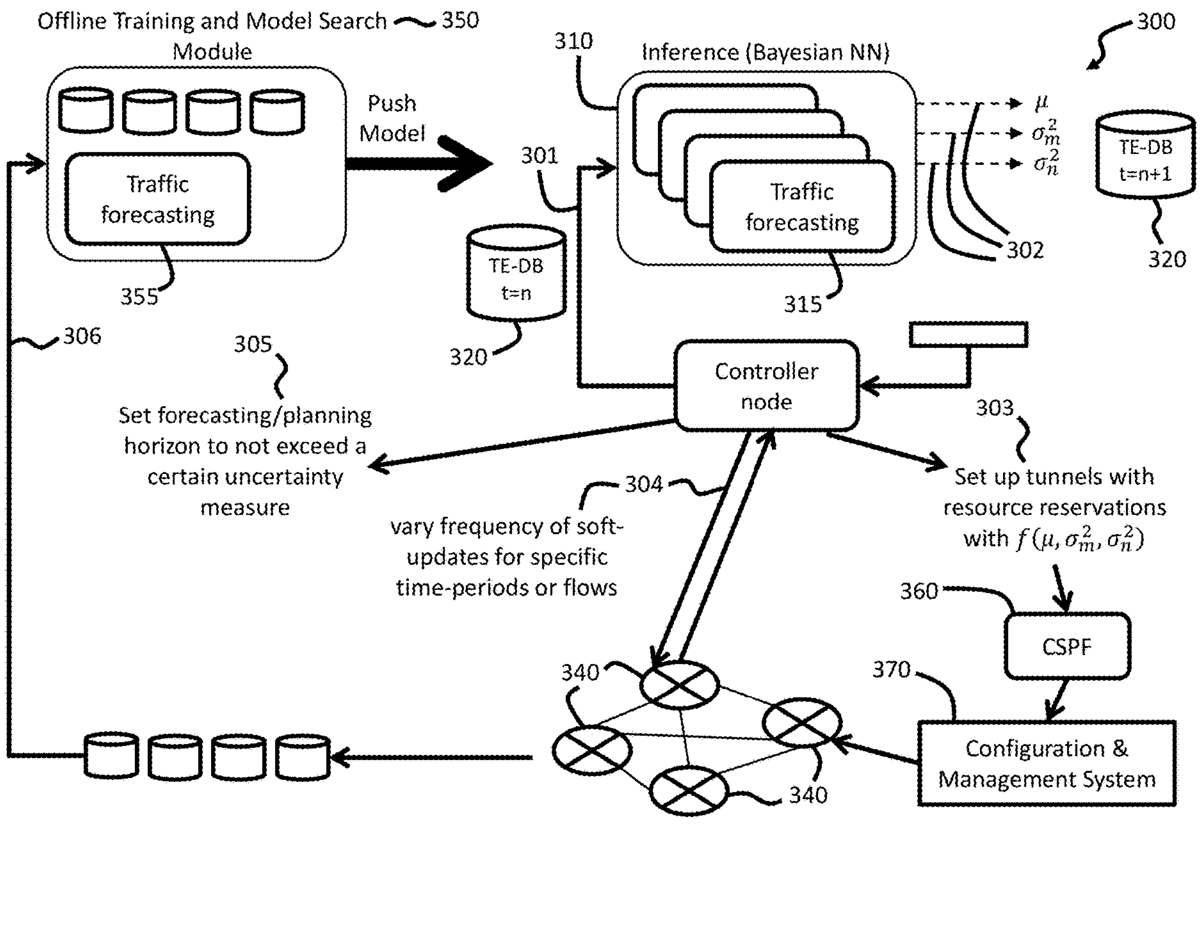
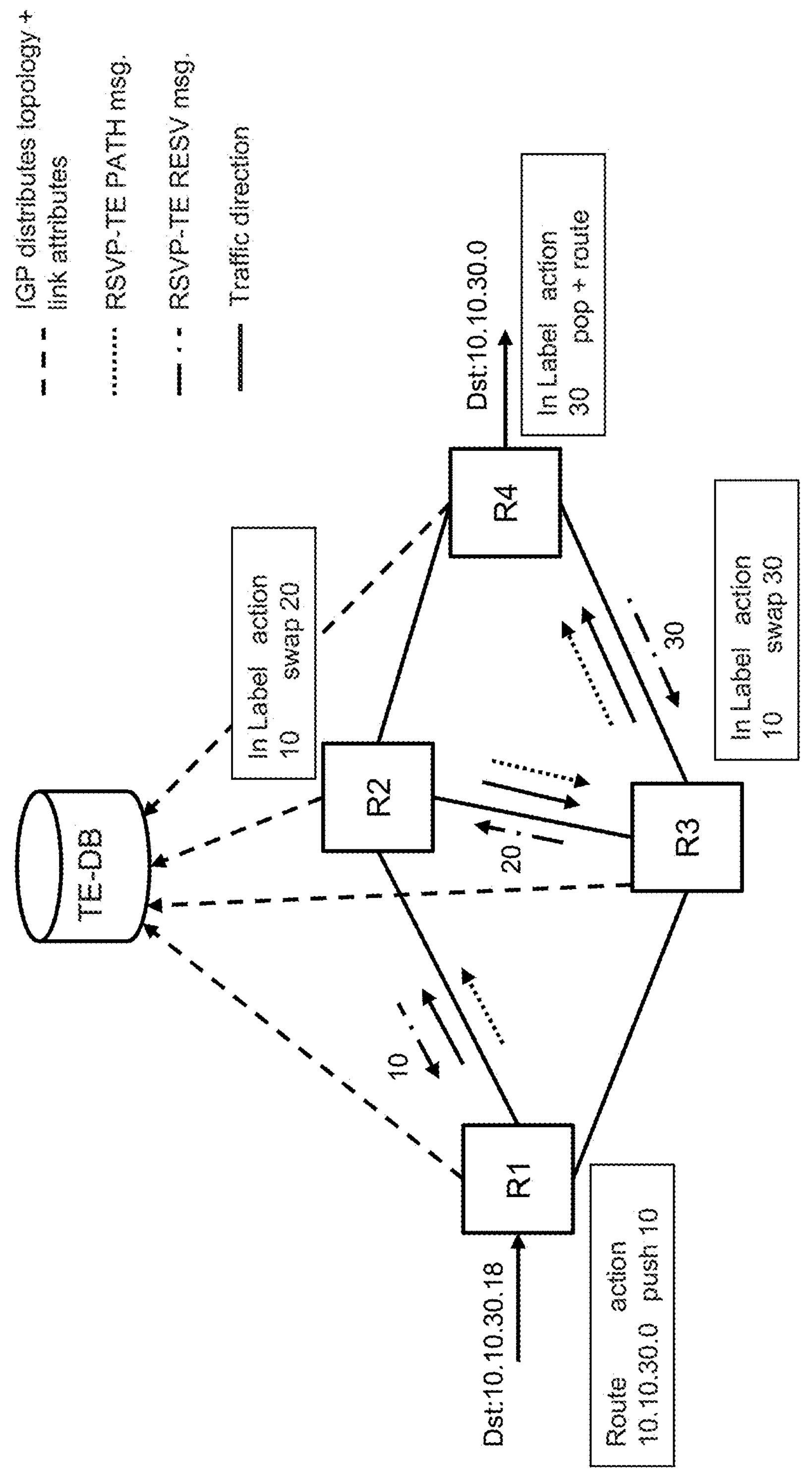
(52) **U.S. Cl.**

CPC ***H04L 47/823*** (2013.01); ***H04L 47/12*** (2013.01); ***H04L 41/145*** (2013.01); ***H04L 41/147*** (2013.01)

(57) **ABSTRACT**

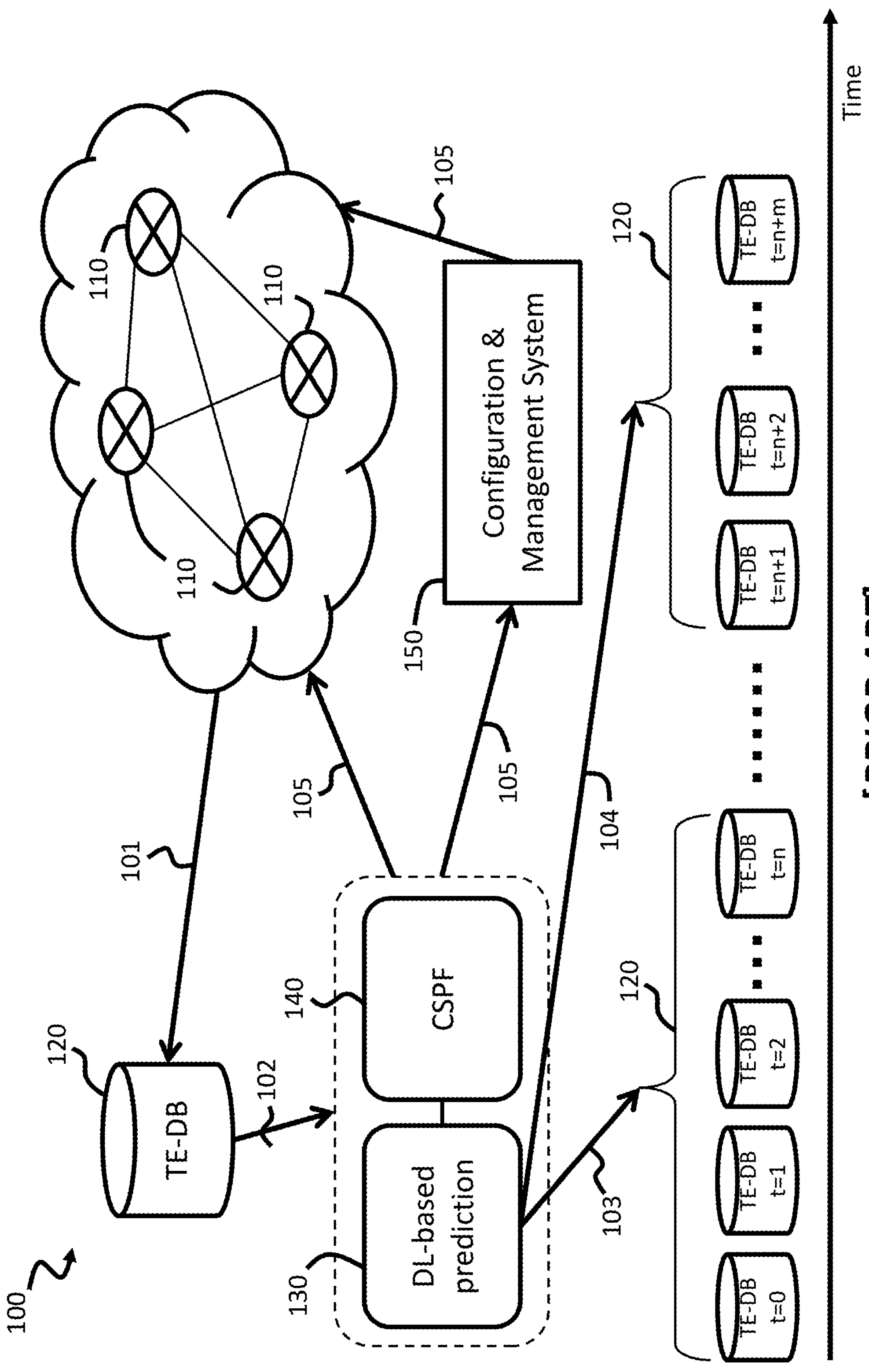
There is provided a method and system for communication network management. There is provided an active TE architecture and procedure that rely on the epistemic uncertainty obtained from traffic forecasting models. According to embodiments, the traffic forecasting models can predict the mean of the network traffic demand and can extract one or more of the features relating epistemic uncertainty and the aleatoric uncertainty. According to embodiments, the epistemic uncertainty is used to vary the sampling frequency of network statistics in TE applications, for specific times or specific flows. A time-window can be used to predict network traffic can be varied (e.g. increased or decreased) to adjust the epistemic uncertainty.


