US011153177B1

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Hermoni et al.

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(45) **Date of Patent: *Oct. 19, 2021**

(54) **SYSTEM, METHOD, AND COMPUTER PROGRAM FOR PREPARING A MULTI-STAGE FRAMEWORK FOR ARTIFICIAL INTELLIGENCE (AI) ANALYSIS**

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(73) Assignee: **AMDOCS DEVELOPMENT LIMITED**, Limassol (CY)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 111 days.

This patent is subject to a terminal disclaimer.

(21) Appl. No.: **16/280,320**

(22) Filed: **Feb. 20, 2019**

Related U.S. Application Data

(60) Provisional application No. 62/660,142, filed on Apr. 19, 2018, provisional application No. 62/648,287, (Continued)

(51) **Int. Cl.**

H04L 12/24	(2006.01)
H04L 12/26	(2006.01)

(52) **U.S. Cl.**
CPC .... ***H04L 41/16*** (2013.01); ***H04L 41/046*** (2013.01); ***H04L 41/0622*** (2013.01); (Continued)

(58) **Field of Classification Search**
CPC H04L 41/16; H04L 43/16; H04L 41/046; H04L 41/0622; H04L 41/147; H04L 43/06
See application file for complete search history.

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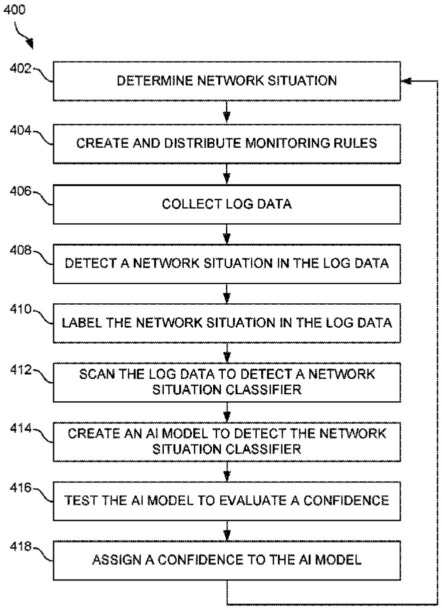
Primary Examiner — Ninos Donabed
Assistant Examiner — Fadi Haj Said
(74) *Attorney, Agent, or Firm* — Zilka-Kotab, P.C.

(57) **ABSTRACT**

A system, method, and computer program product are provided for preparing a multi-stage framework for artificial intelligence (AI) analysis. In use, a first set of monitoring rules used by at least one network entity of a communication network is defined. First event log data of first network activity is collected based on the first monitoring rules, and at least one first network situation is defined. Additionally, at least one first AI model is computed based on the first event log data and the at least one first network situation. A second set of monitoring rules used by the at least one network entity is defined. Second event log data of the first network activity is collected based on the second monitoring rules. Further, at least one second AI model is computed based on the second event log data and the at least one first network situation.

11 Claims, 19 Drawing Sheets


400
402
DETERMINE NETWORK SITUATION
404
CREATE AND DISTRIBUTE MONITORING RULES
406
COLLECT LOG DATA
408
DETECT A NETWORK SITUATION IN THE LOG DATA
410
LABEL THE NETWORK SITUATION IN THE LOG DATA
412
SCAN THE LOG DATA TO DETECT A NETWORK SITUATION CLASSIFIER
414
CREATE AN AI MODEL TO DETECT THE NETWORK SITUATION CLASSIFIER
416
TEST THE AI MODEL TO EVALUATE A CONFIDENCE
418
ASSIGN A CONFIDENCE TO THE AI MODEL

Related U.S. Application Data

filed on Mar. 26, 2018, provisional application No. 62/648,281, filed on Mar. 26, 2018, provisional application No. 62/642,524, filed on Mar. 13, 2018, provisional application No. 62/639,910, filed on Mar. 7, 2018, provisional application No. 62/639,923, filed on Mar. 7, 2018, provisional application No. 62/639,913, filed on Mar. 7, 2018.

(52) **U.S. Cl.**
CPC ***H04L 41/147*** (2013.01); ***H04L 43/06*** (2013.01); ***H04L 43/16*** (2013.01)

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Hermoni et al., U.S. Appl. No. 16/280,513, filed Feb. 20, 2019.

* cited by examiner

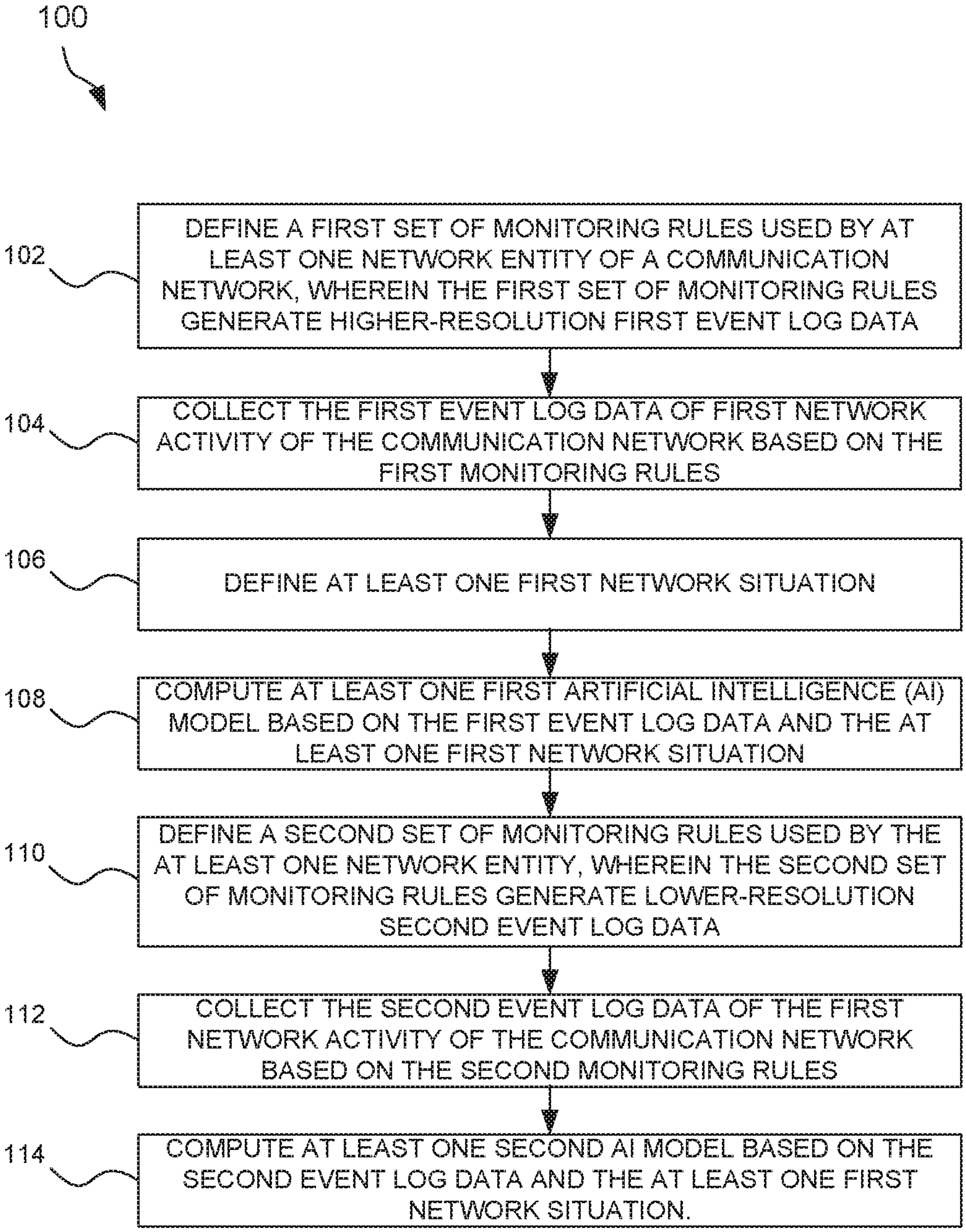
100
102
DEFINE A FIRST SET OF MONITORING RULES USED BY AT LEAST ONE NETWORK ENTITY OF A COMMUNICATION NETWORK, WHEREIN THE FIRST SET OF MONITORING RULES GENERATE HIGHER-RESOLUTION FIRST EVENT LOG DATA
104
COLLECT THE FIRST EVENT LOG DATA OF FIRST NETWORK ACTIVITY OF THE COMMUNICATION NETWORK BASED ON THE FIRST MONITORING RULES
106
DEFINE AT LEAST ONE FIRST NETWORK SITUATION
108
COMPUTE AT LEAST ONE FIRST ARTIFICIAL INTELLIGENCE (AI) MODEL BASED ON THE FIRST EVENT LOG DATA AND THE AT LEAST ONE FIRST NETWORK SITUATION
110
DEFINE A SECOND SET OF MONITORING RULES USED BY THE AT LEAST ONE NETWORK ENTITY, WHEREIN THE SECOND SET OF MONITORING RULES GENERATE LOWER-RESOLUTION SECOND EVENT LOG DATA
112
COLLECT THE SECOND EVENT LOG DATA OF THE FIRST NETWORK ACTIVITY OF THE COMMUNICATION NETWORK BASED ON THE SECOND MONITORING RULES
114
COMPUTE AT LEAST ONE SECOND AI MODEL BASED ON THE SECOND EVENT LOG DATA AND THE AT LEAST ONE FIRST NETWORK SITUATION.

FIG. 1

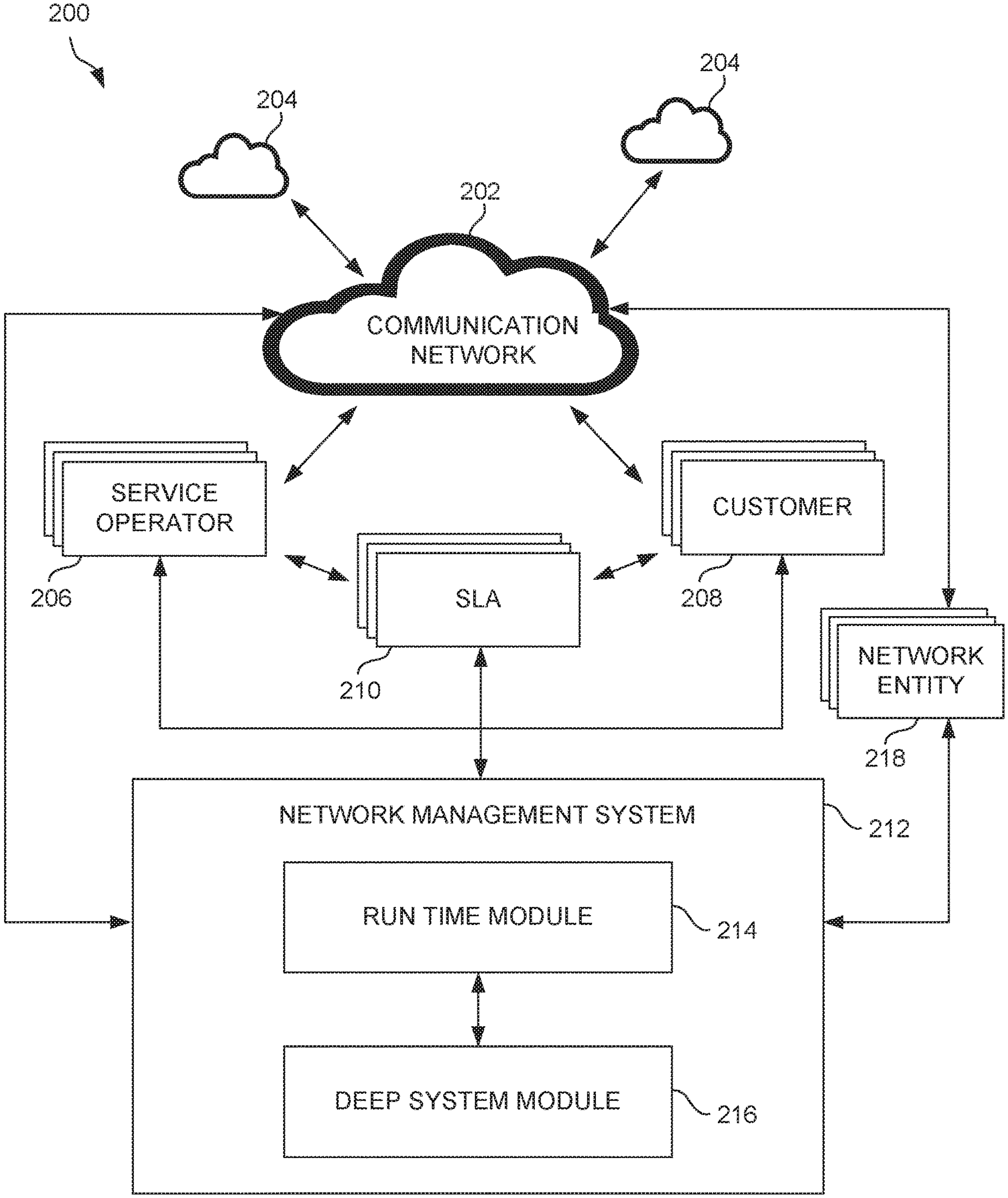
200
204
204
202
COMMUNICATION NETWORK
SERVICE OPERATOR
206
CUSTOMER
208
SLA
210
NETWORK ENTITY
218
NETWORK MANAGEMENT SYSTEM
212
RUN TIME MODULE
214
DEEP SYSTEM MODULE
216

FIG. 2A

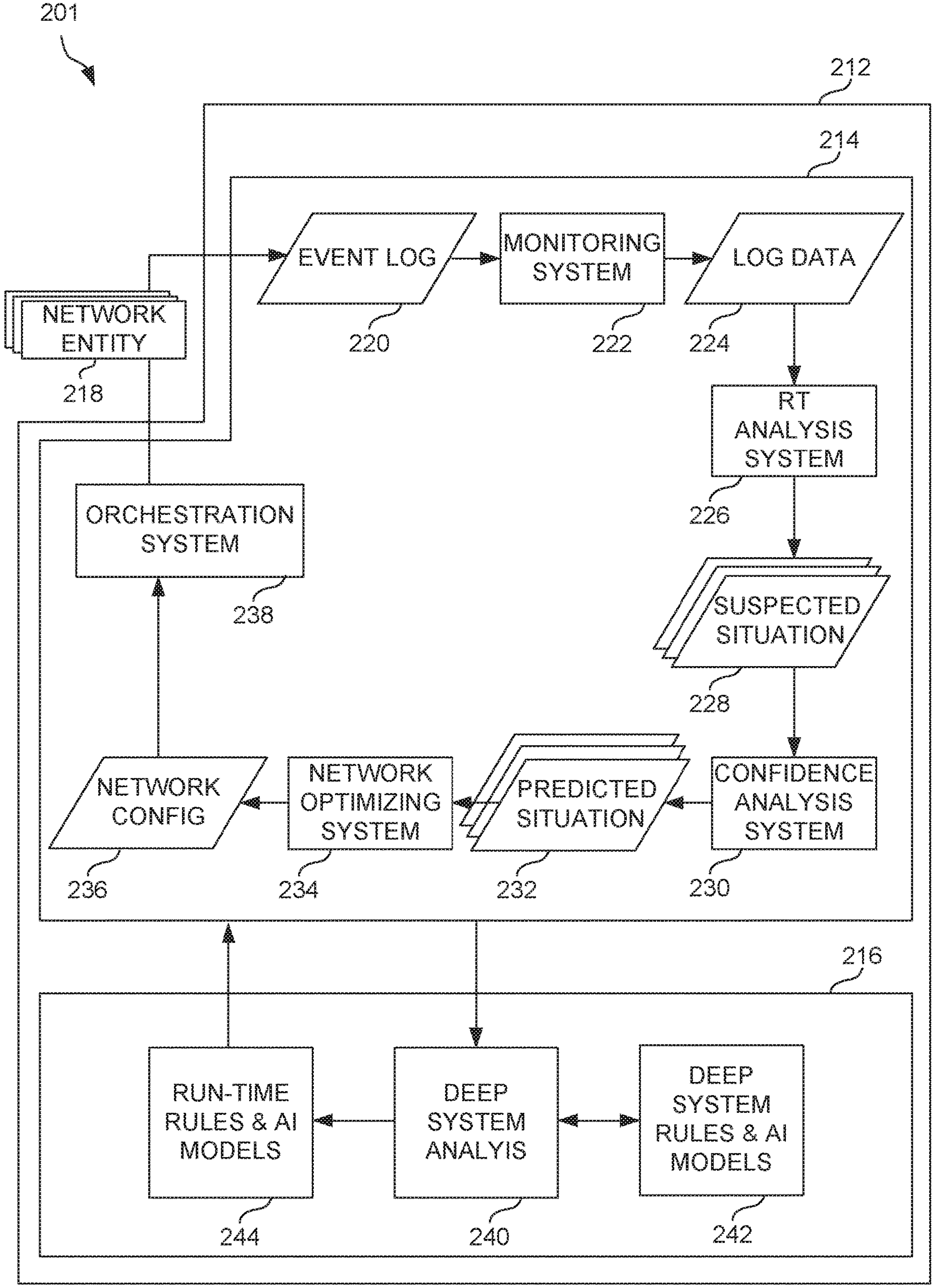
201
212
214
NETWORK ENTITY
218
EVENT LOG
220
MONITORING SYSTEM
222
LOG DATA
224
RT ANALYSIS SYSTEM
226
SUSPECTED SITUATION
228
CONFIDENCE ANALYSIS SYSTEM
230
PREDICTED SITUATION
232
NETWORK OPTIMIZING SYSTEM
234
NETWORK CONFIG
236
ORCHESTRATION SYSTEM
238
216
RUN-TIME RULES & AI MODELS
244
DEEP SYSTEM ANALYIS
240
DEEP SYSTEM RULES & AI MODELS
242

FIG. 2B

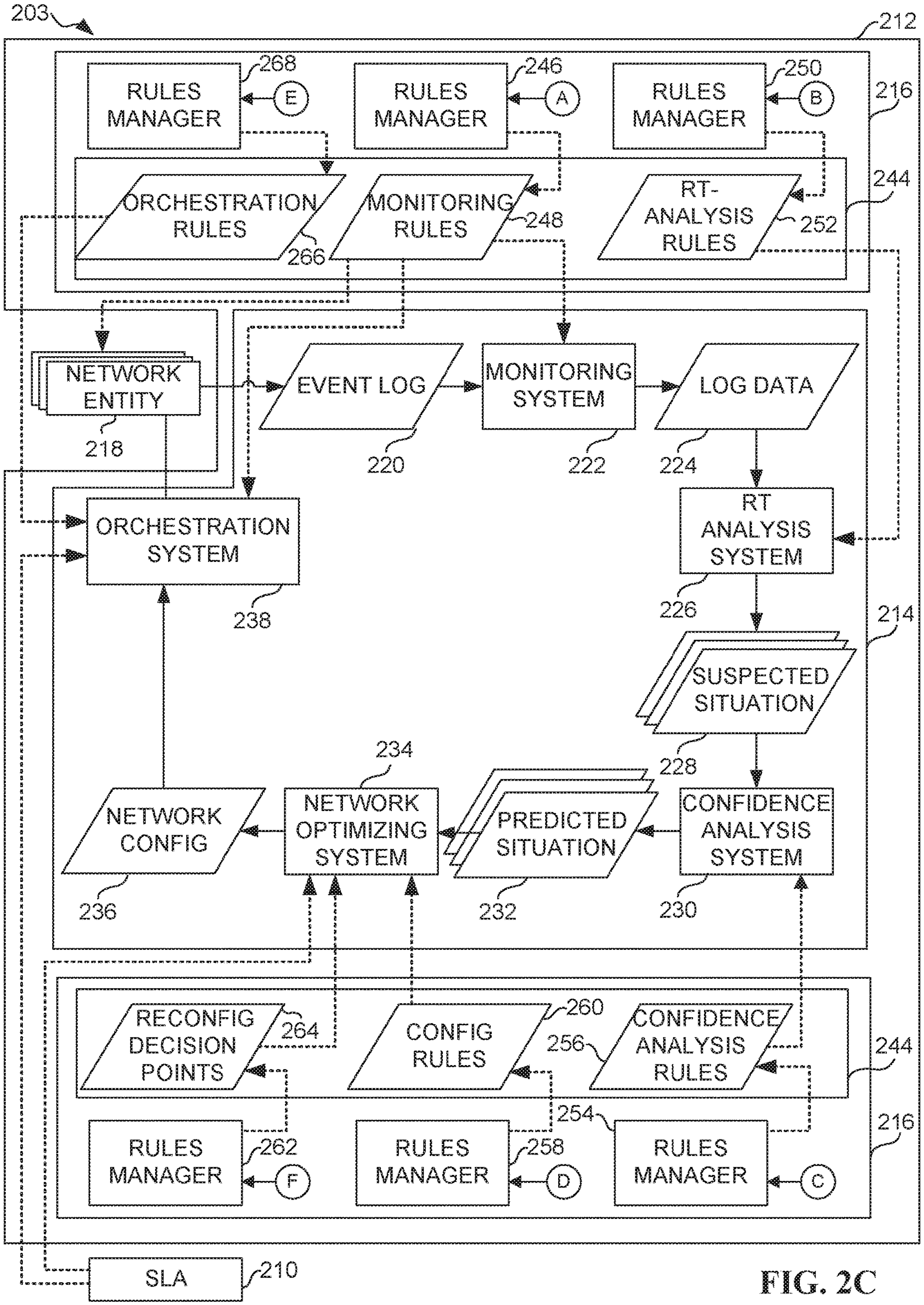
203
212
RULES MANAGER
268
E
RULES MANAGER
246
A
RULES MANAGER
250
B
216
ORCHESTRATION RULES
266
MONITORING RULES
248
RT-ANALYSIS RULES
252
244
NETWORK ENTITY
218
EVENT LOG
220
MONITORING SYSTEM
222
LOG DATA
224
ORCHESTRATION SYSTEM
238
RT ANALYSIS SYSTEM
226
214
SUSPECTED SITUATION
228
234
NETWORK CONFIG
236
NETWORK OPTIMIZING SYSTEM
PREDICTED SITUATION
232
CONFIDENCE ANALYSIS SYSTEM
230
RECONFIG DECISION POINTS
264
CONFIG RULES
260
256
CONFIDENCE ANALYSIS RULES
244
254
RULES MANAGER
262
F
RULES MANAGER
258
D
RULES MANAGER
C
216
SLA
210

FIG. 2C

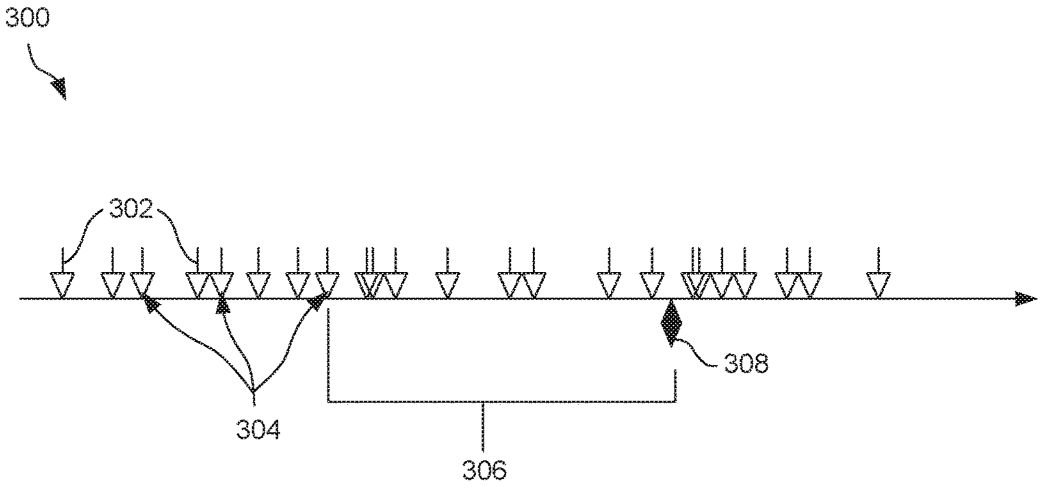

FIG. 3

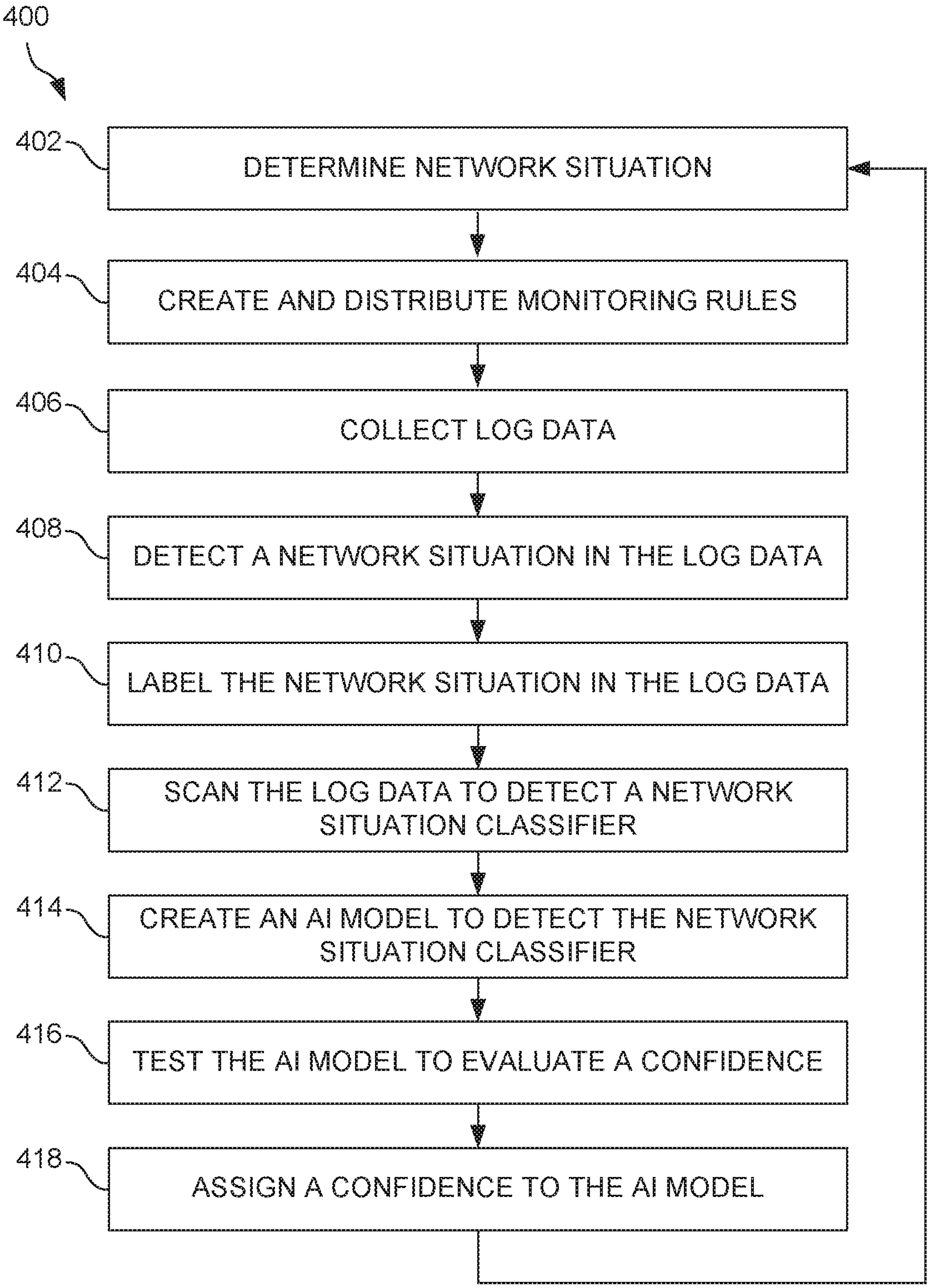
400
402
DETERMINE NETWORK SITUATION
404
CREATE AND DISTRIBUTE MONITORING RULES
406
COLLECT LOG DATA
408
DETECT A NETWORK SITUATION IN THE LOG DATA
410
LABEL THE NETWORK SITUATION IN THE LOG DATA
412
SCAN THE LOG DATA TO DETECT A NETWORK SITUATION CLASSIFIER
414
CREATE AN AI MODEL TO DETECT THE NETWORK SITUATION CLASSIFIER
416
TEST THE AI MODEL TO EVALUATE A CONFIDENCE
418
ASSIGN A CONFIDENCE TO THE AI MODEL