Offline Training and Model Search Module
350
300
310
Inference (Bayesian NN)
Push Model
301
Traffic forecasting
Traffic forecasting
μ
σ_m^2
σ_n^2
TE-DB t=n+1
302
320
355
TE-DB t=n
315
306
305
320
Controller node
303
Set forecasting/planning horizon to not exceed a certain uncertainty measure
304
vary frequency of soft-updates for specific time-periods or flows
Set up tunnels with resource reservations with $f(\mu, \sigma_m^2, \sigma_n^2)$
360
CSPF
340
370
Configuration & Management System
340



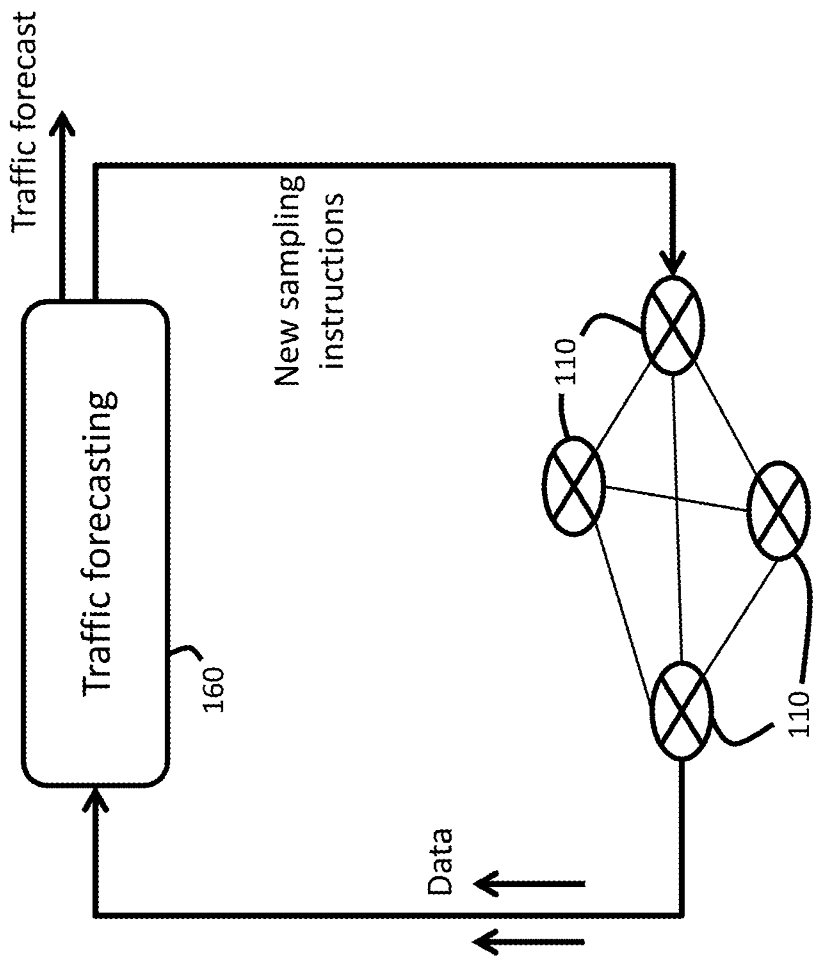
[*PRIOR ART*]

FIG. 1A



[*PRIOR ART*]

FIG. 1B



[*PRIOR ART*]

FIG. 1C

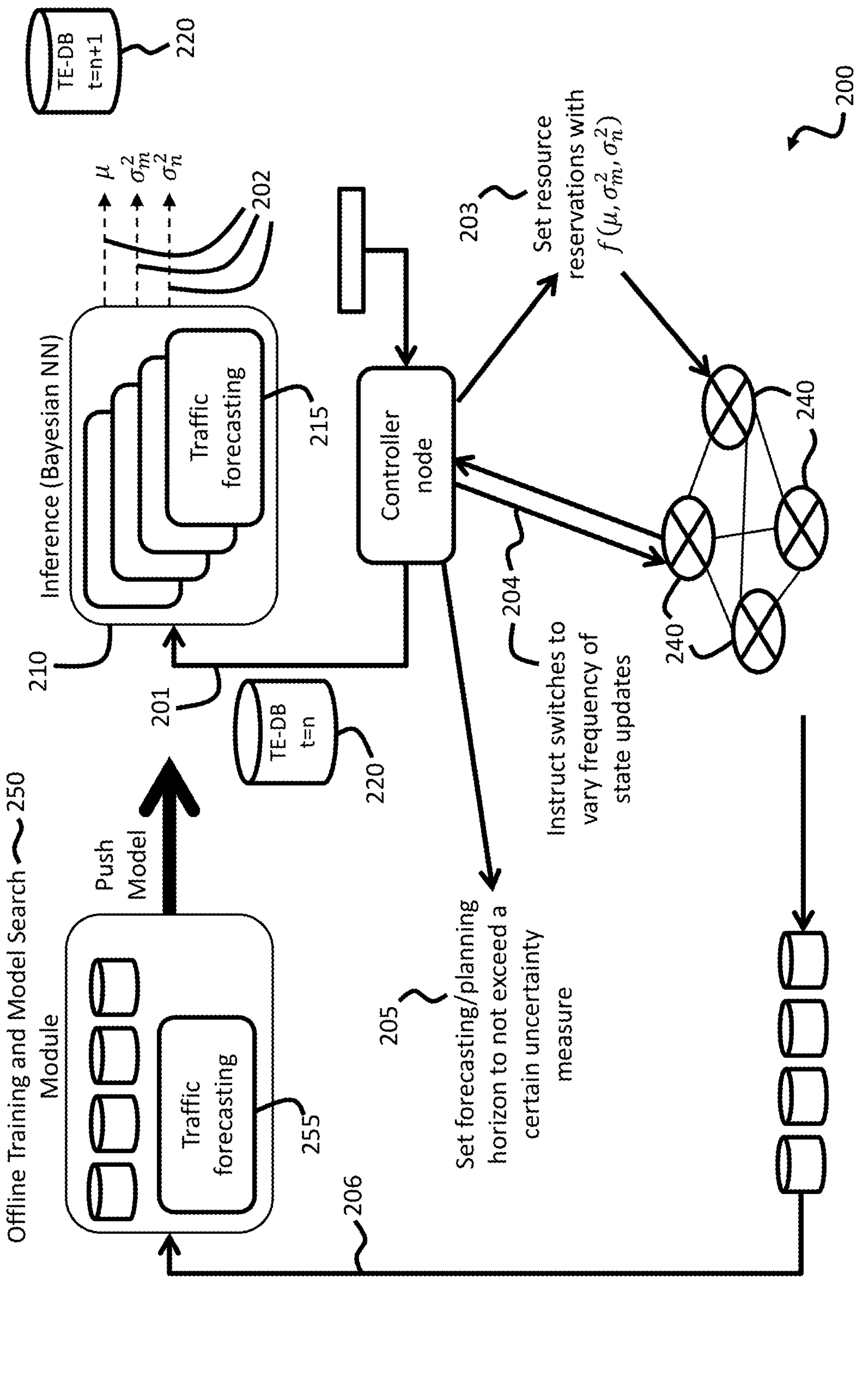

Offline Training and Model Search Module
250
Traffic forecasting
255
Push Model
206
TE-DB t=n
220
201
210
Inference (Bayesian NN)
Traffic forecasting
215
μ
σ_m^2
σ_n^2
202
TE-DB t=n+1
220
Controller node
203
Set resource reservations with $f(\mu, \sigma_m^2, \sigma_n^2)$
204
Instruct switches to vary frequency of state updates
205
Set forecasting/planning horizon to not exceed a certain uncertainty measure
240
240
240
200

FIG. 2

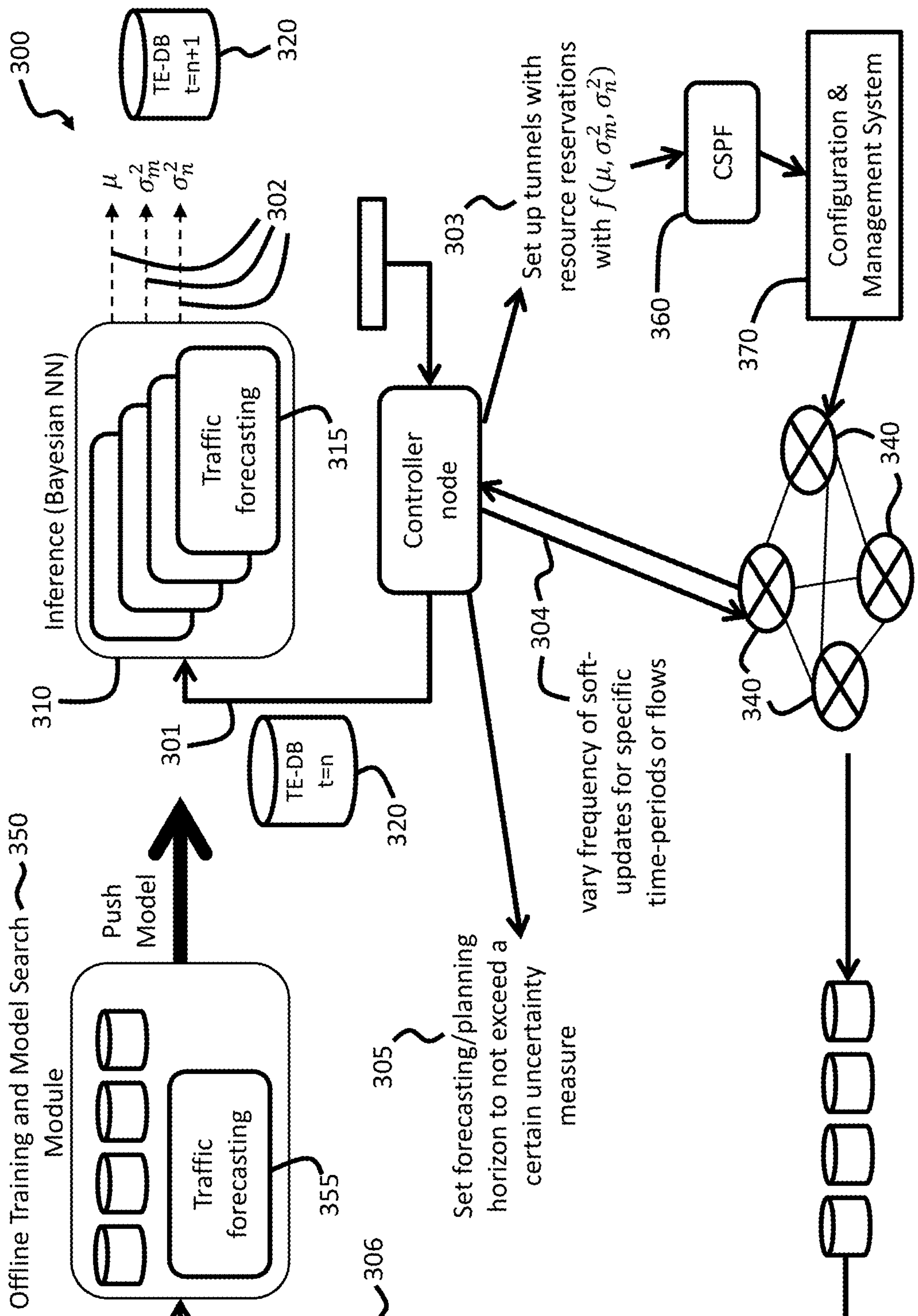

300
Offline Training and Model Search Module
350
Traffic forecasting
355
Push Model
306
Inference (Bayesian NN)
310
Traffic forecasting
315
301
TE-DB t=n
320
μ
σ_m^2
σ_n^2
302
TE-DB t=n+1
320
Controller node
303
Set up tunnels with resource reservations with $f(\mu, \sigma_m^2, \sigma_n^2)$
CSPF
360
Configuration & Management System
370
304
vary frequency of soft-updates for specific time-periods or flows
305
Set forecasting/planning horizon to not exceed a certain uncertainty measure
340
340
340