FIG. 4A

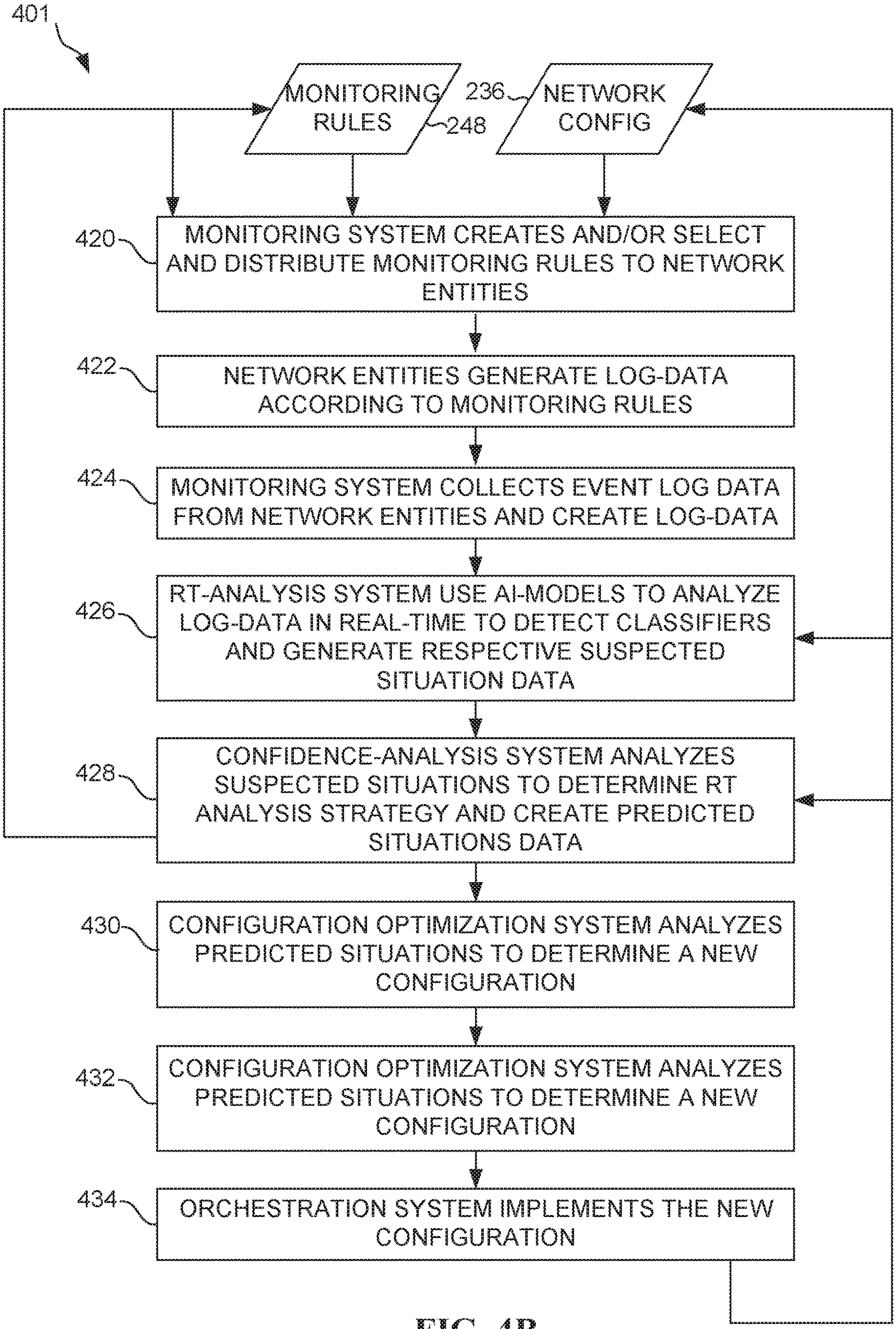
401
MONITORING RULES
248
236
NETWORK CONFIG
420
MONITORING SYSTEM CREATES AND/OR SELECT AND DISTRIBUTE MONITORING RULES TO NETWORK ENTITIES
422
NETWORK ENTITIES GENERATE LOG-DATA ACCORDING TO MONITORING RULES
424
MONITORING SYSTEM COLLECTS EVENT LOG DATA FROM NETWORK ENTITIES AND CREATE LOG-DATA
426
RT-ANALYSIS SYSTEM USE AI-MODELS TO ANALYZE LOG-DATA IN REAL-TIME TO DETECT CLASSIFIERS AND GENERATE RESPECTIVE SUSPECTED SITUATION DATA
428
CONFIDENCE-ANALYSIS SYSTEM ANALYZES SUSPECTED SITUATIONS TO DETERMINE RT ANALYSIS STRATEGY AND CREATE PREDICTED SITUATIONS DATA
430
CONFIGURATION OPTIMIZATION SYSTEM ANALYZES PREDICTED SITUATIONS TO DETERMINE A NEW CONFIGURATION
432
CONFIGURATION OPTIMIZATION SYSTEM ANALYZES PREDICTED SITUATIONS TO DETERMINE A NEW CONFIGURATION
434
ORCHESTRATION SYSTEM IMPLEMENTS THE NEW CONFIGURATION

FIG. 4B

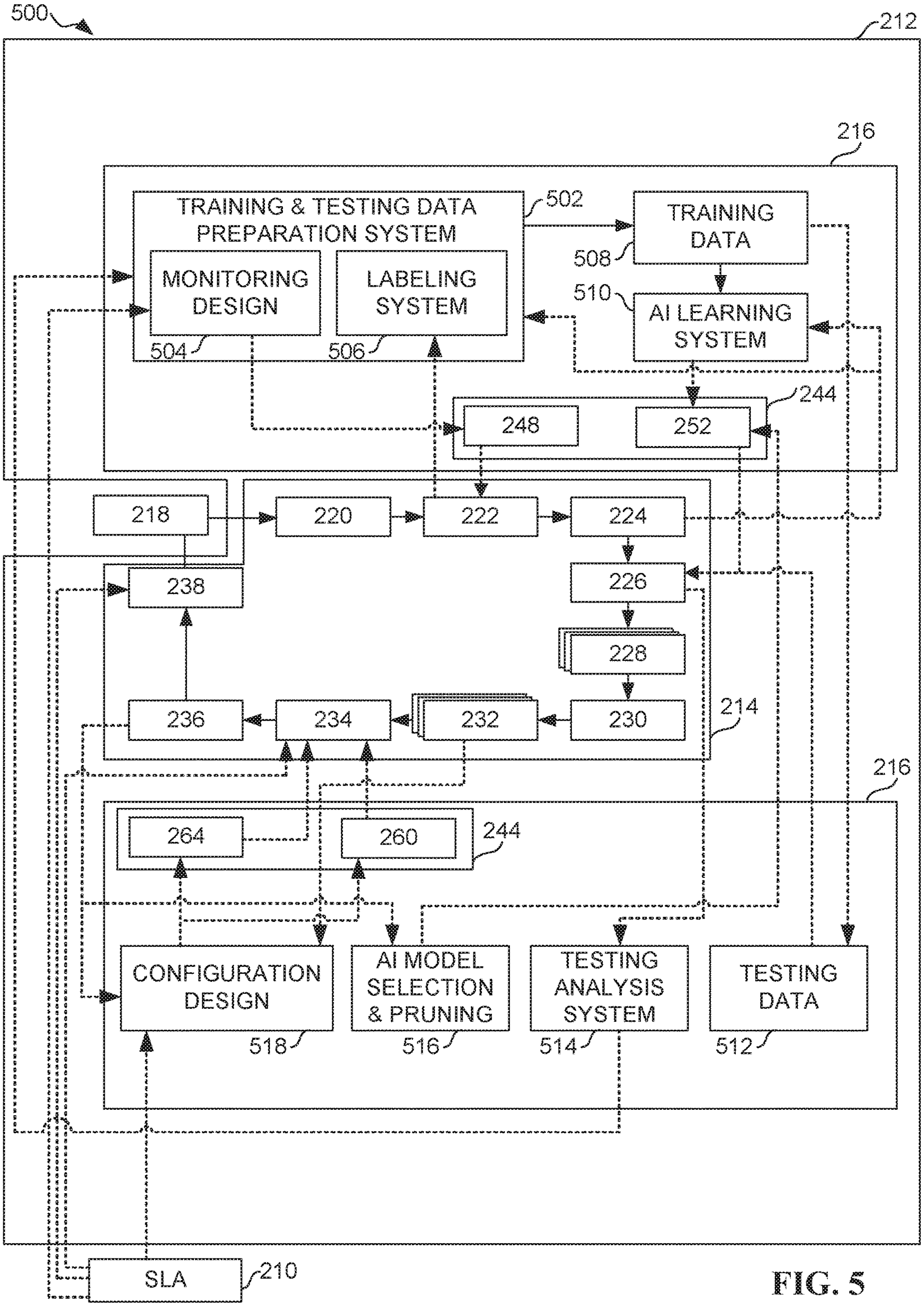
500
212
216
TRAINING & TESTING DATA PREPARATION SYSTEM
502
MONITORING DESIGN
504
LABELING SYSTEM
506
TRAINING DATA
508
510
AI LEARNING SYSTEM
244
248
252
218
220
222
224
226
228
230
232
234
236
238
214
216
264
260
244
CONFIGURATION DESIGN
518
AI MODEL SELECTION & PRUNING
516
TESTING ANALYSIS SYSTEM
514
TESTING DATA
512
SLA
210

FIG. 5

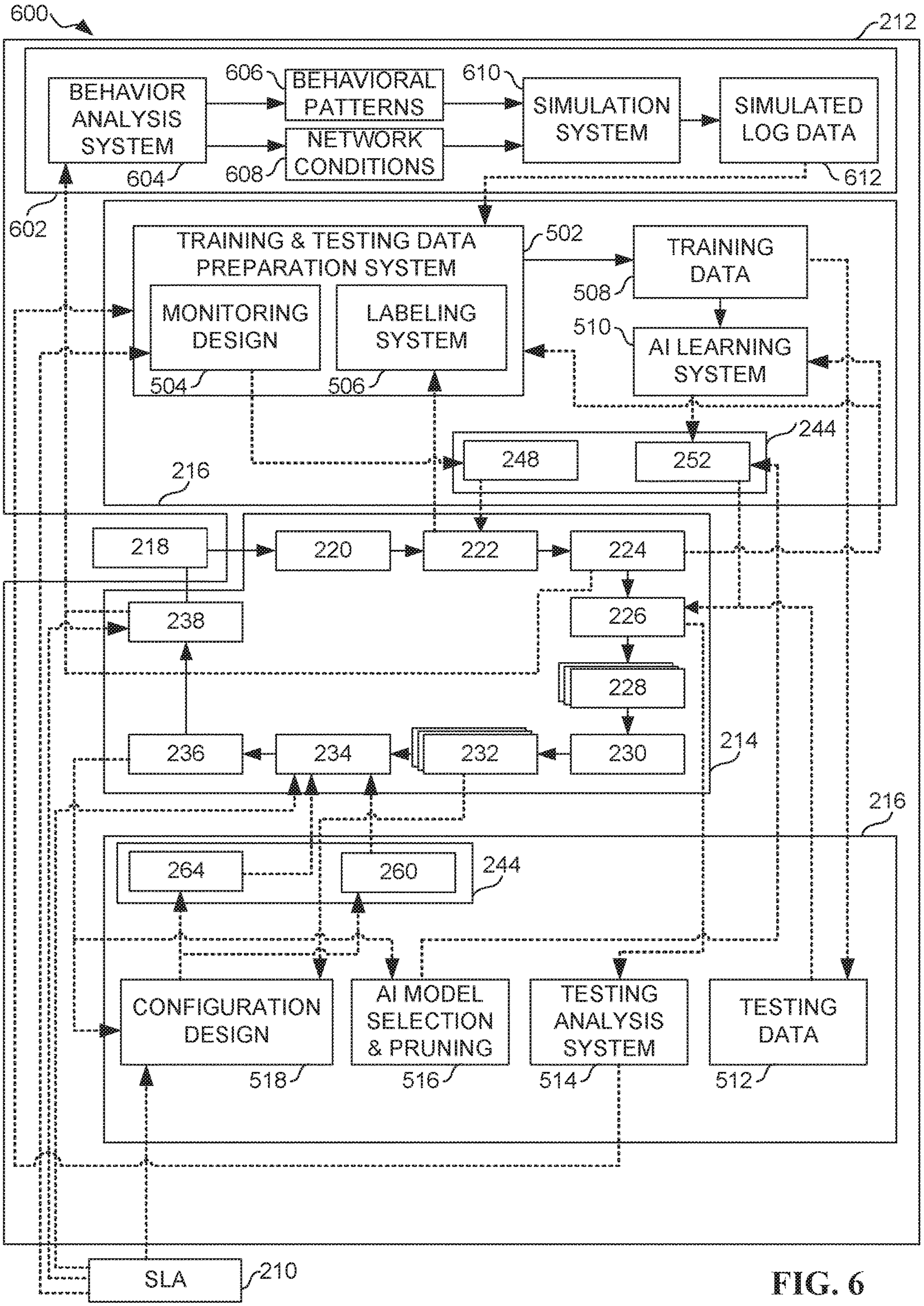
600
212
BEHAVIOR ANALYSIS SYSTEM
604
606
BEHAVIORAL PATTERNS
NETWORK CONDITIONS
608
610
SIMULATION SYSTEM
SIMULATED LOG DATA
612
602
TRAINING & TESTING DATA PREPARATION SYSTEM
502
MONITORING DESIGN
504
LABELING SYSTEM
506
TRAINING DATA
508
510
AI LEARNING SYSTEM
244
248
252
216
218
220
222
224
238
226
228
236
234
232
230
214
216
264
260
244
CONFIGURATION DESIGN
518
AI MODEL SELECTION & PRUNING
516
TESTING ANALYSIS SYSTEM
514
TESTING DATA
512
SLA
210

FIG. 6

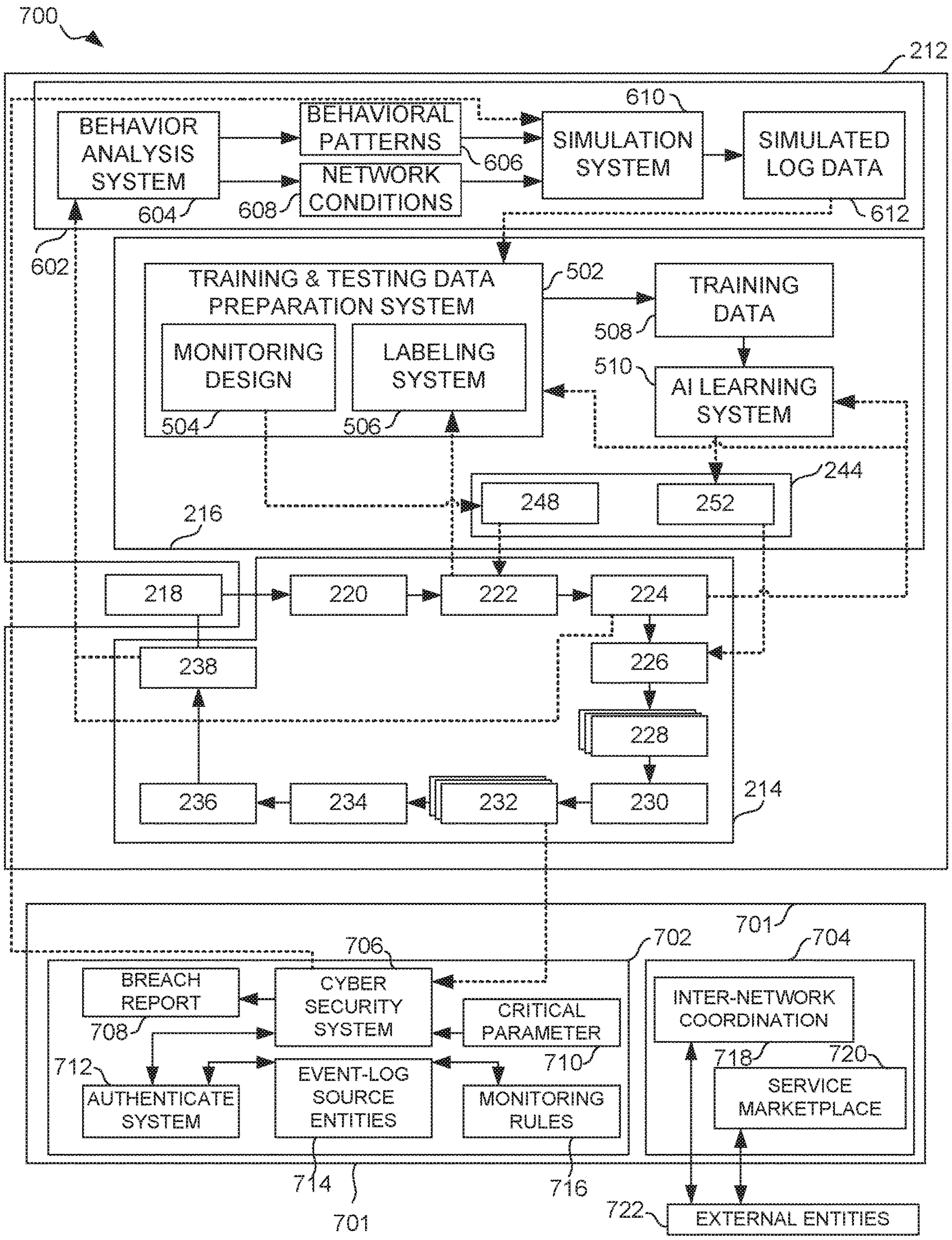
700
212
BEHAVIOR ANALYSIS SYSTEM
604
BEHAVIORAL PATTERNS
606
NETWORK CONDITIONS
608
610
SIMULATION SYSTEM
SIMULATED LOG DATA
612
602
TRAINING & TESTING DATA PREPARATION SYSTEM
502
MONITORING DESIGN
504
LABELING SYSTEM
506
TRAINING DATA
508
510
AI LEARNING SYSTEM
244
248
252
216
218
220
222
224
226
228
230
232
234
236
238
214
701
702
704
706
CYBER SECURITY SYSTEM
BREACH REPORT
708
CRITICAL PARAMETER
710
712
AUTHENTICATE SYSTEM
EVENT-LOG SOURCE ENTITIES
MONITORING RULES
714
716
701
INTER-NETWORK COORDINATION
718
720
SERVICE MARKETPLACE
722
EXTERNAL ENTITIES

FIG. 7

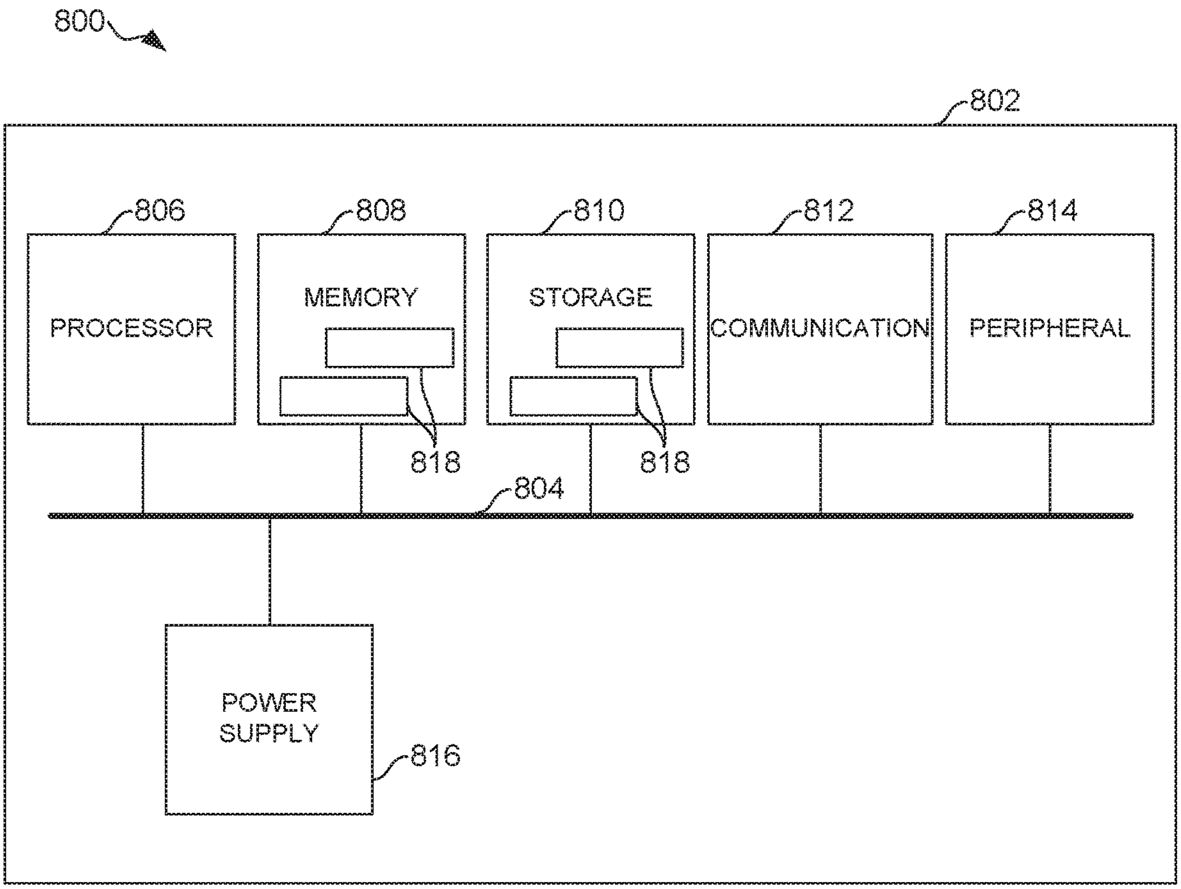
800
802
806
PROCESSOR
808
MEMORY
810
STORAGE
812
COMMUNICATION
814
PERIPHERAL
818
818
804
POWER SUPPLY
816

FIG. 8

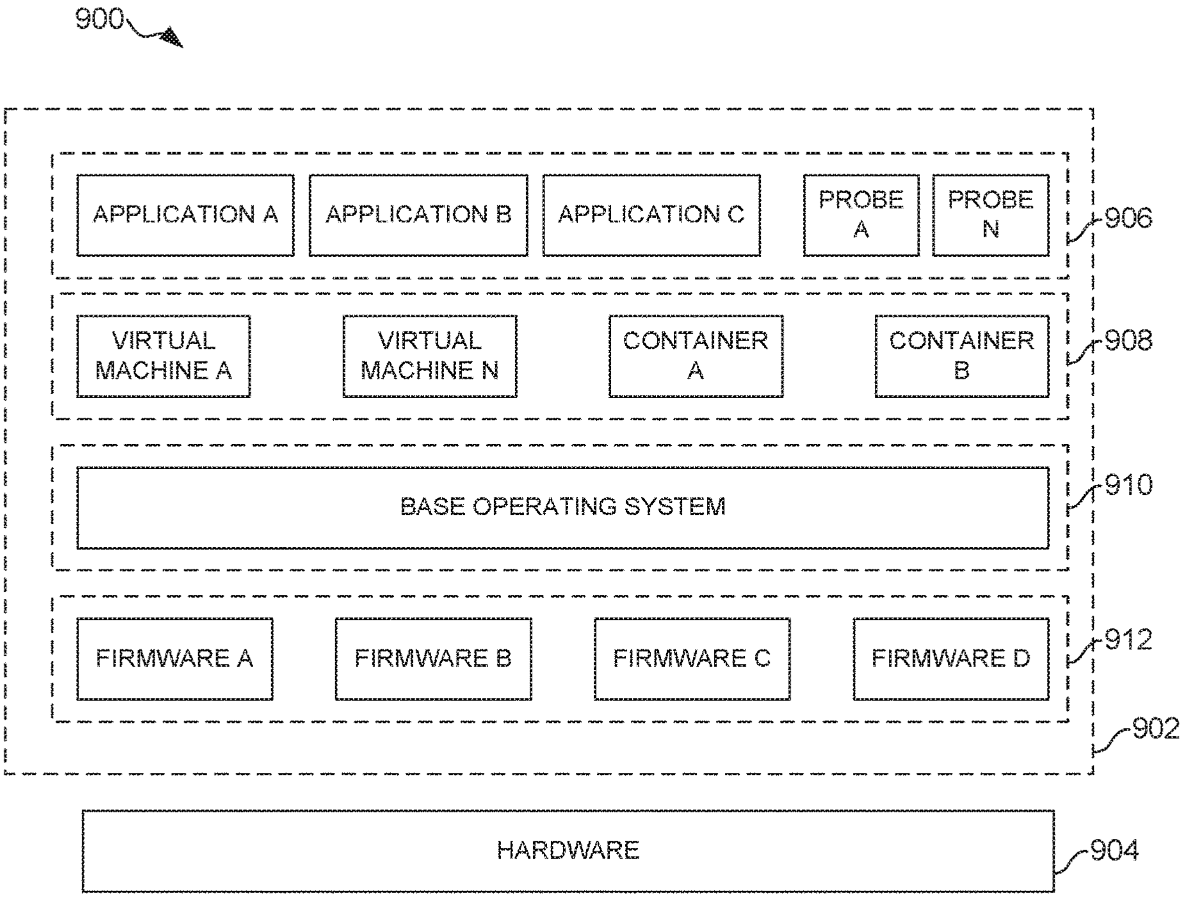
900
APPLICATION A
APPLICATION B
APPLICATION C
PROBE A
PROBE N
906
VIRTUAL MACHINE A
VIRTUAL MACHINE N
CONTAINER A
CONTAINER B
908
BASE OPERATING SYSTEM
910
FIRMWARE A
FIRMWARE B
FIRMWARE C
FIRMWARE D
912
902
HARDWARE
904

FIG. 9

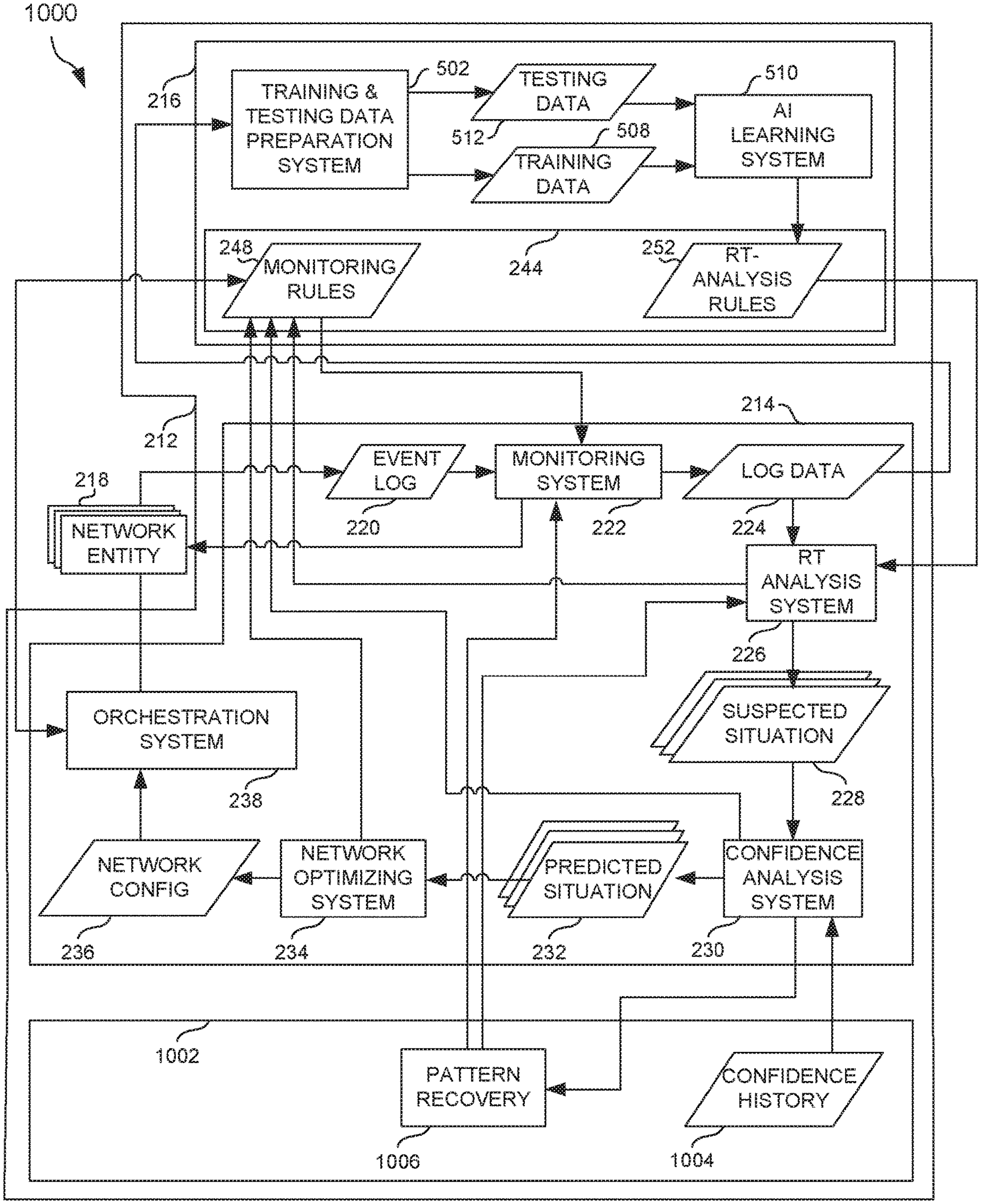
1000
216
TRAINING & TESTING DATA PREPARATION SYSTEM
502
TESTING DATA
512
TRAINING DATA
508
510
AI LEARNING SYSTEM
248
MONITORING RULES
244
252
RT-ANALYSIS RULES
212
214
218
NETWORK ENTITY
EVENT LOG
220
MONITORING SYSTEM
222
LOG DATA
224
RT ANALYSIS SYSTEM
226
SUSPECTED SITUATION
228
ORCHESTRATION SYSTEM
238
NETWORK CONFIG
236
NETWORK OPTIMIZING SYSTEM
234
PREDICTED SITUATION
232
CONFIDENCE ANALYSIS SYSTEM
230
1002
PATTERN RECOVERY
1006
CONFIDENCE HISTORY
1004