FIG. 3

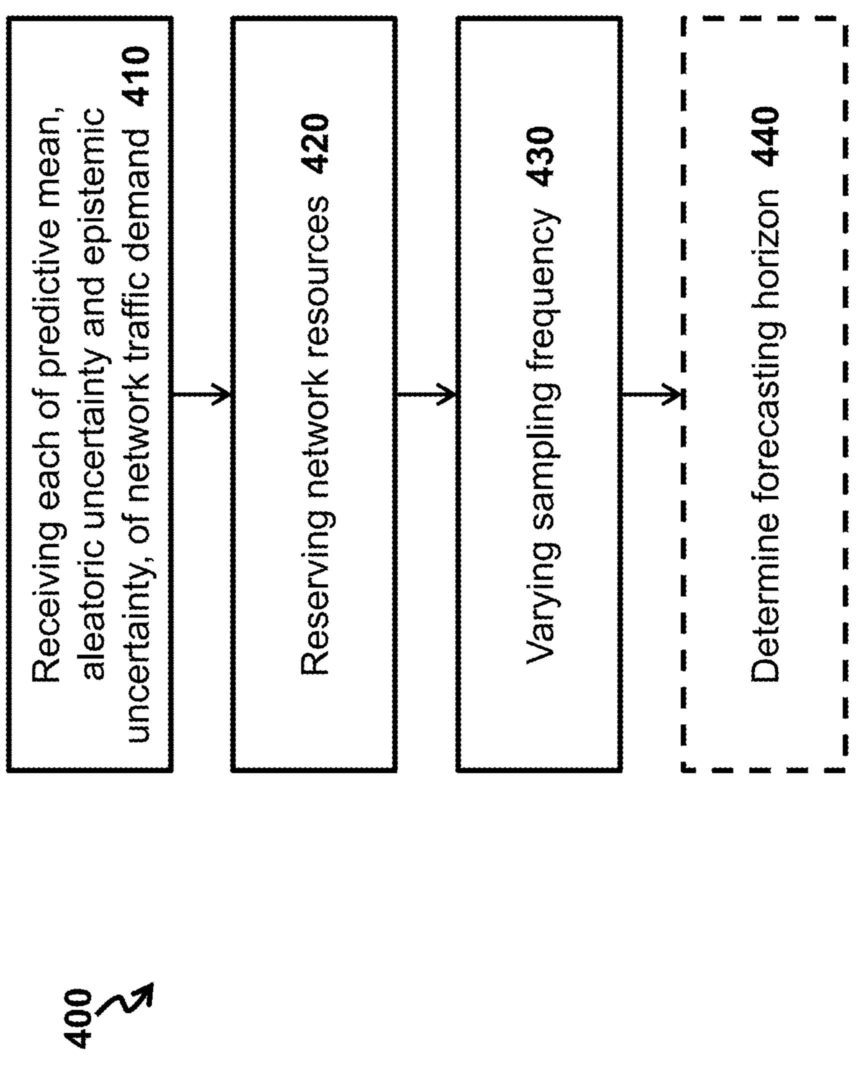

400
Receiving each of predictive mean, aleatoric uncertainty and epistemic uncertainty, of network traffic demand 410
Reserving network resources 420
Varying sampling frequency 430
Determine forecasting horizon 440

FIG. 4

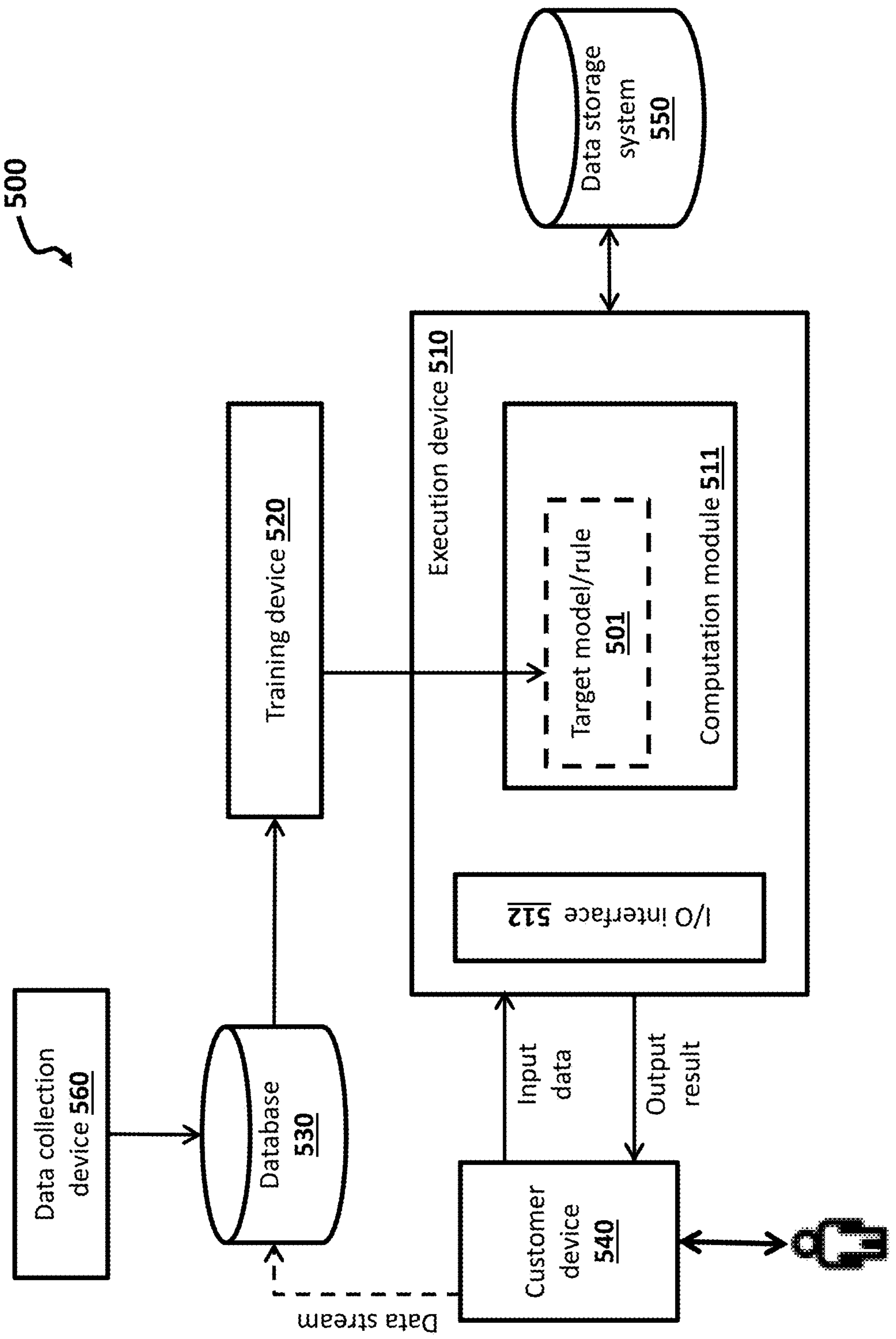

500
Data collection device 560
Database 530
Training device 520
Execution device 510
Target model/rule 501
Computation module 511
I/O interface 512
Data storage system 550
Input data
Output result
Customer device 540
Data stream

FIG. 5

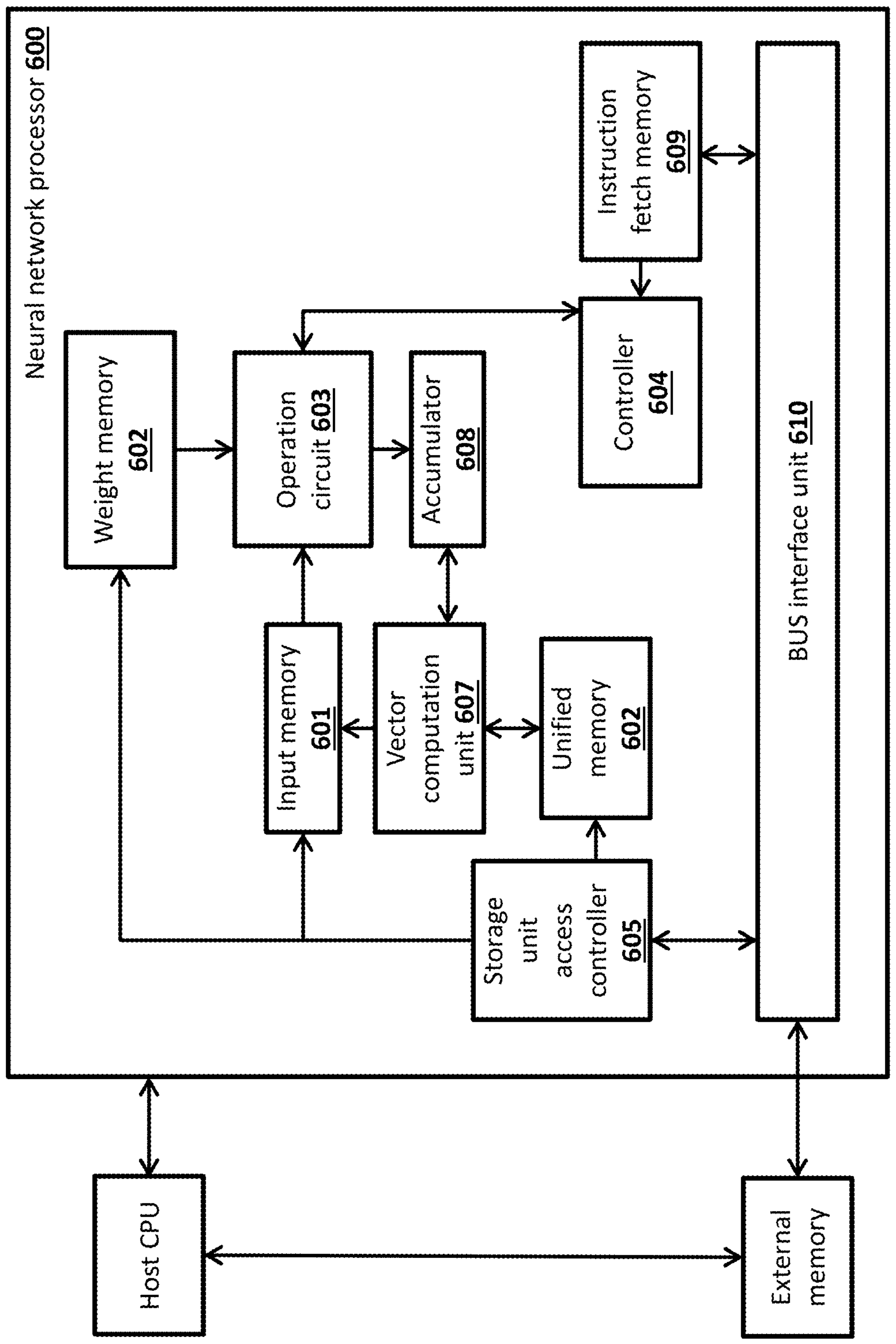

Neural network processor 600
Weight memory 602
Operation circuit 603
Accumulator 608
Controller 604
Instruction fetch memory 609
Input memory 601
Vector computation unit 607
Unified memory 602
Storage unit access controller 605
BUS interface unit 610
Host CPU
External memory

FIG. 6

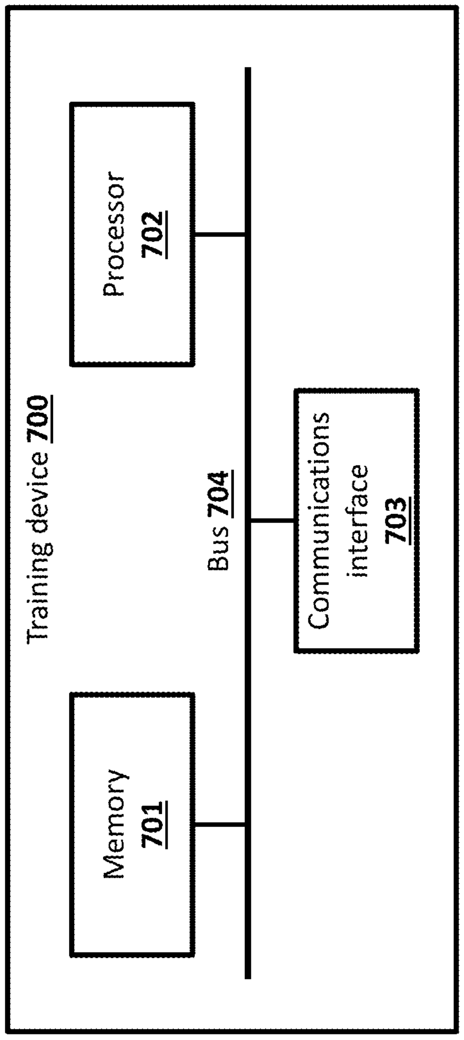

Training device 700
Processor 702
Memory 701
Bus 704
Communications interface 703

FIG. 7

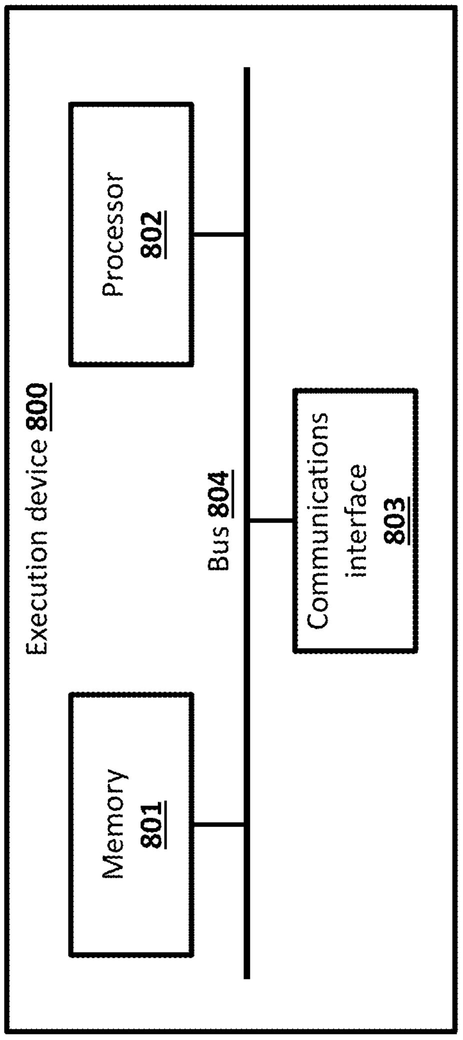

Execution device 800
Processor 802
Memory 801
Bus 804
Communications interface 803