FIG. 10

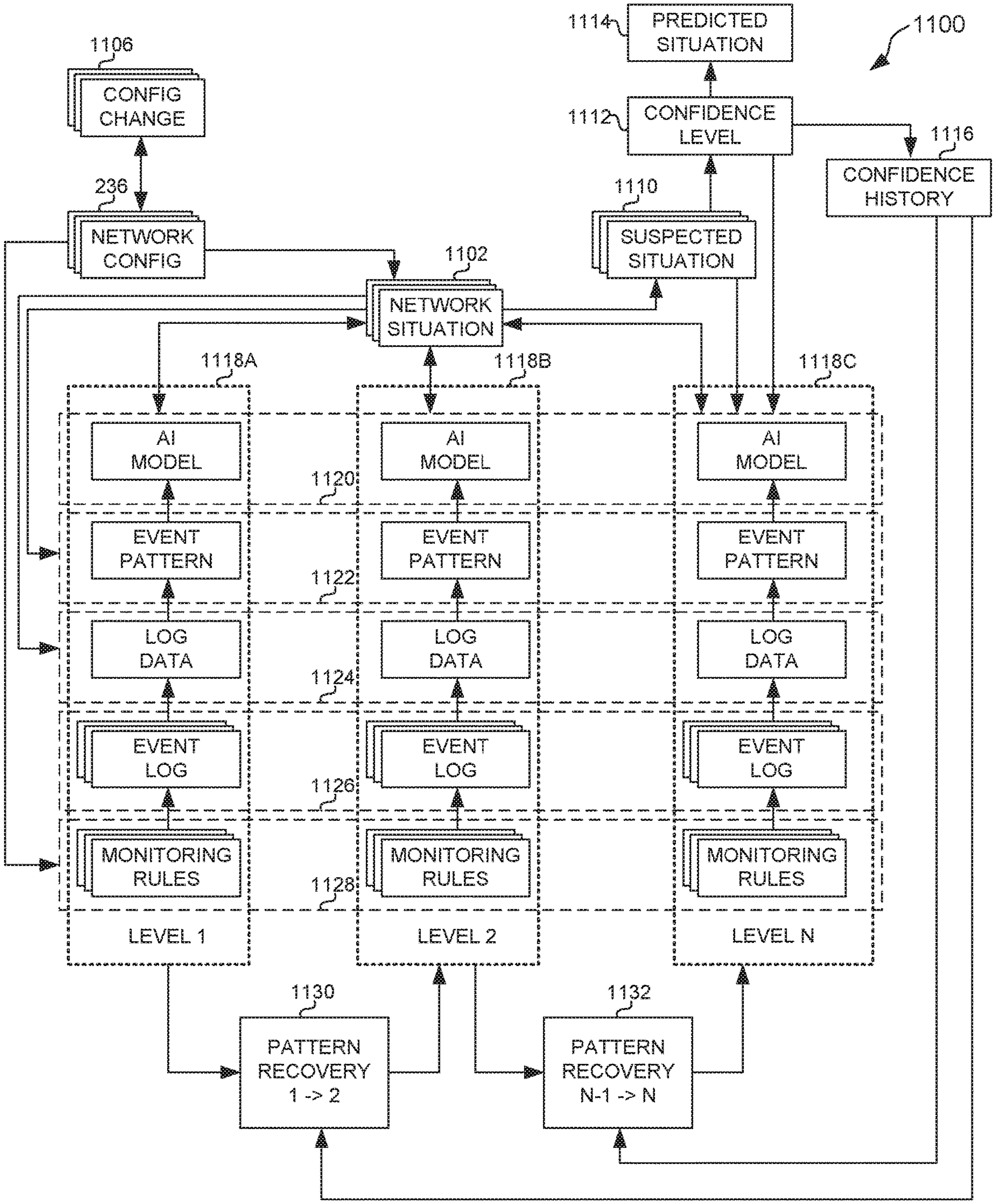
1100
1114
PREDICTED SITUATION
1112
CONFIDENCE LEVEL
1116
CONFIDENCE HISTORY
1106
CONFIG CHANGE
236
NETWORK CONFIG
1110
SUSPECTED SITUATION
1102
NETWORK SITUATION
1118A
1118B
1118C
AI MODEL
AI MODEL
AI MODEL
1120
EVENT PATTERN
EVENT PATTERN
EVENT PATTERN
1122
LOG DATA
LOG DATA
LOG DATA
1124
EVENT LOG
EVENT LOG
EVENT LOG
1126
MONITORING RULES
MONITORING RULES
MONITORING RULES
1128
LEVEL 1
LEVEL 2
LEVEL N
1130
PATTERN RECOVERY 1 -> 2
1132
PATTERN RECOVERY N-1 -> N

FIG. 11

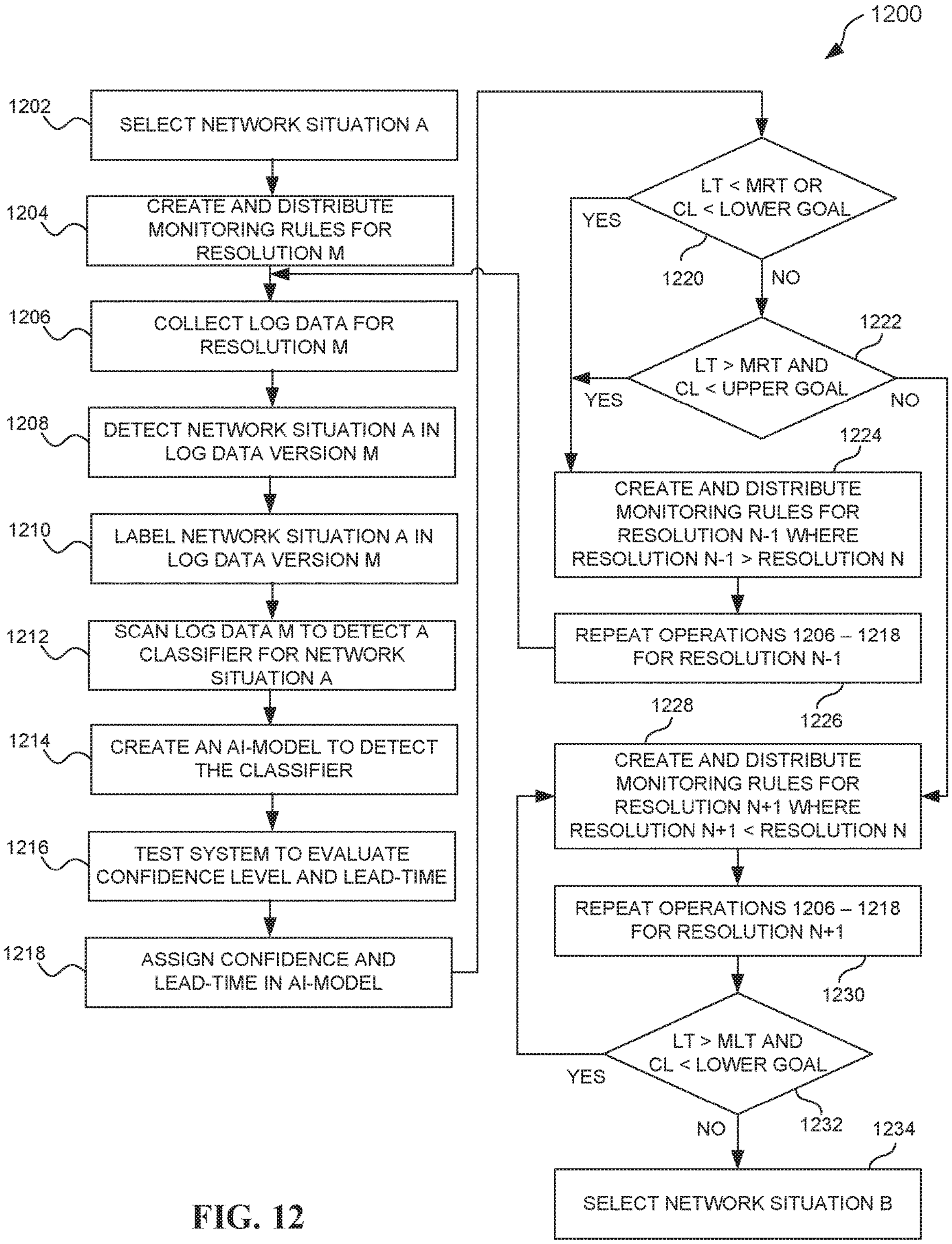
1200
1202
SELECT NETWORK SITUATION A
1204
CREATE AND DISTRIBUTE MONITORING RULES FOR RESOLUTION M
1206
COLLECT LOG DATA FOR RESOLUTION M
1208
DETECT NETWORK SITUATION A IN LOG DATA VERSION M
1210
LABEL NETWORK SITUATION A IN LOG DATA VERSION M
1212
SCAN LOG DATA M TO DETECT A CLASSIFIER FOR NETWORK SITUATION A
1214
CREATE AN AI-MODEL TO DETECT THE CLASSIFIER
1216
TEST SYSTEM TO EVALUATE CONFIDENCE LEVEL AND LEAD-TIME
1218
ASSIGN CONFIDENCE AND LEAD-TIME IN AI-MODEL
LT < MRT OR CL < LOWER GOAL
YES
1220
NO
1222
LT > MRT AND CL < UPPER GOAL
YES
NO
1224
CREATE AND DISTRIBUTE MONITORING RULES FOR RESOLUTION N-1 WHERE RESOLUTION N-1 > RESOLUTION N
REPEAT OPERATIONS 1206 – 1218 FOR RESOLUTION N-1
1228
1226
CREATE AND DISTRIBUTE MONITORING RULES FOR RESOLUTION N+1 WHERE RESOLUTION N+1 < RESOLUTION N
REPEAT OPERATIONS 1206 – 1218 FOR RESOLUTION N+1
1230
LT > MLT AND CL < LOWER GOAL
YES
NO
1232
1234
SELECT NETWORK SITUATION B