FIG. 8

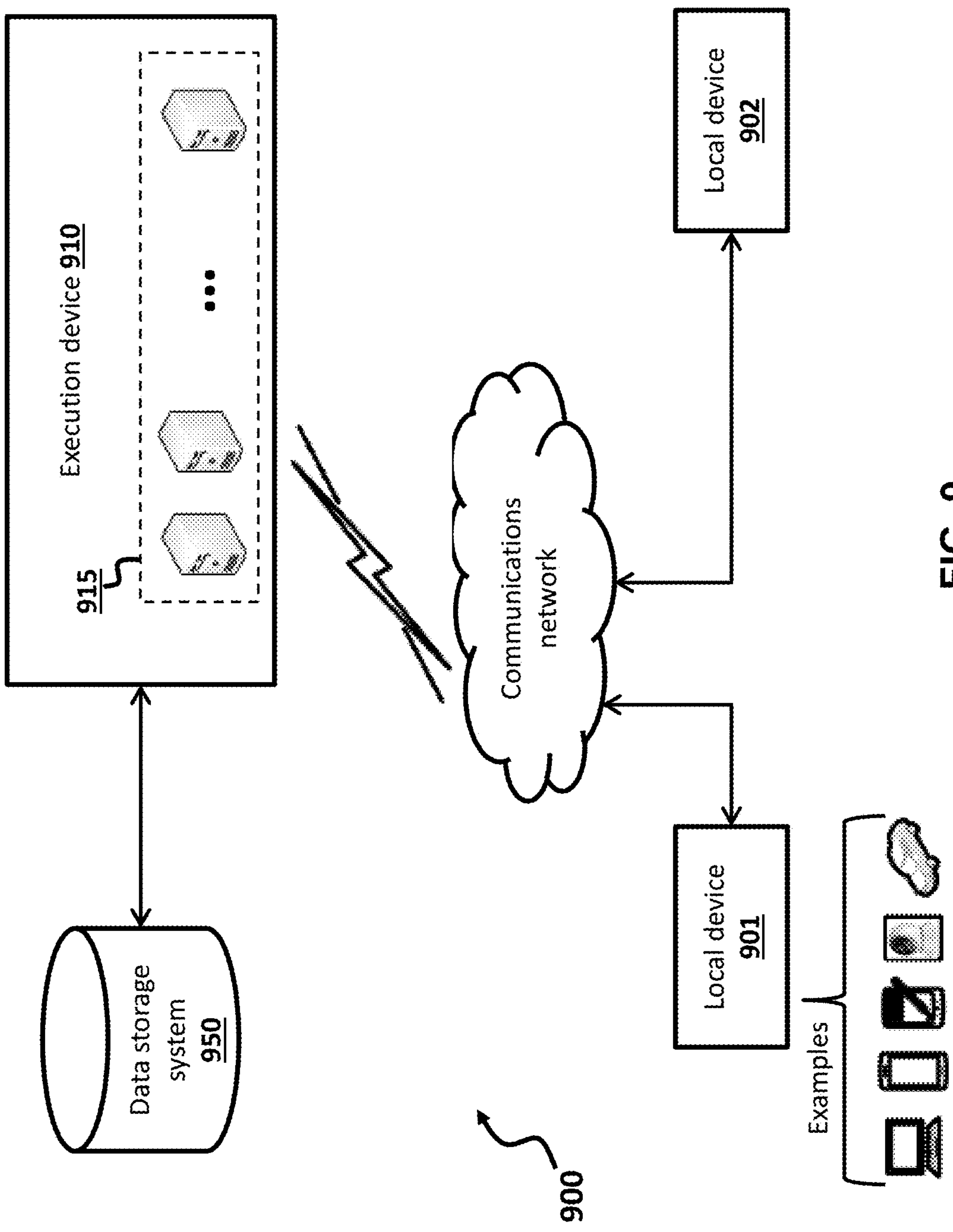

Execution device 910
915
Data storage system 950
Communications network
Local device 902
Local device 901
Examples
900

FIG. 9

METHOD AND APPARATUS FOR MANAGING NETWORK TRAFFIC VIA UNCERTAINTY

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This is the first application filed for the present invention.

FIELD

[0002] The present disclosure pertains to the field of network traffic engineering and in particular to a method and apparatus for managing network traffic in a communication network.

BACKGROUNDS

[0003] Traffic Engineering (TE) is a process of steering the network traffic across the network for more efficient use of network resources and to provide a level of protection against delay or failure of the network nodes and/or links. Network operators may manage and guide network traffic as part of network management. Management and guidance of network traffic is needed as network traffic varies with time and there are often unexpected or sudden network traffic volume peaks, for example bursty network traffic, with unpredictable patterns. For example, to address network traffic congestion, network operators use enablers such as TE tunnels or segment routing to steer network traffic away from the congested area in the network and forward this network traffic towards its respective final destination. An example of resource reservation protocol traffic engineering (RSVP-TE) is illustrated in FIG. **1**A.

[0004] In TE, a traffic forecasting module and a traffic routing/planning module are two important components. A traffic forecasting module predicts the (future) demand or network flow in the network based on network flow statistics collected from the network. The prediction may be provided either per switch, per link or per flow. Then, based on the prediction and other network information, the traffic routing/planning module decides how to steer and forward traffic in the network.

[0005] However, these continue to be several sources of uncertainty when TE is considered.

[0006] Therefore there is a need for a method and apparatus for managing network traffic in a network, that is not subject to one or more limitations of the prior art.

[0007] This background information is provided to reveal information believed by the applicant to be of possible relevance to the present invention. No admission is necessarily intended, nor should be construed, that any of the preceding information constitutes prior art against the present invention.

SUMMARY

[0008] An object of embodiments of the present disclosure is to provide a method and apparatus for managing network traffic in a network. In accordance with embodiments of the present disclosure, there is provided a method for managing network traffic in a communication network. The method includes receiving, by a controller node from a traffic forecasting model, a predictive mean of network traffic demand, an aleatoric uncertainty (σ_n^2) associated with the network traffic demand and an epistemic uncertainty (σ_m^2) associated with the network traffic demand. The method further includes reserving, by the controller node, network resources based on a function of the predictive mean (μ), the aleatoric uncertainty (σ_n^2) and the epistemic uncertainty (σ_m^2). The method additionally includes varying, by the controller node, a sampling frequency of network statistics for a specific time-period or a network flow based at least in part based on the epistemic uncertainty (σ_m^2).

[0009] In some embodiments, the method further includes determining, by the controller node, a forecasting and planning horizon based on one or more of the epistemic uncertainty (σ_m^2) and the aleatoric uncertainty (σ_n^2) such that an overall weighted uncertainty of the traffic forecasting model is below a threshold, the forecasting and planning horizon indicative of a time period for which the traffic forecasting model is applicable. In some embodiments, the sampling frequency is increased upon determination that the epistemic uncertainty is greater than the threshold and the sampling frequency is decreased upon determined that the epistemic uncertainty is lower than the than the threshold. In some embodiments, the threshold is dynamic. In some embodiments, the overall weighted uncertainty is defined by $\gamma_1\sigma_m^2+\gamma_2\sigma_n^2$, wherein each of γ_1 and $\gamma_2$is a scalar coefficient.

[0010] In some embodiments, varying a sampling frequency is at least in part determined based on a threshold associated with the epistemic uncertainty.

[0011] In some embodiments, the traffic forecasting model receives the network statistics from a traffic engineering (TE) database (TE-DB), the network statistics collected from the communication network.

[0012] In some embodiments, varying the sampling frequency includes updating a TE database (TE-DB) containing the network statistics collected from the communication network.

[0013] In some embodiments, the controller node utilizes a constrained shortest path first (CSPF) module and a configuration and management system (CMS), wherein setting resource reservations includes utilizing the CSPF module and the CMS to configure tunnels with resource reservations based on the function of the predictive mean (μ), the aleatoric uncertainty (σ_n^2) and the epistemic uncertainty (σ_m^2).

[0014] In some embodiments, the network statistics are transmitted from a TE database (TE-DB) to an offline training and model search module for training of the traffic forecasting model.

[0015] In some embodiments, the traffic forecasting model is a Bayesian or probabilistic traffic forecasting model.

[0016] In some embodiments, the function is defined by $\mu+\alpha\sigma_m^2+\beta\sigma_n^2$, wherein each of α and β is a scalar coefficient.

[0017] In accordance with embodiments of the present disclosure, there is provided an apparatus for managing network traffic in a communication network. The apparatus includes at least one processor and at least one machine-readable medium storing machine executable instructions. The machine executable instructions, when executed by the at least one processor configure the apparatus to perform one or more of the methods defined above.

[0018] In accordance with embodiments of the present disclosure, there is provided a non-transitory computer-readable medium storing machine executable instructions. The machine executable instructions, when executed by a processor of a device for managing traffic in a communication network, configure the device to perform one or more of the methods defined above.

[0019] Embodiments have been described above in conjunctions with aspects of the present disclosure upon which they can be implemented. Those skilled in the art will appreciate that embodiments may be implemented in conjunction with the aspect with which they are described, but may also be implemented with other embodiments of that aspect. When embodiments are mutually exclusive, or are otherwise incompatible with each other, it will be apparent to those skilled in the art. Some embodiments may be described in relation to one aspect, but may also be applicable to other aspects, as will be apparent to those of skill in the art.

BRIEF DESCRIPTION OF THE FIGURES

[0020] Further features and advantages of the present disclosure will become apparent from the following detailed description, taken in combination with the appended drawings, in which:

[0021] FIG. **1**A illustrates an example of RSVP TE.

[0022] FIG. **1**B illustrates the operation of an existing deep reinforcement learning (DRL) based traffic engineering (TE) framework in a communication network.

[0023] FIG. **10** illustrates an example of TE forecasting and planning horizon with a TE framework according to embodiments of the present disclosure.

[0024] FIG. **2** illustrates a generic TE framework managing the network traffic, in accordance with embodiments of the present disclosure.

[0025] FIG. **3** illustrates a TE framework compatible with existing multiprotocol label switching (MPLS) protocol, in accordance with embodiments of the present disclosure.

[0026] FIG. **4** illustrates a method for managing network traffic in a network, in accordance with embodiments of the present disclosure.

[0027] FIG. **5** is a schematic diagram of a system architecture according to an embodiment of the present disclosure.

[0028] FIG. **6** is a hardware diagram of a chip according to an embodiment of the present disclosure.

[0029] FIG. **7** illustrates a schematic diagram of a hardware structure of a training apparatus according to an embodiment of the present disclosure.

[0030] FIG. **8** illustrates a schematic diagram of a hardware structure of an execution apparatus according to an embodiment of the present disclosure.

[0031] FIG. **9** illustrates a system architecture according to an embodiment of the present disclosure.

[0032] It will be noted that throughout the appended drawings, like features are identified by like reference numerals.

DETAILED DESCRIPTION

[0033] The present disclosure provides a method and system or framework for managing and guiding network traffic in a network based on network traffic demand uncertainty. The traffic demand uncertainty may be extracted from the Bayesian/probabilistic traffic forecasting models or other suitable network traffic forecasting model. Bayesian/probabilistic traffic forecasting models can be generated out of Bayesian neural networks that are extending standard networks with posterior inference for controlling or preventing data overfitting. In Bayesian neural networks, everything has a probability distribution attached thereto, including model parameters, for example weights and biases in neural networks.

[0034] In network traffic engineering applications, there are two main sources of uncertainty, namely aleatoric uncertainty and epistemic uncertainty. Aleatoric uncertainty can be considered to be random uncertainty. Epistemic uncertainty may also be called systematic uncertainty and can be considered to be reflective of model or epistemological inaccuracies for example. While there is a lot of existing work, for example relevant TE literature, focusing on the aleatoric uncertainty, there has been no attempt to quantify the epistemic uncertainty and additionally separate the aleatoric uncertainty and the epistemic uncertainty. It has been realised that there is no known TE work that builds a TE framework that involves actions or procedures to deal with the epistemic uncertainty.

[0035] According to embodiments, there is provided an active and adaptive traffic forecasting or traffic engineering (TE) framework that considers network uncertainty, for example uncertainty in network traffic demand, for TE in the core network, such as in multiprotocol label switching TE (MPLS-TE). In various embodiments, frequency of state updates or soft-updates (for example TE database updates) can be autonomously varied and adjusted by relying on epistemic uncertainty in network traffic demand, in order to enhance sampling operation. According to embodiments, among two different types of the uncertainties for network traffic demand, epistemic uncertainty (or model uncertainty) and aleatoric uncertainty (e.g. data uncertainty or inherent noise or random uncertainty) are utilized to guide TE frameworks and epistemic uncertainty is used for guiding sampling operations in TE frameworks. Specifically, the TE framework asks for prompt MPLS soft-updates based on the epistemic uncertainty. Put another way, the epistemic uncertainty may trigger the TE framework to seek quicker MPLS state-updates.

[0036] According to embodiments, a controller node in a general TE framework can vary the sampling rate of the data collected from the network, for example flow statistics in TE applications, for specific times or specific traffic flows based on epistemic uncertainty for network traffic demand. The controller node can also vary a prediction time-window to adjust for epistemic uncertainty, wherein the prediction time-window is the temporal length of the input to the prediction model. Furthermore, the controller node can set network resource reservations for specific times or specific traffic flows, based on a function of the predictive mean of network traffic demand, epistemic uncertainty in the network traffic demand, and aleatoric uncertainty in the network traffic demand. Moreover, the controller node can set forecasting and planning horizons based on one or more of the aleatoric uncertainty and epistemic uncertainty and may thus account for inherent randomness and epistemic uncertainty.

[0037] FIG. **1**B illustrates the operation of an existing deep reinforcement learning (DRL) based traffic engineering (TE) system or framework **100** in a communication network. The DRL based TE framework **100** and other existing relevant TE systems can predict the TE database (TE-DB) and steer traffic accordingly. In such frameworks, the relevant data is collected at regular intervals based on a predetermined acquisition frequency which may be inefficient.

[0038] Referring to FIG. **1**B, the DRL based TE framework **100** includes various network components (i.e. switches) **110**, TE databases (TE-DBs) **120**, a deep learning (DL) based traffic prediction module **130**, a constrained shortest path first (CSPF) module **140** and a configuration and management system **150**. Each of these components of the DRL based TE framework **100** is communicatively and operatively connected to each other, for example as illustrated in FIG. **1**B.

[0039] With respect to the operation of the DRL based TE framework **100**, the network components (i.e. switches) **110**, at step **101**, update the TE-DB **120** with state updates, for example network state updates. The TE-DB **120** can be updated in accordance with TE routing protocols such as open shortest path first (OSPF) TE (OSPF-TE), intermediate system to intermediate system TE (ISIS-TE) or other TE routing protocol. The TE-DB **120** contains link/switch attributes, for example delay, bandwidth, and utilization. Each attribute shows some characteristics of the network traffic. For example, the link utilization or link utilization level can show a clear seasonality with some growth for the network link usage.

[0040] Through steps **102** to **104**, the DL based traffic prediction module **130** can forecast the future network states in the next time steps (for example in the scale of minutes or other time scale) based on the link/switch attributes contained in the TE-DB **120**. The DL/DRL agent, at step **102**, monitors TE-DB over time, and at step **103**, learns the changing patterns in the TE-DB **120** over time. Then, at step **104**, the DL/DRL agent continuously predicts the next few states of the TE-DB **120**. It should be noted that in some cases, it may be challenging for the DL/DRL agent to accurately predict the next states of the TE-DB **120** as, for example, some network links have less discernable patterns may have a high degree of randomness for their utilization levels.

[0041] After the DL based traffic prediction module **130** predicts the next few states, the CSPF module **140** operates to adjust or re-design the network topology based on the prediction. Specifically, the CSPF module **140** determines the new paths or tunnels in the network based on the prediction.

[0042] Then, the new paths or tunnels may be configured with aid of the configuration and management system **150**. At step **105**, based upon the predicted states of the TE-DB **120**, the DRL agent either directly or via a configuration and management system (CMS) pre-configures or modifies the newly identified set of required TE tunnels between different network nodes, with aid of the CMS **150**.

[0043] Attempts have been made to propose TE frameworks that deal with time-varying network traffic or demand. Network traffic or demand is uncertain as the network traffic cannot be accurately predicted due to the unpredictable nature of human behavior as well as unexpected events or network failures. As such, over-provisioning is often used to maintain network performance in light of traffic variations, as over-provisioning would be less problematic than under-provisioning in TE.

[0044] In existing TE solutions, network traffic uncertainty in traffic engineering applications is modeled probabilistically or using robust modeling methods. Provided that at least some type of network traffic uncertainty is resulted from the unpredictable nature of the network traffic/demand itself, such network traffic uncertainty would not be mitigated merely by adjusting network traffic prediction model or adding more data samples. This type of uncertainty is known as aleatoric uncertainty. The aleatoric uncertainty is a type of uncertainty associated with aleatory sources and is, by definition, random and thus not reducible.

[0045] Another type of uncertainty is the epistemic uncertainty, which is also known as model uncertainty. The epistemic uncertainty or model uncertainty is a type of uncertainty that comes from a lack of knowledge, which can be included in the model, or evaluated based on deficiencies in the prediction model (e.g. traffic forecasting model) itself. Therefore, the epistemic uncertainty may be reduced by collecting information from the network or by adjusting the prediction model, which can be deployed using a neural network. Moreover, provided that deep learning models are black boxes (i.e. not explainable), epistemic uncertainty (or model uncertainty) can be used to understand or define a level of confidence in the model itself.

[0046] It has been realised that present focus has been on the aleatoric uncertainty, while not attempting to disentangle or quantify the different sources of uncertainty in the network traffic or demand. As such, it has been determined that there is a need for a TE framework that involves actions or procedures to account for epistemic uncertainty in association with communication network TE.

[0047] For an existing TE framework, for example the DRL based TE framework illustrated in FIG. **1**B, the TE framework predicts the information of the TE database (TE-DB) and steers the network traffic accordingly. However, in these frameworks, the relevant data is collected at regular intervals based on a predetermined acquisition frequency which can be inefficient. For example, TE-DB updates (soft-updates) are pre-defined for all network flows and time periods as illustrated in FIG. **10**. Referring to FIG. **10**, the traffic forecasting module **160** regularly sends new sampling instructions to the switches **110** for all traffic flows at a predetermined interval, and receives new sampling data from the switches **110**. Then, the traffic forecasting module **160** generates and pushes out a traffic forecast model that is trained with the collected sampling data, for all traffic flows. In other words, no feedback is provided to trigger faster or slower sampling of TE-DB, and therefore the TE forecasting and planning horizon in FIG. **10** is not adaptive, regardless of the network environment and status.

[0048] Bayesian/probabilistic traffic forecasting models can be used to extract a predictive mean of the network traffic demand as well as the epistemic and aleatoric uncertainty measures with respect to the network traffic demand. Based on this, the present disclosure provides a method and system (or TE framework) for managing and guiding network traffic in the network based on the uncertainty measures obtained from a Bayesian neural network. The method and system further provides for revisions and adjustments relating to the uncertainty measures. In particular, among two different types of the uncertainty, the present disclosure focuses on the epistemic uncertainty, as the present disclosure provides a method and system for epistemic uncertainty mitigation.

[0049] The present disclosure provides an active TE architecture and procedure that rely on the epistemic uncertainty obtained from traffic forecasting models (e.g. Bayesian/

probabilistic traffic forecasting models). According to embodiments, the traffic forecasting models can predict the mean of the network traffic demand (i.e. predictive mean) and can extract one or more of the features related to the epistemic uncertainty (i.e. model uncertainty) and the aleatoric uncertainty (i.e. data uncertainty or inherent noise or random uncertainty). It is understood that each uncertainty is related to or associated with the network traffic demand. In the present disclosure, a predictive mean is indicative of a predictive mean of the network traffic demand, and epistemic uncertainty and the aleatoric uncertainty are indicative of epistemic and aleatoric uncertainties in the network traffic demand.

[0050] Based on the traffic forecasting models, a TE framework invokes a set of actions on the network. The set of actions includes, based on the network traffic prediction results, invoking a routing or planning module to reserve network resources with over-provisioning based on one or more of the predictive mean of network traffic demand, the epistemic uncertainty (model uncertainty) and the aleatoric uncertainty (inherent noise) in the network traffic demand. The epistemic uncertainty (model uncertainty) may be extracted from a Bayesian (or Variational) neural network or other Bayesian/probabilistic statistical models. The actions further include sending a signal to a controller node to vary the sampling frequency for the collection of state updates (e.g. determining when to sample more data) based on the epistemic uncertainty. The actions further include increasing the time-window used for the network traffic prediction based on the epistemic uncertainty. In various embodiments, a feedback/exploration loop is provided to determine when to sample more data or to determine when to increase the time-window for the prediction. The actions further include setting traffic forecasting and planning horizons based on one or more of the epistemic uncertainty and the aleatoric uncertainty.

[0051] The present disclosure separates the epistemic uncertainty (model uncertainty) from the aleatoric uncertainty (data uncertainty or inherent randomness) for TE. According to embodiments, the epistemic uncertainty is used to vary the sampling frequency of network statistics (e.g. flow statistics) in TE applications, for specific times or specific flows. Also, according to embodiments, the time-window used to predict network traffic can be varied (e.g. increased or decreased) to adjust the epistemic uncertainty. It should be noted that the epistemic uncertainty may be essentially reduced to zero with correct (e.g. perfect) data sampling and model parameters. Further, traffic forecasting and planning horizons can be set based on one or more of the aleatoric uncertainty (e.g. inherent randomness) and the epistemic uncertainty.

[0052] In some embodiments, the varying of the sampling frequency is at least in part determined based on a threshold associated with the epistemic uncertainty. For example, the sampling frequency can be increased upon determination that the epistemic uncertainty is greater than the threshold. As a further example the sampling frequency can be decreased upon determination that the epistemic uncertainty is lower than the than the threshold. The threshold can be a static threshold or can be a dynamic threshold. For example the selection of the threshold can be defined based on the priority of the network traffic over a particular period of time and as such, as the priority of the network traffic changes the threshold associated with the sampling can be adjusted. In addition, when the selection of the threshold is static, this selection of the threshold can be defined or determined based on a minimum desired level of communication network operation or other parameter as would be readily understood.

[0053] FIG. **2** illustrates a generic TE framework **200** managing/guiding the network traffic, in accordance with embodiments of the present disclosure. Referring to FIG. **2**, the TE framework **200** includes an inference block **210**, TE database (TE-DB) **220**, a controller node **230**, a variety of network components (for example switches and/or there such network components) **240**, and an offline training and model search module **250**. Each of these components of the generic TE framework **200** is communicatively and operatively connected to each other, as illustrated in FIG. **2**.

[0054] According to embodiments, at step **201**, the inference block **210** (for example the Bayesian neural network or other suitable model) is continuously or at predetermined intervals or intermittently provided with one or more network statistics from the changing database **220**. These network statistics can be provided as discrete time epochs, which can be defined as a period of time in past history of network operation that may be identified by one or more a notable events or one or more particular characteristics, The changing database **220** contains various network statistics collected from the network. The network statistics contained in the database **220** may include one or more of per-flow statistics, per-link statistics and per-node statistics and other statistics as would be readily understood.

[0055] In various embodiments, the inference block **210** (e.g. Bayesian neural network or other suitable model as would be readily understood) resembles a Bayesian or probabilistic traffic forecasting model **215** that is capable of extracting the predictive mean (μ), the model uncertainty (σ_m^2), and the inherent noise or aleatoric uncertainty (σ_n^2) associated with the forecasting model. At step **202**, the inference block **210** (e.g. Bayesian neural network) extracts the predictive mean (μ), the model uncertainty (σ_m^2), and the inherent noise or aleatoric uncertainty (σ_n^2). In some embodiments, the extracted predictive mean (μ), the model uncertainty (σ_n^2), and the inherent noise or aleatoric uncertainty (σ_n^2) may be stored in the changing database **220**.

[0056] The extracted values, for example the predictive mean (μ), the model uncertainty (σ_m^2), and the inherent noise or aleatoric uncertainty (σ_n^2), are transmitted to the controller node **230** in the network. The controller node **230** is configured to re-configure or re-design the network topology, and set or assign the network resource reservations for the existing network services and requests. The controller node **230**, at step **203**, sets resource reservations based on a function of the extracted values (i.e. the predictive mean (μ), the epistemic uncertainty (model uncertainty) (σ_m^2), and the inherent noise or aleatoric uncertainty (σ_n^2)). For example, the controller node **230** sets network resource reservation for a link or a path according to a function defined in Equation 1:

$$f(\mu, \sigma_m^2, \sigma_n^2)=\mu+\sigma_m^2+\beta\sigma_n^2 \quad (1)$$

[0057] where: α, β are scalar coefficients.