FIG. 12

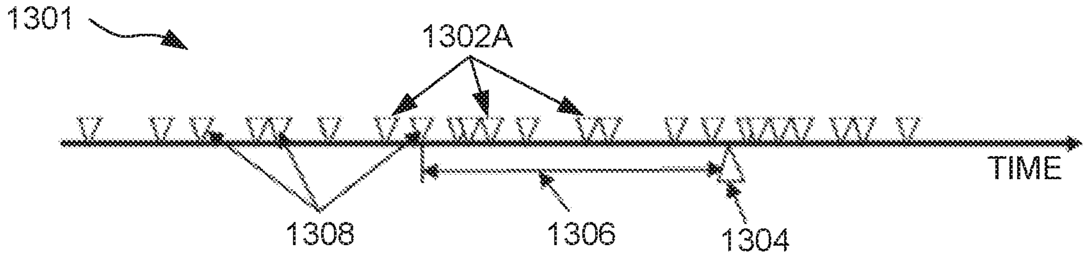

FIG. 13A

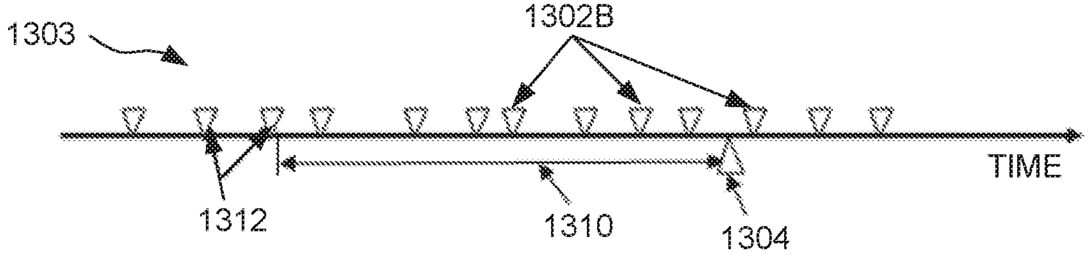

FIG. 13B

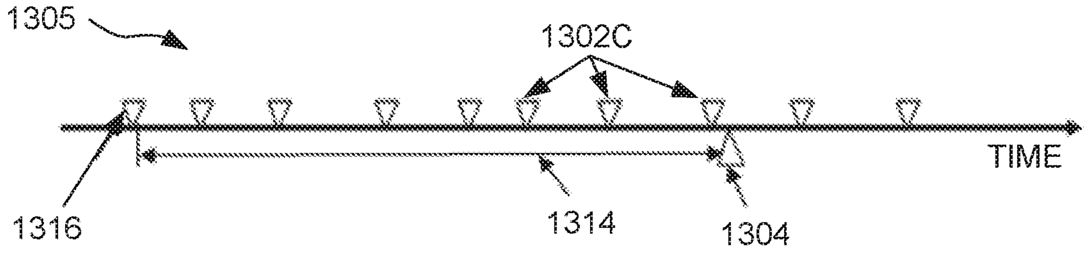

FIG. 13C

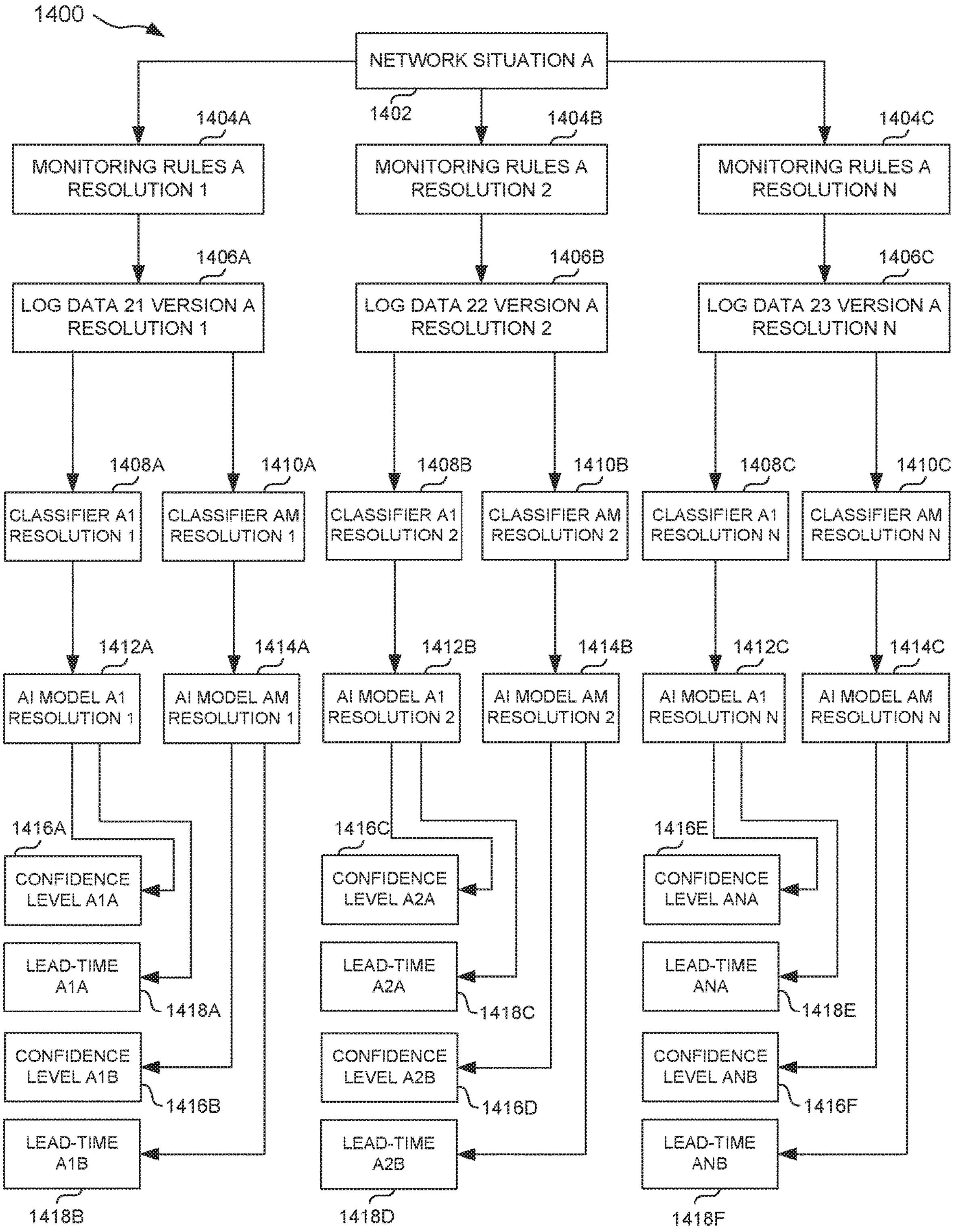
1400
NETWORK SITUATION A
1402
1404A
MONITORING RULES A RESOLUTION 1
1404B
MONITORING RULES A RESOLUTION 2
1404C
MONITORING RULES A RESOLUTION N
1406A
LOG DATA 21 VERSION A RESOLUTION 1
1406B
LOG DATA 22 VERSION A RESOLUTION 2
1406C
LOG DATA 23 VERSION A RESOLUTION N
1408A
CLASSIFIER A1 RESOLUTION 1
1410A
CLASSIFIER AM RESOLUTION 1
1408B
CLASSIFIER A1 RESOLUTION 2
1410B
CLASSIFIER AM RESOLUTION 2
1408C
CLASSIFIER A1 RESOLUTION N
1410C
CLASSIFIER AM RESOLUTION N
1412A
AI MODEL A1 RESOLUTION 1
1414A
AI MODEL AM RESOLUTION 1
1412B
AI MODEL A1 RESOLUTION 2
1414B
AI MODEL AM RESOLUTION 2
1412C
AI MODEL A1 RESOLUTION N
1414C
AI MODEL AM RESOLUTION N
1416A
CONFIDENCE LEVEL A1A
LEAD-TIME A1A
1418A
CONFIDENCE LEVEL A1B
1416B
LEAD-TIME A1B
1418B
1416C
CONFIDENCE LEVEL A2A
LEAD-TIME A2A
1418C
CONFIDENCE LEVEL A2B
1416D
LEAD-TIME A2B
1418D
1416E
CONFIDENCE LEVEL ANA
LEAD-TIME ANA
1418E
CONFIDENCE LEVEL ANB
1416F
LEAD-TIME ANB
1418F

FIG. 14

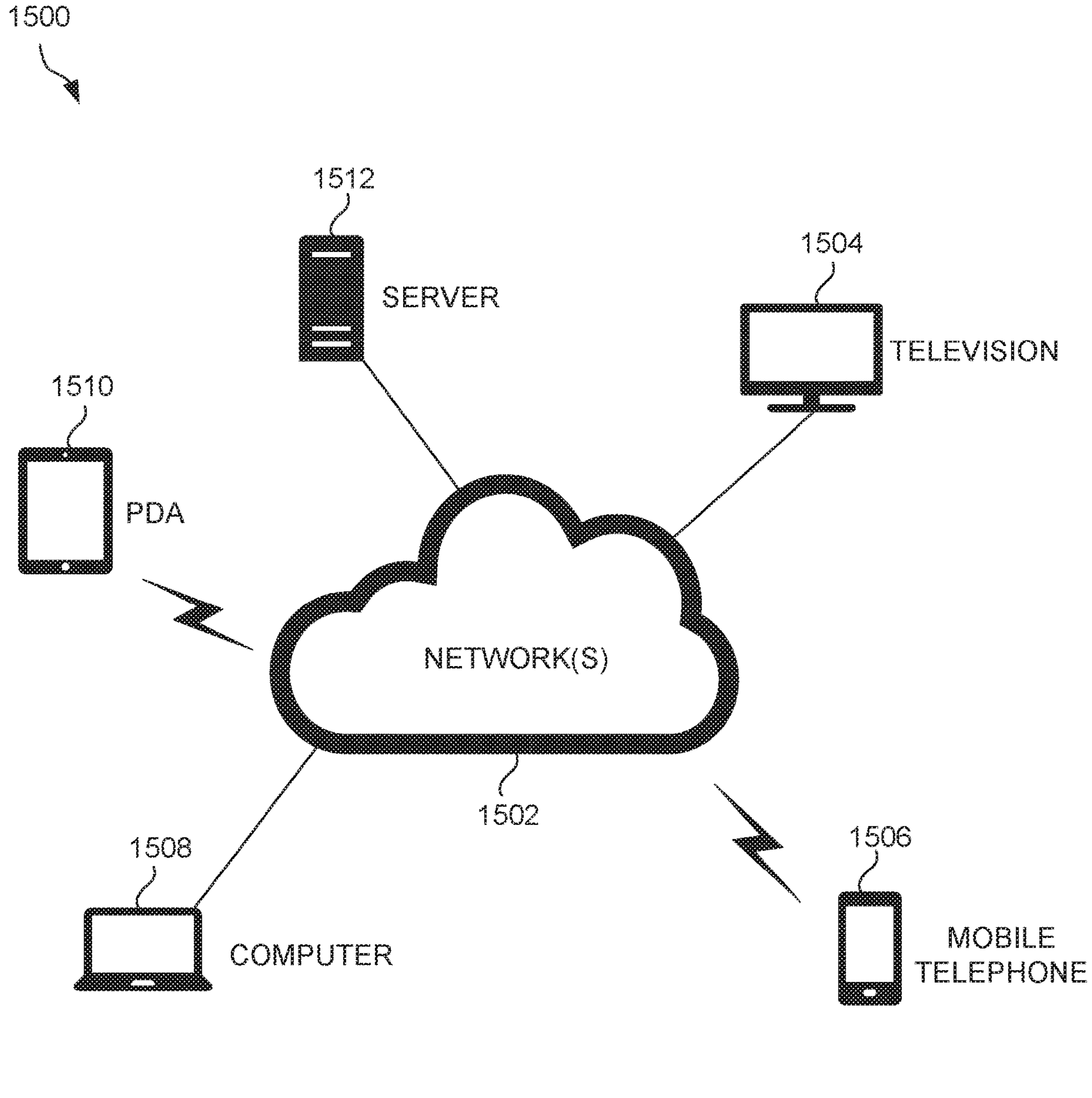
1500
1512
SERVER
1504
TELEVISION
1510
PDA
NETWORK(S)
1502
1508
COMPUTER
1506
MOBILE
TELEPHONE

FIG. 15

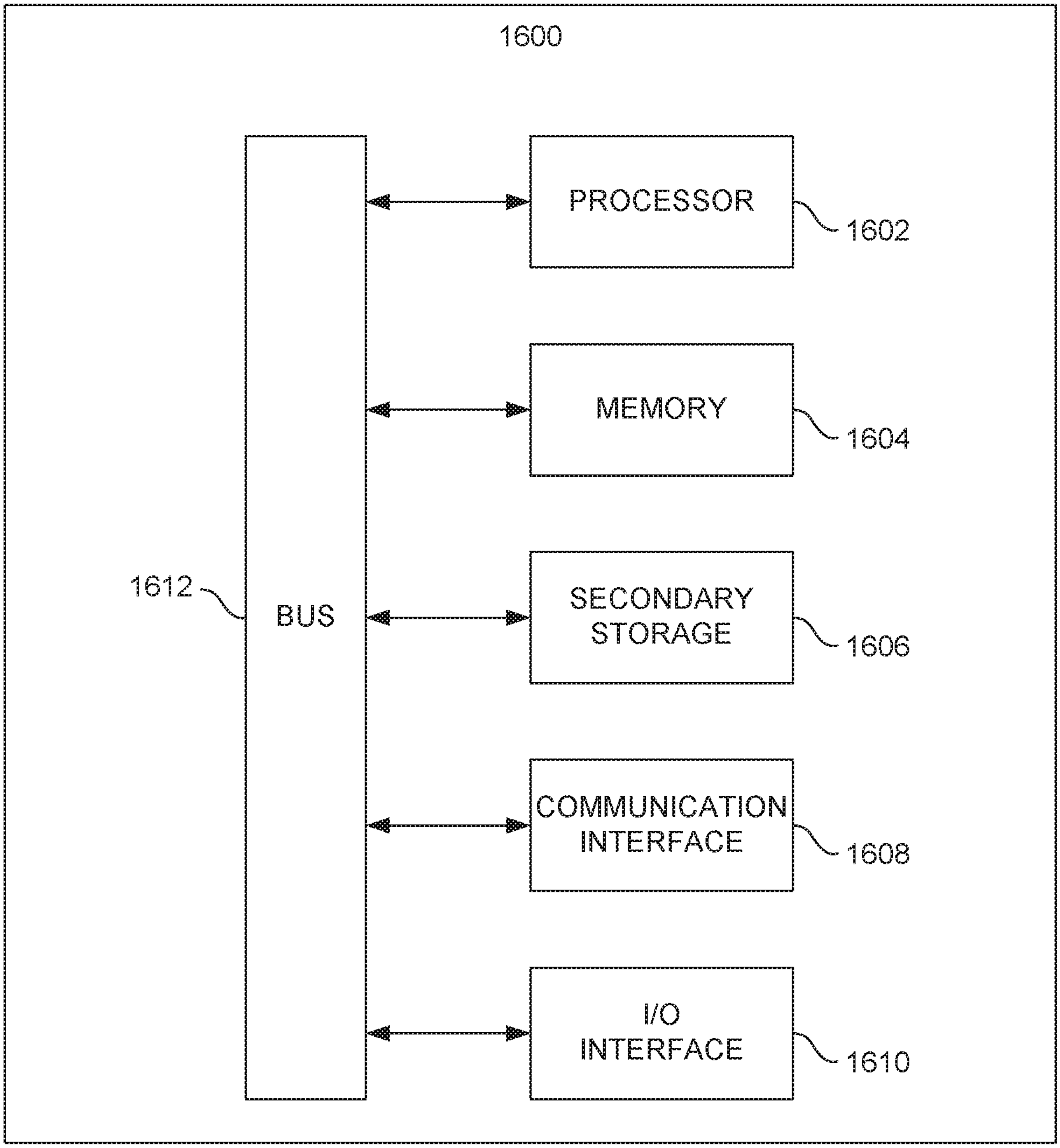
1600
PROCESSOR
1602
MEMORY
1604
1612
BUS
SECONDARY STORAGE
1606
COMMUNICATION INTERFACE
1608
I/O INTERFACE
1610

FIG. 16

SYSTEM, METHOD, AND COMPUTER PROGRAM FOR PREPARING A MULTI-STAGE FRAMEWORK FOR ARTIFICIAL INTELLIGENCE (AI) ANALYSIS

RELATED APPLICATIONS

The present application claims priority to: U.S. Provisional Application No. 62/639,910, entitled "SYSTEM, METHOD, AND COMPUTER PROGRAM FOR IMPLEMENTING PRUNING RULES IN AN ARTIFICIAL INTELLIGENCE (AI) BASED NETWORK MANAGEMENT SYSTEM," filed on Mar. 7, 2018; U.S. Provisional Application No. 62/639,913, entitled "SYSTEM, METHOD, AND COMPUTER PROGRAM FOR DAMPING A FEEDBACK LOAD-CHANGE IN A COMMUNICATION NETWORK MANAGED BY AN AUTOMATIC NETWORK MANAGEMENT SYSTEM," filed on Mar. 7, 2018; U.S. Provisional Application No. 62/639,923, entitled "SYSTEM, METHOD, AND COMPUTER PROGRAM FOR IMPLEMENTING A MARKETPLACE FOR ARTIFICIAL INTELLIGENCE (AI) BASED MANAGED NETWORK SERVICES," filed on Mar. 7, 2018; U.S. Provisional Application No. 62/642,524, entitled "A METHOD AND A SYSTEM FOR MITIGATING AN ATTACK ON A NETWORK BY EFFECTING FALSE ALARMS," filed on Mar. 13, 2018; U.S. Provisional Application No. 62/648,281, entitled "SYSTEM, METHOD, AND COMPUTER PROGRAM FOR AUTOMATICALLY GENERATING TRAINING DATA FOR ANALYZING A NEW CONFIGURATION OF A COMMUNICATION NETWORK," filed on Mar. 26, 2018; U.S. Provisional Application No. 62/648,287, entitled "SYSTEM, METHOD, AND COMPUTER PROGRAM FOR IMPLEMENTING A MARKETPLACE FOR EDGE COMPUTING," filed on Mar. 26, 2018; and U.S. Provisional Application No. 62/660,142, entitled "SYSTEM, METHOD, AND COMPUTER PROGRAM FOR MITIGATING FALSIFIED LOG DATA PROVIDED TO AN AI-LEARNING SYSTEM MANAGING A COMMUNICATION NETWORK," filed on Apr. 19, 2018, the entire contents of each of the listed applications which are incorporated herein by reference.

FIELD OF THE INVENTION

The present invention relates to telecommunications and/or data communications, and more particularly to network management using multi-stage artificial intelligence (AI) analysis of log-data.

BACKGROUND

A communication network may include network entities (such as hardware components) and software components (such as virtual network functions (VNFs)), which may be reconfigured as needed. To predict situations requiring network reconfiguration, however, a network management system may use log-data collected from as many network entities as possible.

An artificial intelligence (AI) part of a network management system may include two main parts: an AI learning system and a real-time, or run-time, (RT) analysis system. The AI learning system may create at least one AI-model that the RT-analysis system may use to detect respective network situations requiring a network reconfiguration. Such AI model may analyze log-data as it is being collected.

The ability to detect a network situation, or a classifier predicting a network situation, in time to implement the required network configuration, may depend on the amount of detail associated with the analyzed log-data. However, reporting detailed log-data by each network entity, collecting and managing the detailed log-data, and analyzing the detailed log data may involve heavy load processing, communication, and storage.

As such, there is thus a need for addressing these and/or other issues associated with the prior art.

SUMMARY

A system, method, and computer program product are provided for preparing a multi-stage framework for artificial intelligence (AI) analysis. In use, a first set of monitoring rules used by at least one network entity of a communication network is defined. First event log data of first network activity is collected based on the first monitoring rules, and at least one first network situation is defined. Additionally, at least one first AI model is computed based on the first event log data and the at least one first network situation. A second set of monitoring rules used by the at least one network entity is defined. Second event log data of the first network activity is collected based on the second monitoring rules. Further, at least one second AI model is computed based on the second event log data and the at least one first network situation.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** illustrates a method for preparing a multi-stage framework for artificial intelligence (AI) analysis, in accordance with one embodiment.