[0058] The controller node **230**, at step **204**, can vary the frequency of state updates for specific time-periods or specific flows based on the epistemic uncertainty (model uncertainty), σ_m^2. For example, the controller node **230** can instruct the switches **240** in the data plane to vary the frequency of state updates for specific time-periods or specific flows based on the epistemic uncertainty (model uncertainty), σ_m^2. In some embodiments, when the controller node **230** determines that the uncertainty of the traffic forecasting model for a certain time period or traffic flow is outside of a threshold (e.g. predetermined value), the controller node **230** adjusts the sampling frequency of state updates for that time period or traffic flow based on the epistemic uncertainty.

[0059] At step **205**, the controller node **230** can set a planning horizon (i.e. the length of time into the future for which the plan is made) and equivalently the forecasting horizon (i.e. the length of time into the future for which forecasts are to be prepared) of the traffic forecasting module to mitigate instances where an overall weighted uncertainty measure exceeds a threshold. The overall weighted uncertainty measure can be defined as provided in Equation 2.

$$\gamma_1\sigma_m^2+\gamma_2\sigma_n^2 \tag{2}$$

[0060] where: γ_1, γ_2 are scalar coefficients

[0061] In some embodiments, the scalar coefficients for the overall weighted uncertainty (γ_1, γ_2) may be determined based on a network tolerance level (for example based on one or more of a network fault tolerance and a network delay tolerance). The controller node **230** may define the forecasting and planning horizon based on one or more of the epistemic uncertainty and the aleatoric uncertainty. It should be noted that by having more data samples available (either through more frequent data samplings or using data samples from further in past, resulting in longer time periods), the model uncertainty or epistemic uncertainty may be reduced. It should be also noted that the further into the future that the traffic forecasting model is projecting, it is likely that the epistemic uncertainty will increase.

[0062] At step **206**, the one or more network statistics contained in the TE-DB **220** are collected and continuously or periodically or intermittently provided to the offline training and model search module **250**. According to embodiments, the traffic forecasting model **255** may be additionally trained or updated using the offline training and model search module **250**. Once the training of the traffic forecasting model is completed, the trained or updated traffic forecasting model **255** can be pushed to the inference block **210** (for example a Bayesian neural network) for use thereby and enabling an enhanced network operation, for example due to the use of an enhanced or updated traffic forecasting model.

[0063] FIG. **3** illustrates a TE framework **300** compatible with existing multiprotocol label switching (MPLS) protocol, in accordance with embodiments of the present disclosure. The MPLS-TE framework **300** is generally similar to the generic TE framework **200** illustrated in FIG. **2**. Compared to the generic TE framework **200**, there are additional network components added in the TE framework **300** to work with the multiprotocol label switching (MPLS) protocol. For example, TE framework **300** includes a constrained shortest path first (CSPF) module **360** and a configuration and management system **370** in order for the TE framework **300** to be suitable for application with MPLS protocol(s). In MPLS-TE, the switches in the data plane send regular information and/or network statistics to the controller node, and such updates are referred to as soft-updates.

[0064] Referring to FIG. **3**, the TE framework **300** includes the inference block **310**, TE databases (TE-DBs) **320**, the controller node **330**, various network components (i.e. switches) **340**, the offline training and model search module **350**, constrained shortest path first (CSPF) module **360** and the configuration and management system **370**. Each of these components of the MPLS-TE framework **300** is communicatively and operatively connected to each other, as illustrated in FIG. **3**.

[0065] According to embodiments, at step **301**, the inference block **310** (for example a Bayesian neural network or other suitable neural network configuration) is continuously or at predetermined intervals or intermittently provided with one or more network statistics from the changing database **320**. These network statistics can be provided as discrete time epochs, which can be defined as a period of time in past history of network operation that may be identified by one or more a notable events or one or more particular characteristics. The changing database **320** contains various network statistics collected from the network. The network statistics contained in the database **320** may include one or more of per-flow statistics, per-link statistics and per-node statistics and other statistics as would be readily understood.

[0066] In various embodiments, the inference block **310** e.g. Bayesian neural network or other suitable neural network as would be readily understood) resembles a Bayesian or probabilistic traffic forecasting model **315** that is capable of extracting the predictive mean (μ), the model or epistemic uncertainty (σ_m^2), and the inherent noise or aleatoric uncertainty (σ_n^2) associated with the forecasting model. At step **302**, the inference block **310** (e.g. Bayesian neural network) extracts the predictive mean (μ), the model or epistemic uncertainty (σ_m^2), and the inherent noise or aleatoric uncertainty (σ_n^2) associated with the forecasting model. In some embodiments, the extracted predictive mean (μ), the model or epistemic uncertainty (σ_m^2), and the inherent noise or aleatoric uncertainty (σ_n^2) may be stored in the changing database **320**.

[0067] The extracted values, for example the predictive mean (μ), the model uncertainty (σ_m^2), and the inherent noise or aleatoric uncertainty (σ_n^2), are transmitted to the controller node **330** in the network. The controller node **330** is configured to re-configure or re-design the network topology. According to embodiments, the controller node **330** utilizes the CSPF module **360** and the configuration and management system **370** to reserve tunnels (e.g. paths) with network resource reservations based on a function of the predictive mean, epistemic uncertainty (e.g. model uncertainty), and aleatoric uncertainty (e.g. inherent noise). The controller node **330**, at step **303**, sets up tunnels (e.g. paths) with network resource reservations based on a function of the the predictive mean (μ), the epistemic uncertainty (e.g. model uncertainty) (σ_m^2), and the inherent noise or aleatoric uncertainty (σ_n^2). For example, the controller node **330** sets up tunnels (paths) with network resource reservation according to a function as defined in Equation 3.

$$f(\mu, \sigma_m^2, \sigma_n^2)=\mu+\alpha\sigma_m^2+\beta\sigma_n^2 \tag{3}$$

[0068] where: α, β are scalar coefficients.

[0069] The controller node **330**, at step **304**, receives the soft-updates from the switches **340** in the data plane, and changes the frequency of the soft-updates (received from switches **340**) for specific times or specific flows based on the epistemic uncertainty (e.g. model uncertainty), σ_m^2. In some embodiments, when the controller node **230** determines that the uncertainty of the traffic forecasting model for a certain time period or traffic flow is outside of a threshold (e.g. predetermined value), the controller node **330** adjusts the sampling frequency of state updates for that time period or traffic flow based on the epistemic uncertainty.

[0070] At step **305**, the controller node **330** can set a planning horizon and equivalently the forecasting horizon (i.e. the length of time into the future for which forecasts are to be prepared) of the traffic forecasting module to mitigate instances where an overall weighted uncertainty measure exceeds a threshold. The overall weighted uncertainty measure can be defined as provided in Equation 4.

$$\gamma_1\sigma_m^2+\gamma_2\sigma_n^2 \tag{4}$$

[0071] where: γ_1, γ_2 are scalar coefficients

[0072] In some embodiments, the scalar coefficients for the overall weighted uncertainty (γ_1, γ_2) may be determined based on network tolerance level (for example based on one or more of network fault tolerance and network delay tolerance). The controller node **330** may define the forecasting and planning horizon based on one or more of the epistemic uncertainty and the aleatoric uncertainty. It should be noted that by having more data samples available (either through more frequent data samplings or using data samples from further in past, resulting in longer time periods), the model uncertainty or epistemic uncertainty may be reduced. It should be also noted that the further into the future that the traffic forecasting model is projecting, it is likely that the epistemic uncertainty will increase.

[0073] At step **306**, the one or more network statistics contained in the TE-DB **320** are collected and continuously or periodically or intermittently provided to the offline training and model search module **350**. According to embodiments, the traffic forecasting model **355** may be additionally trained or updated using the offline training and model search module **350**. Once the training of the traffic forecasting model is completed, the trained or updated traffic forecasting model **355** can be pushed to the inference block **310** (for example a Bayesian neural network) for use thereby and enabling an enhanced network operation, for example due to the use of an enhanced or updated traffic forecasting model.

[0074] It should be noted that unlike the MPLS-TE framework **300** according to embodiments, existing MPLS-TE protocols and implementations do not take account into uncertainty, and therefore also do not provide any method for varying the frequency of state updates or soft-updates based on the epistemic uncertainty.

[0075] FIG. **4** illustrates a method **400** for managing network traffic in a communication network in accordance with embodiments of the present disclosure. The method includes receiving **410**, by a controller node from a traffic forecasting model, a predictive mean of network traffic demand, an aleatoric uncertainty (σ_n^2) associated with the network traffic demand and an epistemic uncertainty (σ_m^2) associated with the network traffic demand. The method further includes reserving **420**, by the controller node, network resources based on a function of the predictive mean (μ), the aleatoric uncertainty (σ_n^2) and the epistemic uncertainty (σ_m^2). The method additionally includes varying **430**, by the controller node, a sampling frequency of network statistics for a specific time-period or a network flow based at least in part based on the epistemic uncertainty (σ_m^2).

[0076] In some embodiments, the method further includes determining **440**, by the controller node, a forecasting and planning horizon based on one or more of the epistemic uncertainty (σ_m^2) and the aleatoric uncertainty (σ_n^2) such that an overall weighted uncertainty of the traffic forecasting model is below a threshold, the forecasting and planning horizon indicative of a time period for which the traffic forecasting model is applicable.

[0077] In some embodiments, the varying of the sampling frequency is at least in part determined based on a threshold associated with the epistemic uncertainty. For example, the sampling frequency can be increased upon determination that the epistemic uncertainty is greater than the threshold. As a further example the sampling frequency can be decreased upon determination that the epistemic uncertainty is lower than the than the threshold. The threshold can be a static threshold or can be a dynamic threshold. For example the selection of the threshold can be defined based on the priority of the network traffic over a particular period of time and as such, as the priority of the network traffic changes the threshold associated with the sampling can be adjusted. In addition, when the selection of the threshold is static, this selection of the threshold can be defined or determined based on a minimum communication network operational limitation or other parameter as would be readily understood.

[0078] In some embodiments, the controller node utilizes a constrained shortest path first (CSPF) module and a configuration and management system (CMS), wherein setting resource reservations includes utilizing the CSPF module and the CMS to configure tunnels with resource reservations based on the function of the predictive mean (μ), the aleatoric uncertainty (σ_n^2) and the epistemic uncertainty (σ_m^2).

[0079] Various embodiments of the present disclosure, including those illustrated above, propose to method and system or framework for reserving network resources while taking into account uncertainty, which may include one or more of aleatoric uncertainty and epistemic uncertainty. This method and framework may be further generalized to many applications in the fields of network communication and sensing network or other relevant fields of technology. For example, a communication tower, such as evolved node B (eNB) or gNB, can be configured to vary sampling or sensing of data received from a user equipment (UE) based on uncertainty measures.

[0080] FIG. **5** is a schematic structural diagram of a system architecture **500** according to an embodiment of the present disclosure. As illustrated in FIG. **5**, a data collection device **560** is configured to collect network traffic data (e.g. network statistics, per-flow statistics, per-link statistics, per-node statistics) and store the data into a database **530**. A training device **520** generates a target model/rule **501** based on the network traffic data maintained in the database **530** (e.g. TE-DB **220**, TE-DB **320**).

[0081] The target model/rule **501** may refer to the trained traffic forecasting model (e.g. traffic forecasting models **255**, **355**) having applied the training embodiments described herein, for example, embodiments described in reference to FIGS. **2** and **3**. Accordingly, the training device **520** may refer to the offline training and model search modules **250**,

350 and perform the model training, for example, as described in the embodiments described in FIGS. **2** and **3**. The following describes in more detail how the training device **520** (e.g. the offline training and model search modules **250**, **350**) obtains the target model/rule **501** (e.g. traffic forecasting models **255**, **355**) based on the collected network traffic data (e.g. network statistics, per-flow statistics, per-link statistics, per-node statistics) contained in the database **530** (e.g. TE-DB **220**, TE-DB **320**). It should be noted that the one or more methods described herein may be processed by a CPU, or may be jointly processed by a central processing unit (CPU) and a graphics processing unit (GPU), or may not be processed by a GPU, but processed by another processor that is applicable to neural network computation. This is not limited in the instant application.

[0082] Work at each layer of a deep neural network may be described by using a mathematical expression $\vec{y}=a(W\square\vec{x}+b)$: From a physical perspective, the work at each layer of the deep neural network can be understood as performing five operations on input space (a set of input vectors), to complete a conversion from the input space into output space (in other words, from row space to column space of a matrix). The five operations include: 1. Dimensionality increase/reduction; 2. zooming in/out; 3. rotation; 4. panning; and 5. "bending". The operations 1, 2, and 3 are performed by $W\square\vec{x}$, the operation 4 is performed by $+b$, and the operation 5 is implemented by a( ). Herein, a reason why the word "space" is used for description is that objects to be classified are not single matters, but are a type of matters. The space indicates a set of all individuals in this type of matters. W denotes a weight vector. Each value in the vector indicates a weight value of one neural cell at the layer of neural network. The vector W decides the foregoing spatial conversion from the input space to the output space. In other words, the weight W of each layer controls how to convert space. A purpose of training the deep neural network is to finally obtain a weight matrix (a weight matrix consisting of vectors W of a plurality of layers) of all layers of the trained neural network. Therefore, in essence, the training process of the neural network is learning a manner of controlling spatial conversion, and more specifically, learning a weight matrix.

[0083] To enable the deep neural network to output a predicted value that is as close to a truly desired value as possible, a predicted value of a current network and a truly desired target value may be compared, and a weight vector of each layer of the neural network is updated based on a difference between the predicted value and the truly desired target value (Certainly, there is usually an initialization process before a first update. To be specific, a parameter is preconfigured for each layer of the deep neural network). For example, if the predicted value of a network is excessively high, continuously adjust a weight vector to lower the predicted value, until the neural network can predict the truly desired target value. Therefore, "how to compare a difference between a predicted value and a target value" needs to be predefined. To be specific, a loss function (loss function) or an objective function (objective function) needs to be predefined. The loss function and the objective function are important equations used to measure the difference between a predicted value and a target value. For example, the loss function is used as an example. A higher output value (loss) of the loss function indicates a greater difference. In this case, training the deep neural network is a process of minimizing the loss.

[0084] The target module/rule **501** obtained by the training device **520** may be applied to different systems or devices. In FIG. **5**, an execution device **510** is provided with an I/O interface **512** to perform data interaction with an external device. A "user" may input data to the I/O interface **512** by using a customer device **540**.

[0085] The execution device **510** may refer to the inference block **210** or **310** or the controller node **230** or **330**, having applied the embodiments described herein, for example, the embodiments described in FIGS. **2** and **3**. The execution device **510** may invoke data, code, and the like from a data storage system **550** (e.g. TE-DB **220**, TE-DB **320**), and may store the data, an instruction, and the like into the data storage system **550**. For example, the execution device **510** may invoke the collected network statistics, at discrete time epochs, from the data storage system **550** (e.g. TE-DB **220**, TE-DB **320**) and, in some embodiments, may store a predictive mean (μ), a model uncertainty (σ_m^2), and an inherent noise or aleatoric uncertainty (σ_n^2) in the the data storage system **550**.

[0086] The I/O interface **512** may return a processing result to the customer device **540** and provides the processing result to the user. More deeply, the training device **520** may generate a corresponding target model/rule **501** for different targets based on different network traffic data (e.g. network statistics, per-flow statistics, per-link statistics, per-node statistics). The corresponding target model/rule **501** may be used to implement the foregoing target to provide a desired result for the user.

[0087] In a case shown in FIG. **5**, the user may manually specify data to be input to the execution device **510**, for example, an operation in a screen provided by the I/O interface **512**. In another case, the customer device **540** may automatically input data to the I/O interface **512** and obtain a result. If the customer device **540** automatically inputs data, authorization of the user needs to be obtained. The user can specify a corresponding permission in the customer device **540**. The user may view, in the customer device **540**, the result output by the execution device **510**. A specific presentation form may be display content, a voice, an action, and the like. In addition, the customer device **540** may be used as a data collector to store collected network traffic data (e.g. network statistics, per-flow statistics, per-link statistics, per-node statistics) into the database **530**.

[0088] It should be noted that FIG. **5** is merely a schematic diagram of a system architecture according to an embodiment of the present disclosure. Position relationships between the device, the component, the module, and the like that are shown in FIG. **5** do not constitute any limitation. For example, in FIG. **5**, the data storage system **550** is an external memory relative to the execution device **510**. In another case, the data storage system **550** may be located in the execution device **510**.

[0089] According to embodiments, a configuration of the neural network applicable to the instant application is a Bayesian neural network (BNN). A BNN refers to extending standard neural networks with posterior inference in order to control over-fitting. The Bayesian approach uses a statistical methodology so that everything has a probability distribution attached to it, including model parameters (for example the weights and biases in a neural network). In the Bayesian neural network, you can have similar entities also known as random variables that will give you a different value each time the BNN is applied. In Bayesian terms, the historical data represents prior knowledge of the overall behavior with each variable, such that each variable has statistical properties that can vary with time. Bayesian methods can allow the consideration of an entire distribution of answers, which can address issues relating to regularization, for example overfitting, and model selection or comparison without a need for a separate cross validation data set.

[0090] FIG. **6** is a structural hardware diagram of a chip according to an embodiment of the present disclosure. The chip includes a neural network processor **600**. The chip may be provided in the execution device **510** shown in FIG. **5**, to perform computation for the computation module **511**. Alternatively, the chip may be provided in the training device **520** shown in FIG. **5**, to perform training and output the target model/rule **501**. All the algorithms of layers (not shown in FIG. **2** or **3**) of the Bayesian neural network in FIGS. **2** and. **3** may be implemented in the chip shown in FIG. **6**.

[0091] The neural network processor **600** may be any processor that is applicable to massive exclusive OR operations, for example, a neural processing unit (NPU), a tensor processing unit (TPU), a graphics processing unit (GPU), or the like. The NPU is used as an example. The NPU may be mounted, as a coprocessor, to a host central processing unit (CPU), and the host CPU may allocate a task to the NPU. A core part of the NPU is an operation circuit **603**. A controller **604** controls the operation circuit **603** to extract matrix data from memories (**601** and **602**) and perform multiplication and addition operations.

[0092] In some implementations, the operation circuit **603** internally includes a plurality of processing units (e.g., Process Engine, PE). In some implementations, the operation circuit **603** is a bi-dimensional systolic array. In addition, the operation circuit **603** may be a unidimensional systolic array or another electronic circuit that can implement a mathematical operation such as multiplication and addition. In some implementations, the operation circuit **603** is a general matrix processor.

[0093] For example, it is assumed that there are an input matrix A, a weight matrix B, and an output matrix C. The operation circuit **603** may obtain, from a weight memory **602**, weight data of the matrix B, and cache the data in each PE in the operation circuit **603**. The operation circuit **603** may obtain input data of the matrix A from an input memory **601**, and perform a matrix operation based on the input data of the matrix A and the weight data of the matrix B. An obtained partial or final matrix result may be stored in an accumulator (accumulator) **608**.

[0094] A unified memory **606** may be configured to store input data and output data. Weight data may be directly moved to the weight memory **602** by using a storage unit access controller (e.g., direct memory access controller, DMAC) **605**. The input data may also be moved to the unified memory **606** by using the DMAC.

[0095] A bus interface unit (BIU) **610** may be used for interaction between the storage unit access controller (e.g., DMAC) **605** and an instruction fetch memory (Instruction Fetch Buffer) **609**. The bus interface unit **610** may further be configured to enable the instruction fetch memory **609** to obtain an instruction from an external memory. The BIU **610** may further be configured to enable the storage unit access controller **605** to obtain, from the external memory, source data of the input matrix A or the weight matrix B.

[0096] The storage unit access controller (e.g., DMAC) **605** is mainly configured to move input data from an external memory DDR to the unified memory **606**, or move the weight data to the weight memory **602**, or move the input data to the input memory **601**.

[0097] A vector computation unit **607** may include a plurality of operation processing units. If needed, the vector computation unit **607** may perform further processing, for example, vector multiplication, vector addition, an exponent operation, a logarithm operation, or magnitude comparison, on an output from the operation circuit **603**. The vector computation unit **607** may be mainly used for computation at a non-convolutional layer or fully-connected layers (FC, fully connected layers) of a neural network, for example, pooling (pooling), batch normalization (batch normalization), or local response normalization (local response normalization).

[0098] In some implementations, the vector computation unit **607** may store, to the unified memory **606**, a vector output through processing (or a processed vector). For example, the vector computation unit **607** may apply a nonlinear function to an output of the operation circuit **603**, for example, a vector of an accumulated value, to generate an activation value. In some implementations, the vector computation unit **607** may generate a normalized value, a combined value, or both a normalized value and a combined value.

[0099] In some implementations, the vector output through processing (the vector processed by the vector computation unit **607**) may be used as activation input to the operation circuit **603**, for example, to be used in some layer(s) of the Bayesian neural network.

[0100] The instruction fetch memory (instruction fetch buffer) **609** connected to the controller **604** may be configured to store an instruction used by the controller **604**. The unified memory **606**, the input memory **601**, the weight memory **602**, and the instruction fetch memory **609** may all be on-chip memories. The external memory may be independent from the hardware architecture of the NPU.

[0101] Operations of the layers of the Bayesian neural network may be performed by the operation circuit **603** or the vector computation unit **607**.

[0102] FIG. **7** illustrates a schematic diagram of a hardware structure of a training apparatus according to an embodiment of the present disclosure. A training apparatus **700** (the apparatus **700** may be a computer device and may refer to the training device **520** or a device containing the offline training and model search module **250** or **350**) may include a memory **701**, a processor **702**, a communications interface **703**, and a bus **704**. A communication connection is implemented between the memory **701**, the processor **702**, and the communications interface **703** by using the bus **704**.

[0103] The memory **701** may be a read-only memory (ROM), a static storage device, a dynamic storage device, or a random-access memory (RAM). The memory **701** may store a program. The processor **702** and the communications interface **703** may be configured to perform, when the program stored in the memory **701** is executed by the processor **702**, steps of one or more embodiments described herein, for example, embodiments described in reference to FIG. **2** and FIG. **3**.

[0104] The processor **702** may be a general central processing unit (CPU), a microprocessor, an application-specific integrated circuit (ASIC), a graphics processing unit (GPU), or one or more integrated circuits. The processor **702** may be configured to execute a related program to implement a function that needs to be performed by a unit in the training apparatus according to one or more embodiments described herein, for example, embodiments described in reference to FIG. **2** and FIG. **3**.

[0105] In addition, the processor **702** may be an integrated circuit chip with a signal processing capability. In an implementation process, steps of one or more training methods described herein may be performed by an integrated logical circuit in a form of hardware or by an instruction in a form of software in the processor **702**. In addition, the foregoing processor **702** may be a general-purpose processor, a digital signal processor (DSP), an application-specific integrated circuit (ASIC), a field programmable gate array (FPGA) or other programmable logic device, a discrete gate or a transistor logic device, or a discrete hardware assembly. The processor **702** may implement or execute the methods, steps, and logical block diagrams that are disclosed in the embodiments of this disclosure. The general purpose processor may be a microprocessor, or the processor may be any conventional processor or the like. The steps of the method disclosed with reference to the embodiments of this disclosure may be directly performed by a hardware decoding processor, or may be performed by using a combination of hardware in the decoding processor and a software module. The software module may be located in a mature storage medium in the art, such as a random access memory, a flash memory, a read-only memory, a programmable read-only memory, an electrically erasable programmable memory, or a register. The storage medium may be located in the memory **701**. The processor **702** may read information from the memory **701**, and completes, by using hardware in the processor **702**, the functions that need to be performed by the units included in the training device according to one or more embodiment described herein, for example, embodiments described in reference to FIG. **2** and FIG. **3**.

[0106] The communications interface **703** may implement communication between the apparatus **700** and another device or communications network by using a transceiver apparatus, for example, including but not limited to a transceiver. For example, training data (for example, network traffic data such as network statistics, per-flow statistics, per-link statistics, per-node statistics) may be obtained by using the communications interface **703**.

[0107] The bus **704** may include a path that transfers information between all the components (for example, the memory **701**, the processor **702**, and the communications interface **703**) of the apparatus **700**.

[0108] FIG. **8** illustrates a schematic diagram of a hardware structure of an execution apparatus according to an embodiment of the present disclosure. The execution apparatus may refer to the execution device **510** of FIG. **5**. Execution apparatus **800** (which may be a computing device) includes a memory **801**, a processor **802**, a communications interface **803**, and a bus **804**. A communication connection is implemented between the memory **801**, the processor **802**, and the communications interface **803** by using the bus **804**.

[0109] The memory **801**may be a read-only memory (ROM), a static storage device, a dynamic storage device, or a random-access memory (RAM). The memory **801** may store a program. The processor **802** and the communications interface **803** are configured to perform, when the program stored in the memory **801** is executed by the processor **802**, step(s) of one or more embodiments described herein, for example, embodiments described in reference to FIG. **2** and FIG. **3**.