FIG. **2**A illustrates a communication network and network management system, in accordance with one embodiment.

FIG. **2**B illustrates a network management system, in accordance with one embodiment.

FIG. **2**C illustrates a network management system, in accordance with one embodiment.

FIG. **3** illustrates an event-log timeline, in accordance with one embodiment.

FIG. **4**A illustrates a method for processing log data, in accordance with one embodiment.

FIG. **4**B illustrates a method of a run time process using an AI-model, in accordance with one embodiment.

FIG. **5** illustrates a network management system, in accordance with one embodiment.

FIG. **6** illustrates a network management system, in accordance with one embodiment.

FIG. **7** illustrates a system, in accordance with one embodiment.

FIG. **8** illustrates a block diagram, in accordance with one embodiment.

FIG. **9** illustrates a block diagram of software programs, in accordance with one embodiment.

FIG. **10** illustrates a multi-stage analysis system, in accordance with one embodiment.

FIG. **11** illustrates a data structure, in accordance with one embodiment.

FIG. **12** illustrates a method for multi-stage monitoring and learning, in accordance with one embodiment.

FIG. **13**A illustrates a timeline, in accordance with one embodiment.

FIG. **13**B illustrates a timeline, in accordance with one embodiment.

FIG. **13**C illustrates a timeline, in accordance with one embodiment.

FIG. **13**A illustrates a timeline, in accordance with one embodiment.

FIG. **14** illustrates a data structure produced by a multi-stage monitoring and learning system, in accordance with one embodiment.

FIG. **15** illustrates a network architecture, in accordance with one possible embodiment.

FIG. **16** illustrates an exemplary system, in accordance with one embodiment.

DETAILED DESCRIPTION

A modern public digital communication network provides many communication-related services to a very large number of customers where each customer may use a variety of services. Additionally, each service may be used by each customer in a variety of ways. In one embodiment, the business needs of many customers may rapidly change, thereby affecting the manner in which the communication services may be used. As such, business dynamics (and especially increasing business dynamics) may affect the network dynamics, as well as the configuration of the network and the network's services.

One purpose of Network Function Virtualization (NFV) is to implement as many functions of the network as software running over a generic computer. As such, a virtual(ized) network function (VNF) can be instantiated almost anywhere on the network, based on a network/cluster of generic computers. This ability to instantiate VNFs allows network functions to be migrated throughout the network, which in turn, may lead to network reconfiguration. Additionally, fast migration and network reconfiguration may provide cost savings in both capital spending (CAPEX) and operational spending (OPEX).

In the context of the present description, the term "cost" may refer to any type of expenditure (such as associated with increased capital expenditure (CAPEX), and/or increased operational expenditure (OPEX)), as well as decreased revenues or a limitation on revenue increase. In one embodiment, OPEX may include, for example, a cost of electricity to power any network entity and/or dissipate heat resulting from the operation of any network entity. Additionally, OPEX may also include payment to any third party for using any type of hardware and/or software, including processing power, storage, transmission, etc.

Further, in the context of the present description, the term service configuration" may refer to a network configuration applicable for a particular service. Such particular service may be requested by, and/or proposed to, a particular customer (herein referred to as "requesting party"), for a specific time period, locality, and/or business structure. As such, a service configuration may apply to an entire basis or subset of a communication network(s).

For example, instead of planning a network to a combined worst case (such as a highest expected cumulative demand), CAPEX can be reduced by more accurately planning the network according to an optimized, time-dependent configuration. Thereafter, OPEX can be reduced in periods of low demand by migrating the operating VNFs to one or more central locations and shutting down unused data centers. This cost saving may be one the driving forces behind NFV. Therefore, fast and effective reconfiguration of the network may be a key element in the evolution of NFV and the telecom market.

In addition, the ability to reconfigure the network quickly (and cost effectively) may enable network operators to introduce new services faster, reduce time-to-market, and reduce onboarding costs. Fast and automatic reconfiguration also enable customers to place a demand for a service (e.g., a service level agreement or SLA) shortly before actual use, and request the service for a limited time. Together, fast and automatic reconfiguration may reduce the time and cost of doing business between network operators, operators of software service(s), and/or customers (such as consumers).

The network may be expected to adapt to a constant flow of service demands by continuously optimizing and reconfiguring the network. An optimized network (configuration) may include a network that runs close to its current maximum capacity while providing all required services (based on service level agreements (SLAs) or a similar form of service requirements definition). As the actual (real-time) demand changes, the network configuration may be changed, both by adding or removing infrastructure (e.g., turning hardware on or off), and by migrating and instantiating, or removing VNFs.

The network management system should be able to predict situations requiring network reconfiguration early enough to enable the network to compute the optimized new configuration and effect (orchestrate) it before the actual need arises. Due to the network complexity and the speed of change of demands, the use of artificial intelligence (AI) may be required to meet such a technical demand.

As such, the network management system may generally relate to telecommunications and/or data communications, and, more particularly to the management of a telecommunication network and/or a data network, and, more particularly to network management using artificial intelligence (AI).

In various embodiments, methods and systems disclosed herein may be used to manage the reporting, collecting, and analyzing of system log-data to provide log data as needed. In another embodiment, the methods and systems disclosed herein may be used to create a plurality of levels associated with network reporting, and to create detection mechanisms (such as AI models), where each reporting level and detection mechanism may enable detection of an appropriate network situation. Additionally, in one embodiment, the methods and systems disclosed herein may be used to create a multi-stage reporting and analysis mechanism, where lower resolution (less detailed) stages do not load the system, and higher resolution (more detailed) stages may provide a higher level of confidence to detect a potential or actual network situation. In other words, the multi-stage system may enable managing in real-time a mix of log-data resolutions to provide high confidence detection of network situations at a predetermined (processing communication and/or storage) load.

FIG. **1** illustrates a method **100** for preparing a multi-stage framework for artificial intelligence (AI) analysis, in accordance with one embodiment. As shown, a first set of monitoring rules used by at least one network entity of a communication network is defined, wherein the first set of monitoring rules generate higher-resolution first event log data. See operation **102**. In the context of the present description, a resolution refers to a density of event logs, and/or a number of event logs per a predetermined space of time. As such, a higher resolution may refer to a higher density of event logs, and a lower resolution may refer to a lower density of event logs.

Additionally, the first event log data of first network activity of the communication network is collected based on the first monitoring rules. See operation **104**. In the context of the present description, event log data may include one or more values for parameters relating to a performance of a communication network and/or to one or more network entities. Further, at least one first network situation is defined. See operation **106**. In the context of the present description, a network situation may refer to a condition of a communication network that may require a configuration change, or a network reconfiguration.

In addition, at least one first artificial intelligence (AI) model is computed based on the first event log data and the at least one first network situation. See operation **108**. In the context of the present description, an AI model may refer to any collection of rules generated by an AI-learning system.

In one embodiment, the at least one first AI model may be used to detect the first network activity. In an additional embodiment, the first AI model may detect a first classifier preceding the first network situation, where the first classifier includes at least one first parameter found in first prior event log data collected before the first network situation by a first time period.

Additionally, using the first AI model, the first network activity may be detected, a confidence level for the detection may be computed, and it may be determined that the confidence level exceeds a predetermined threshold. Further, in response to the determination that the confidence level exceeds the predetermined threshold, a third set of monitoring rules used by the at least one network entity may be defined, third event log data of the first network activity of the communication network based on the third monitoring rules may be collected, at least one first network situation may be determined, and at least one third AI model based on the third event log data and the at least one first network situation may be computed.

Moreover, using the first AI model, the first network activity may be detected, a confidence level for the detection may be computed, and it may be determined that the confidence level is below a predetermined threshold. Further, in response to the determination that the confidence level is below the predetermined threshold, a third set of monitoring rules used by the at least one network entity may be defined, third event log data of first network activity of the communication network based on the third monitoring rules may be collected, and at least one third AI model based on the third event log data and the at least one first network situation may be computed.

Still yet, using the first AI model, a first classifier may be detected which precedes the first network situation, where the first classifier includes at least one first parameter found in first prior event log data collected before the first network situation by a first time period. Additionally, a first confidence may be computed based on the detection, wherein the first confidence level represents a probability of the first network situation.

A second set of monitoring rules used by the at least one network entity is defined, wherein the second set of monitoring rules generate lower-resolution second event log data. See operation **110**. In one embodiment, the lower resolution rule may include a resolution lower than the higher resolution rule.

Furthermore, the second event log data of the first network activity of the communication network is collected based on the second monitoring rules. See operation **112**. In one embodiment, a number of data elements of the second event log data may be less than a number of data elements of the first event log data.

Moreover, at least one second AI model based on the second event log data and the at least one first network situation is computed. See operation **114**. In one embodiment, the at least one second AI model may be used to detect the first network activity. In another embodiment, the second AI model may detect a classifier preceding the first network situation, where the second classifier includes at least one second parameter found in second prior log data collected before the first network situation by a second time period. Additionally, the first time period may be smaller than the second time period.

Additionally, using the second AI model, the first network activity may be detected, a confidence level for the detection may be computed, it may be determined that the confidence level exceeds a predetermined threshold. Further, in response to the determination that the confidence level exceeds the predetermined threshold, a third set of monitoring rules used by the at least one network entity may be defined, third event log data of first network activity of the communication network based on the third monitoring rules may be collected, at least one third AI model based on the third event log data and the at least one first network situation may be computed.

Moreover, using the second AI model, the first network activity may be detected, a confidence level for the detection may be computed, and it may be determined that the confidence level is below a predetermined threshold. In response to the determination that the confidence level is below the predetermined threshold, a third set of monitoring rules used by the at least one network entity may be defined, third event log data of the first network activity of the communication network based on the third monitoring rules may be collected, and at least one third AI model based on the third event log data and the at least one first network situation may be computed.

Still yet, using the second AI model, a second classifier may be detected which precedes second first network situation, where the second classifier includes at least one second parameter found in second prior event log data collected before the first network situation by a second time period. Additionally, a second confidence may be computed based on the detection, wherein the second confidence level represents a probability of the first network situation.

FIG. **2**A illustrates a communication network and network management system **200**, in accordance with one embodiment. As an option, the network management system **200** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the network management system **200** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

In one embodiment, the communication network and network management system **200** may relate to managing a communication network using artificial intelligence (AI).

As shown, the network management system **200** includes a communication network **202**, one or more secondary networks **204**, a network management system **212** including a run-time module **214** and a deep system module **216**. In one embodiment, the one or more secondary networks **204** may be communicatively coupled to the communication network **202**.

Communication network **202**, and/or any of the one or more secondary networks **204** may be associated with one or more service operators **206** (such as operators of third-party services such as software as a service (SaaS)), customers (such as communication customers **208** and/or consumers using the services of communication network **202** or any of the software services of service operators **206**). In one embodiment, a customer of the communication network **202** may be a service operator (such as service operators **206**) or a service consumer (such as the communication customers **208**). Both the service operator or the service consumer may use services of the communication network **202**, as well as services provided by a service provider. Further, the communication network **202** may be connected directly to the network management system **212**, and/or may be connected to one or more network entities **218**.

In one embodiment, the service operators **206** and/or the communication customers **208** may have an arrangement and/or agreement with an operator of communication network **202**, such as one or more service level agreements (SLAs) **210**, which may define various parameters of the service(s) provided by communication network **202**.

In the context of the present description, the term "communication network", and/or simply "network", may refer to any type of network, including analog and/or digital communication networks, wired and/or wireless communication networks, wide area network (WAN), local area network (LAN), personal area network (PAN), etc., as well as combinations thereof. For example, network may refer to a public service telephony network (PSTN), a public service data network (PSDN), a public land mobile network (PLMN), cellular network, and/or cable network, as well as any other network type and any combination thereof. Further, the term network may include communication hardware, communication software and/or both.

A network may also refer to a sub-network, any type of a part of a network, or a combination of networks, and/or sub-networks, any of which may be overlying and/or overlapping one or more networks and/or subnetworks (such as a virtual network, and/or a network slice, etc.).

In one embodiment, a network may be operated by a network operator, a virtual network operator (VNO), a mobile virtual network operator (MVNO), a business enterprise operating one or more communication services, a business enterprise subscribing to one or more communication networks, one or more virtual communication networks, and/or one or more communication services, etc.

In the context of the present description, the term "network entity" may refer to any type of communication hardware, communication software, and/or communication service including instances of any particular software and/or service. For example, network entity may refer to software executed by a network entity (such as a network node or server), an operating-system (OS), a hypervisor software, a virtual machine, a container, a virtual network function (VNF), a micro-service, etc.

Further, in the context of the present description, the term "network configuration" may refer to any type of arrangement, configuration, topology, etc., of a network, interconnected computing devices (such as cloud computing), network nodes, servers, network entities, etc. In one embodiment, the network configuration may relate to a part (or slice) of a network, or a sub-network. Additionally, network configuration may also refer to any type of arrangement, deployment, installation, instantiation, etc. of any type of software processed and/or executed by any computational entity in the network.

In one embodiment, network configuration may refer to a configuration of any part of a network, or a combination of network, including network slicing, self-organizing networks (SON), edge computing, etc. Network configuration may also include configuration of any type of "communication service", which may include one or more network hardware elements as well as one or more software packages installed and operative in one or more hardware elements of the network.

In the context of the present description, "network service" may refer to any combination of network or communication services, facilities, or resources, as well as associated parameters such as bandwidth, latency, jitter, etc. For example, a network service may include any type of computing services, facilities, resources, as well as their parameters such as processing power, memory, storage, etc. Further, in one embodiment, network service may include a communication service, such as required network service, proposed network service, and/or communication service requirements (such as requirements specified in the SLAs **210**).

FIG. **2**B illustrates a network management system **201**, in accordance with one embodiment. As an option, the network management system **201** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the network management system **201** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

In one embodiment, communication network **202** may include one or more network entities **218** that provide communication services of the communication network **202**. For example, the network entities **218** may be arranged in a particular configuration optimized to deliver the communication services (of the communication network **202**) according to the one or more SLAs **210**. The network management system **212** may determine, implement and manage such optimized configuration of the network entities **218**. Additionally, configuration of the network entities **218** may be associated with the deep system module **216**, and in particular, the run-time module **214** through use of run time rules and/or AI-models **244**, while the deep system module **216** may create, adapt and modify the run-time rules and/or AI-models **244**, as well as deep system rules and/or AI models **242** by which the deep system module **216** operates.

In addition, the network management system **212** may include the run-time module **214**, which may include an event log, **220**, a monitoring system **222**, log data **224**, a real-time (RT) analysis system **226**, one or more suspected situations **228**, a confidence analysis system **230**, one or more predicted situations **232**, a network optimization system **234**, network configuration **236**, and an orchestration system **238**. In one embodiment, the network entities **218**, the monitoring system **222**, the RT analysis system **226**, the confidence analysis system **230**, the network optimization system **234**, and the orchestration system **238** may function as system components. Similarly, the event log **220**, the log data **224**, the one or more suspected situations **228**, the one or more predicted situations **232**, and the network configuration **236** may function as data elements.