[0110] The processor **802** may be a general central processing unit (CPU), a microprocessor, an application-specific integrated circuit (ASIC), a graphics processing unit (GPU), or one or more integrated circuits. The processor **802** may be configured to execute a related program to implement a function that needs to be performed by a unit in the execution apparatus according to one or more embodiments described herein, for example, embodiments described in reference to FIG. **2** and FIG. **3**.

[0111] In addition, the processor **802** may be an integrated circuit chip with a signal processing capability. In an implementation process, steps of one or more execution methods described herein (e.g. varying frequency of state updates) may be performed by an integrated logical circuit in a form of hardware or by an instruction in a form of software in the processor **802**. In addition, the processor **802** may be a general-purpose processor, a digital signal processor (DSP), an application-specific integrated circuit (ASIC), a field programmable gate array (FPGA) or other programmable logic device, a discrete gate or a transistor logic device, or a discrete hardware assembly. The general-purpose processor may be a microprocessor, or the processor may be any conventional processor or the like. The steps of the method disclosed with reference to the embodiments of this application may be directly performed by a hardware decoding processor, or may be performed by using a combination of hardware in the decoding processor and a software module. The software module may be located in a mature storage medium in the art, such as a random-access memory, a flash memory, a read-only memory, a programmable read-only memory, an electrically erasable programmable memory, or a register. The storage medium may be located in the memory **801**. The processor **802** may read information from the memory **801**, and completes, by using hardware in the processor **802**, to perform the functions that need to be performed by the units included in the execution device according to one or more embodiment described herein, for example, embodiments described in reference to FIG. **2** and FIG. **3**.

[0112] The communications interface **803** may implement communication between the apparatus **800** and another device or communications network by using a transceiver apparatus, for example, including but not limited to a transceiver. For example, training data for one or more downstream tasks may be obtained by using the communications interface **803**.

[0113] The bus **804** may include a path that transfers information between all the components (for example, the memory **801**, the processor **802**, and the communications interface **803**) of the apparatus **800**.

[0114] It should be noted that, although only the memory, the processor, and the communications interface are shown in the apparatuses **700** (in FIGS. **7**) and **800** (in FIG. **8**), a person skilled in the art should understand that the apparatuses **1300** and **800** may further include other components that are necessary for implementing normal running. In addition, based on specific needs, a person skilled in the art should understand that the apparatuses **700** and **800** may further include hardware components that implement other additional functions. In addition, a person skilled in the art should understand that the apparatuses **700** and **800** may include only a component required for implementing the embodiments of the present disclosure, without a need to include all the components shown in FIG. **7** or FIG. **8**.

[0115] It may be understood that the apparatus **700** is equivalent to the training device **520** in FIG. **5**, and the apparatus **800** is equivalent to the execution device **510** in FIG. **5**. A person of ordinary skill in the art may be aware that, in combination with the examples described in the embodiments disclosed in this specification, units and algorithm steps may be implemented by electronic hardware or a combination of computer software and electronic hardware. Whether the functions are performed by hardware or software depends on particular applications and design constraint conditions of the technical solutions. A person skilled in the art may use different methods to implement the described functions for each particular application, but it should not be considered that the implementation goes beyond the scope of this application.

[0116] FIG. **9** illustrates a system architecture **900** according to an embodiment of the present disclosure. The execution device **910** may be implemented by one or more servers **915**, and optionally, supported by another computation device, for example, a data memory, a router, a load balancer, or another device. The execution device **910** may be arranged in a physical station or be distributed to a plurality of physical stations. The execution device **910** may use data in a data storage system **950** or invoke program code in a data storage system **950**, to implement steps of the method disclosed with reference to the embodiments of this application.

[0117] Users may operate respective user equipment (such as a local device **901** and a local device **902**) of the users to interact with the execution device **910**. Each local device may indicate any computation device, for example, a personal computer, a computer work station, a smartphone, a tablet computer, a smart camera, a smart car, or another type of cellular phone, a media consumption device, a wearable device, a set-top box, or a game console.

[0118] The local device of each user may interact with the execution device **910** by using a communications network of any communications mechanism/communications standard. The communications network may be a wide area network, a local area network, a point-to-point connected network, or any combination thereof.

[0119] In another implementation, one or more aspects of the execution devices **910** may be implemented by each local device. For example, the local device **901** may provide local data for the execution device **910** or feedback a computation result.

[0120] It should be noted that all functionalities of the execution device **910** may be implemented by the local device. For example, the local device **901** may implement a function of the execution device **910** and provides a service for a user of the local device **901**, or provides a service for a user of the local device **902**.

[0121] It may be clearly understood by a person skilled in the art that, for the purpose of convenient and brief description, for a detailed working process of the foregoing system, apparatus, and unit, refer to a corresponding process in the foregoing method embodiments, and details are not described herein again.

[0122] In the several embodiments provided in this application, it should be understood that the disclosed system, apparatus, and method may be implemented in other manners. For example, the described apparatus embodiment is merely an example. For example, the unit division is merely logical function division and may be other division in actual implementation. For example, a plurality of units or components may be combined or integrated into another system, or some features may be ignored or not performed. In addition, the displayed or discussed mutual couplings or direct couplings or communication connections may be implemented by using some interfaces. The indirect couplings or communication connections between the apparatuses or units may be implemented in electronic, mechanical, or other forms.

[0123] The units described as separate parts may or may not be physically separate, and parts displayed as units may or may not be physical units, may be located in one position, or may be distributed on a plurality of network units. Some or all of the units may be selected according to actual requirements to achieve the objectives of the solutions of the embodiments.

[0124] In addition, functional units in the embodiments of this application may be integrated into one processing unit, or each of the units may exist alone physically, or two or more units are integrated into one unit.

[0125] When the functions are implemented in the form of a software functional unit and sold or used as an independent product, the functions may be stored in a computer-readable storage medium. Based on such an understanding, the technical solutions of this application essentially, or the part contributing to the prior art, or some of the technical solutions may be implemented in a form of a software product. The software product is stored in a storage medium, and includes several instructions for instructing a computer device (which may be a personal computer, a server, or a network device) to perform all or some of the steps of the methods described in the embodiments of this application. The foregoing storage medium includes any medium that can store program code, such as a USB flash drive, a removable hard disk, a read-only memory (ROM), a random access memory (RAM), a magnetic disk, or an optical disc.

[0126] The foregoing descriptions are merely specific implementations of this application, but are not intended to limit the protection scope of this application. Any variation or replacement readily figured out by a person skilled in the art within the technical scope disclosed in this application shall fall within the protection scope of this application. Therefore, the protection scope of this application shall be subject to the protection scope of the claims.

We claim:

1. A method for managing network traffic in a communication network, the method comprising:

receiving, by a controller node from a traffic forecasting model, a predictive mean of network traffic demand, an aleatoric uncertainty (σ_n^2) associated with the network traffic demand and an epistemic uncertainty (σ_m^2) associated with the network traffic demand;

reserving, by the controller node, network resources based on a function of the predictive mean (μ), the aleatoric uncertainty (σ_n^2) and the epistemic uncertainty (σ_m^2); and

varying, by the controller node, a sampling frequency of network statistics for a specific time-period or a network flow based at least in part based on the epistemic uncertainty (σ_m^2).

2. The method according to claim **1**, further comprising determining, by the controller node, a forecasting and planning horizon based on one or more of the epistemic uncertainty (σ_m^2) and the aleatoric uncertainty (σ_n^2) such that an overall weighted uncertainty of the traffic forecasting model is below a threshold, the forecasting and planning horizon indicative of a time period for which the traffic forecasting model is applicable.

3. The method of claim **1**, wherein varying a sampling frequency is at least in part determined based on a threshold associated with the epistemic uncertainty.

4. The method of claim **3**, wherein the sampling frequency is increased upon determination that the epistemic uncertainty is greater than the threshold and the sampling frequency is decreased upon determined that the epistemic uncertainty is lower than the than the threshold.

5. The method of claim **3**, wherein the threshold is dynamic.

6. The method of claim **1**, wherein the traffic forecasting model receives the network statistics from a traffic engineering (TE) database (TE-DB), the network statistics collected from the communication network.

7. The method of claim **1**, wherein varying the sampling frequency includes updating a TE database (TE-DB) containing the network statistics collected from the communication network.

8. The method of claim **1**, wherein the controller node utilizes a constrained shortest path first (CSPF) module and a configuration and management system (CMS), wherein setting resource reservations includes utilizing the CSPF module and the CMS to configure tunnels with resource reservations based on the function of the predictive mean (μ), the aleatoric uncertainty (σ_n^2) and the epistemic uncertainty (σ_m^2).

9. The method of claim **1**, wherein the network statistics are transmitted from a TE database (TE-DB) to an offline training and model search module for training of the traffic forecasting model.

10. The method of claim **1**, wherein the traffic forecasting model is a Bayesian or probabilistic traffic forecasting model.

11. The method of claim **1**, wherein the function is defined by $\mu+\alpha\sigma_m^2+\beta\sigma_n^2$, wherein each of α and β is a scalar coefficient.

12. The method of claim **2**, wherein the overall weighted uncertainty is defined by $\gamma_1\sigma_m^2+\gamma_2\sigma_n^2$, wherein each of γ_1 and $\gamma_2$is a scalar coefficient.

13. An apparatus for managing network traffic in a communication network, the apparatus comprising:

at least one processor; and

at least one machine-readable medium storing machine executable instructions which when executed by the at least one processor configure the apparatus to:

receive from a traffic forecasting model, a predictive mean of network traffic demand, an aleatoric uncertainty (σ_n^2) associated with the network traffic demand and an epistemic uncertainty (σ_m^2) associated with the network traffic demand;

reserve network resources based on a function of the predictive mean (μ), the aleatoric uncertainty (σ_n^2) and the epistemic uncertainty (σ_m^2); and

vary a sampling frequency of network statistics for a specific time-period or a network flow based at least in part based on the epistemic uncertainty (σ_m^2).

14. The apparatus according to claim **13**, wherein the machine executable instructions when executed by the at least one processor further configure the apparatus to determine a forecasting and planning horizon based on one or more of the epistemic uncertainty (σ_m^2) and the aleatoric uncertainty (σ_n^2) such that an overall weighted uncertainty of the traffic forecasting model is below a threshold, the forecasting and planning horizon indicative of a time period for which the traffic forecasting model is applicable.

15. The apparatus of claim **13**, wherein varying a sampling frequency is at least in part determined based on a threshold associated with the epistemic uncertainty.

16. The apparatus of claim **15**, wherein the sampling frequency is increased upon determination that the epistemic uncertainty is greater than the threshold and the sampling frequency is decreased upon determined that the epistemic uncertainty is lower than the than the threshold.

17. The apparatus of claim **15**, wherein the threshold is dynamic.

18. The apparatus of claim **13**, wherein the traffic forecasting model receives the network statistics from a traffic engineering (TE) database (TE-DB), the network statistics collected from the communication network.

19. The apparatus of claim **13**, wherein varying the sampling frequency includes updating a TE database (TE-DB) containing the network statistics collected from the communication network.

20. The apparatus of claim **13**, wherein the controller node utilizes a constrained shortest path first (CSPF) module and a configuration and management system (CMS), wherein setting resource reservations includes utilizing the CSPF module and the CMS to configure tunnels with resource reservations based on the function of the predictive mean (μ), the aleatoric uncertainty (σ_n^2) and the epistemic uncertainty (σ_m^2).

21. The apparatus of claim **13**, wherein the network statistics are transmitted from a TE database (TE-DB) to an offline training and model search module for training of the traffic forecasting model.

22. The apparatus of claim **13**, wherein the traffic forecasting model is a Bayesian or probabilistic traffic forecasting model.

23. The apparatus of claim **13**, wherein the function is defined by $\mu+\alpha\sigma_m^2+\beta\sigma_n^2$, wherein each of α and β is a scalar coefficient.

24. The apparatus of claim **14**, wherein the overall weighted uncertainty is defined by $\gamma_1\sigma_m^2+\gamma_2\sigma_n^2$, wherein each of γ_1 and $\gamma_2$is a scalar coefficient.

25. A non-transitory computer-readable medium storing machine executable instructions which when executed by a processor of a device for managing network traffic in a communication network, configure the device to:

receive, by a controller node from a traffic forecasting model, a predictive mean of network traffic demand, an aleatoric uncertainty (σ_n^2) associated with the network traffic demand and an epistemic uncertainty (σ_m^2) associated with the network traffic demand;

reserve, by the controller node, network resources based on a function of the predictive mean (μ), the aleatoric uncertainty (σ_n^2) and the epistemic uncertainty (σ_m^2);

vary, by the controller node, a sampling frequency of network statistics for a specific time-period or a network flow based at least in part based on the epistemic uncertainty (σ_m^2).

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