The one or more network entities **218** may compute and communicate to the monitoring system **222** the event log **220**, typically including values for parameters relating to the performance of the communication network **202** and/or the one or more network entities **218**. The monitoring system **222** may then collect the event log **220** (including data records) to create the log data **224**. RT-analysis system **226** may then analyze the log data **224** to detect the one or more suspected situations **228**. Confidence analysis system **230** may then collect, compare and analyze the one or more suspected situations **228** to determine one or more predicted situations **232**. Based on the current predicted situation of the one or more predicted situations **232** the network optimization system **234** may create an optimal network configuration **236**. Next, the orchestration system **238** implements the optimal network configuration **236** by reconfiguring the one or more network entities **218**.

In one embodiment, deep system module **216** may supervise the operation of the run-time module **214**. For example, the run-time module **214** may operate on the basis of run-time rules and/or AI-models **244**, which in turn are created and/or managed by the deep system analysis system **240** which operates on the basis of deep-system rules and AI models **242**. The deep system analysis system **240** may be a collection of systems, arranged for example in stratified levels with their respective deep-system rules and AI models **242**, as explained hereinbelow.

Further, the run-time rules and AI models **244** as well as the deep-system rules and AI models **242**, may be created manually, or automatically using respective AI-learning systems operating in the deep system module **216**. For example, the deep system module **216** may include any AI learning and/or RT-analysis system (including, for example, AI learning system **510** hereinbelow described). Further, the run time rules and AI models **244** as well as the deep system rules and AI models **242**, may be updated, modified and/or adapted manually, or automatically using respective AI-analysis (serving) systems operating in the deep system module **216**.

In one embodiment, an entity operating a network may use the network management system **212** and/or the orchestration system to manage one or more network configurations. Additionally, in the context of the present description, the term "configuration change" and/or "reconfiguration" may refer to any type of change in network configuration. In one embodiment, the type of change may include a load-change, network fault, preventive maintenance, cyber-attack, etc. Additionally, a network optimizing system (such as network optimizing system **234**) and/or orchestration system (such as orchestration system **238**) may analyze load conditions, requirements, and/or changes to determine if a configuration change is necessary, and if so, determine optimal configuration settings, including generating and/or applying a configuration change.

In one embodiment, a configuration change may be analyzed, determined and affected by an AI-based network optimizing system **234** and/or orchestration system **238** using one or more artificial intelligence (AI) engines. Such an AI-engine may use AI rules (e.g., AI-Model(s)), which may be created by an AI-engine using deep learning and/or machine learning technology to analyze training data based on, or sourced from, log-data. For example, the AI-based network optimizing system **234** and/or orchestration system **238** may use AI rules (AI-Models) to analyze load-changes, determine a configuration change, and/or effect an appropriate configuration change.

In the context of the present description, the term "load" may refer to any type of network characteristic, parameter, and/or service. For example, load may include bandwidth, latency, jitter, processing power, memory, storage, etc. Additionally, load may include any requirement (such as used by such network characteristic, parameter, and/or service). Additionally, the term "load-change" may refer to any change in load. For example, load-change may include a change of a load requirement, use, and/or consumption, associated with a network characteristic, parameter, and/or service. In one embodiment, load-change may cause a configuration change. As such, load-change may include other causes for a configuration change, such as a network fault, anticipated network fault (such as requiring preventive maintenance), cyber-attack and/or security breach, etc. Further, load-change may include a change in load (such as a load decrease) that may be used in turn to shut down equipment and reduce operating costs or may include an anticipated load-change which may be used to anticipate the development of a particular load-change.

Additionally, in the context of the present description, the term "log-data" may refer to any record (including a file, repository, and/or database) which may represent an event detected in the network. Such an event may be detected by one or more network nodes or servers, by software executed by such network nodes or servers, by a network management system or software (including, but not limited to, a network orchestration system or software), and/or by a network-monitoring system. Additionally, the log-data may include identification of an event (such as a network event), associated data characterizing the particular event, and/or identification of the current network configuration or topology. As such, log-data may include event-log data as well. In one embodiment, log-data may include a link to a file, repository, and/or database, or may be included within an application programming interface (API) for such file, repository, and/or database. If log-data is communicated, it may be communicated in a computer readable format such as XML.

Further, log-data may be used to train and/or test an AI-engine (including an AI-based network design and/or management system).

In the context of the present description, the term "characterization" may refer to defining any type(s) of network or communication services, facilities, resources, etc. For example, characterization may include defining a network service that is required, including associated computing services, facilities, resources, etc. In one embodiment, characterization may include the term "characteristic".

Moreover, in the context of the present description, the term "current network configuration" and/or "current network topology" may refer to a network configuration and/or topology in use at the time of logging an event and/or at the time of executing a rule. Additionally, the term "configuration representation" may refer to a mechanism that can represent a network configuration. For example, configuration representation may include software (e.g., VNF) deployment, service definitions, respective allocation of network and processing resources (e.g., bandwidth, latency, jitter, etc., processing power, memory, storage, etc.). A configuration representation may enable re-creation of a particular network configuration and/or topology, may enable simulation or emulation of the operation of a particular network configuration and/or topology, and/or may enable identification of a re-occurrence of a particular network configuration and/or topology.

Further, in the context of the present description, the term "network situation" may refer to a condition of the communication network (such as communication network **202**) that may require a configuration change, or network reconfiguration. The network situation may be an unwanted situation (such as a failure), or a wanted situation (such as an opportunity to reduce cost, for example, by turning off a network entity). The network situation may be determined for the communication network (or any part of the communication network), for a service (or any part of the service), and/or for a network entity (such as one or more network entities **218**), etc.

For example, the network situation may be determined for a particular SLA (such as one of the one or more SLAs **210**). A network situation associated with an SLA may represent a situation where the network (or an associated service) does not perform according to the SLA. As such, the characteristics of the network situation may be any collection of parameters representing a fault or an opportunity (e.g., to reduce cost), etc. Such cause for the network situation may be associated with a load, or a load change.

Additionally, the network situation may be associated with a network fault (such as a hardware fault and/or a software fault), anticipated network fault (such as requiring preventive maintenance), cyber-attack, and/or security breach, etc.

In one embodiment, the network management system (such as network management system **212**) may be used to detect a developing network situation before it adversely affects the network behavior, or to exploit an opportunity to save cost.

In this respect, in the context of the present description, the term "death expectancy" may refer to a period of time remaining for a particular predicted network situation until it adversely affects a particular service and/or SLA.

In one embodiment, the term or "minimal reconfiguration time", may refer to the minimal period required to reconfigure the network to avoid a respective failure, or to exploit a respective opportunity. For example, to resolve a predicted situation before it adversely affects the particular service and/or SLA. Therefore, the minimal reconfiguration time should be smaller than the death expectancy.

In one embodiment, resolving a particular predicted situation may be delayed until the death expectancy approaches the respective minimal reconfiguration time. Additionally, death expectancy may also refer to a period of time remaining to exploit a particular predicted situation.

Further, the term "life expectancy" may refer to a period of time where the particular network configuration may remain useful before the utility diminishes (and it may then be in need of being replaced with a different network configuration).

FIG. **2**C illustrates a network management system **203**, in accordance with one embodiment. As an option, the network management system **203** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the network management system **203** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

As shown, the network management system **203** includes the network management system **212** which includes run-time module **214** and run-time rules and/or AI-models **244** of deep system module **216**.

Run-time rules and/or AI-models **244** may be in communication with various components of the run time module **214**, such as: monitoring rules **248** (in communication with monitoring system **222**), real time (RT)-analysis rules **252** (in communication with RT analysis system **226**) which may be used to analyze the log data **224** and/or to detect the one or more suspected situations **228**, confidence analysis rules **256** (in communication with confidence analysis system **230**) to analyze the one or more suspected situations **228** and determine the one or more predicted situations **232**, configuration rules **260** (in communication with the network optimization system **234** and/or the reconfiguration decision points **264**) to analyze the one or more predicted situations **232** and create network configurations **236**, reconfiguration decision points **264** (in communication with configuration rules **260** and network optimizing system **234**), and orchestration rules **266** (in communication with orchestration system **238**) to implement the network configuration **236**.

The run-time module **214** may also receive data including from SLAs **210**. Of course, any of the monitoring rules **248**, RT-analysis rules **252**, confidence analysis rules **256**, configuration rules **260**, reconfiguration decision points **264**, and/or orchestration rules **266** may be in communication with any specific element of run-time module **214**.

Configuration rules **260** may be used by the Network Configuration **236** to create an optimal network configuration according to a network infrastructure, a current state of the network, available predictions of near-future network behavior, SLAs (or similar requirement definitions), cost considerations, available resources, etc. In one embodiment, cost considerations may include the cost of installing, updating and/or synchronizing a new network entity and/or a new virtual network function, moving data from one new network entity (and/or virtual network function) to another network entity (and/or virtual network function), and/or the cost of specific resource in a specific location, etc.

Reconfiguration decision points **264** may include network situation(s) where a new network configuration may be computed and determined. For example, a reconfiguration decision point may be determined according to a predicted situation, or a combination of predicted situations. Additionally, the network optimizing system may determine a point in time when a new network configuration may be required by applying rules associated with the reconfiguration decision points **264** (which may relate to the predicted situations **232**). Additionally, a predicted situation data may contain sufficient information (such that an action can be implemented via the network optimizing system **234**) about a near future predicted behavior of particular network entities. Further, the network optimizing system **234** may receive current values and corresponding near-future predictions of value changes for any and all parameters of all the network entities **218**.

In the context of the present description, a reconfiguration decision point includes a situation where a new network configuration may be computed and determined. In one embodiment, a reconfiguration point may be determined according to a predicted situation, or a combination of predicted situations.

It is appreciated that each collection of rules such as monitoring rules **248**, RT-analysis rules **252**, confidence analysis rules **256**, configuration rules **260**, reconfiguration decision points **264**, and orchestration rules **266**, may be implemented in the form of a file, a repository, or a database. Additionally, such implementation may include a same entity (e.g., file, repository, etc.) for all rules, or may include a different entity (e.g., file, repository, etc.) for each collection of rules.

Additionally, each collection of rules may apply to one or more systems. For example, monitoring rules **248** may apply to network entities **218**, monitoring system **222**, and/or orchestration system **238**. Monitoring rules **248** may direct each of the network entities **218** how and when to report an event log **220**, including specifying parameters and/or values to report, etc. Further, monitoring rules **248** may direct monitoring system **222** how to arrange the log data **224**.

Further, each collection of rules may be managed by one or more systems. For example, monitoring rules **248** may be created and/or modified by one or more administrators as well as by monitoring system **222**, orchestration system **238**, and/or confidence analysis system **230**. Therefore each collection of rules may be managed by a rules manager, which may receive inputs via a respective hook and determine the respective rule change. In particular, monitoring rules **248** may receive input from rules manager **246**, RT-analysis rules **252** may receive input from rules manager **250**, confidence analysis rules **256** may receive input from rules manager **254**, configuration rules **260** may receive input from rules manager **258**, reconfiguration decision points **264** may receive input from rules manager **262**, and/or orchestration rules **266** may receive input from rules manager **268**.

In one embodiment, each collection of rules may be formed to enable simple addition, removal, selection, and/or deselection (prunning) of rules. Additionally, a system providing an input to any collection of rules (such as monitoring rules **248**, RT-analysis rules **252**, confidence analysis rules **256**, configuration rules **260**, reconfiguration decision points **264**, and/or orchestration rules **266**) may create a new rule, remove a rule, select/deselect (prune) a rule, and/or modify parameters of a rule.

A rules manager (such as any, some, or all of rules manager **246**, **250**, **254**, **258**, **262**, and/or **268**) may eliminate and/or reduce repetitive, too frequent, and/or possibly conflicting rule changes by implementing hysteresis and/or a dead-time period, a majority vote, weights and priorities, etc. For example, a system creating a rule may have priority and/or preference over any other system with respect to a particular rule. Additionally, the system may be particular to the rule managers **246**, **250**, **254**, **258**, **262** and/or **268** to prevent an over-ruling event where a first system runs-over a second (or another) system.

In the context of the present description, the term "parametrization" may refer to defining one or more values, or range(s) of values, for any characteristic of the required network or communication service, facility, resource, etc. In one embodiment, parametrization may include alternative acceptable values, or value ranges, with alternative respective priorities. The term "prioritization" may refer to defining priorities for, or between, the various required network or communication services, facilities, resources, etc., as well as their respective parameters.

Additionally, in the context of the present description, the term "weighting" may refer to defining and/or associating evaluation weights to characteristics and/or parameters for computing at least one value. In one embodiment, weighting may include a weighting factor. Additionally, the at least one value may be used for evaluating a particular proposed network service with a minimum requirement, and/or comparing between alternative proposals.

Monitoring rules **248** may instruct the one or more network entities **218** which parameters (such as parameters of the event log **220**) to measure, when to measure each parameter, how to measure the parameter, and how to report any measurement. Additionally, one or more network entities may derive the rules directly from a database associated with the monitoring rules **248**, or receive the rules from the monitoring system **222** periodically, or per a preconfigured schedule. In another embodiment, the monitoring rules **248** may instruct the monitoring system **222** how to measure inter-network entity parameters, including parameters involving, correlating, or synchronized between, more than one network entity of the one or more network entities **218**. Further, the monitoring rules **248** may instruct the monitoring system **222** how to create, format, arrange, and/or maintain a log-data file (such as log data **224**) or a database associated with the log data **224**. In this manner, the monitoring rules **248** may be conditional upon network situations, and transform according to such network situations (including a progression of the network situations).

The monitoring rules **248** may additionally guide the orchestration system **238** where to instantiate a monitoring probe. After the monitoring probe is instantiated, the monitoring system **222** may instruct such probe (or a monitoring function, or any other reporting network entity) which parameter (or parameters) to measure and report, a frequency of reporting, and a timing to report, such as when a measured value crosses a particular (or preconfigured) threshold, or characteristics of a particular service follow a particular temporal pattern (such as set time intervals, etc.).

FIG. **3** illustrates an event-log timeline **300**, in accordance with one embodiment. As an option, the event-log timeline **300** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the event-log timeline **300** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

As shown, event-log timeline **300** includes event-log records **302**, including log-pattern/classifier **304**, and a label for a particular network situation **308**.

The log-pattern/classifiers **304** precedes the particular network situation **308** by a time period **306**. The time period **306** may be a minimal reconfiguration time. In one embodiment, the time period **306** may be larger or equal to the minimal reconfiguration time. Additionally, the particular pattern of the log-pattern/classifiers **304** may be construed as a classifier for the particular network situation indicated by a label for the particular network situation **308**.

FIG. **4**A illustrates a method **400** for processing log data, in accordance with one embodiment. As an option, the method **400** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the method **400** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

Method **400** shows part of log data (such as the log data **224**) processed for creating an AI-model. In one embodiment, the method **400** illustrates a flow chart of a process for creating an AI-model for the RT analysis system **226**. As shown, a network situation is determined. See operation **402**. In one embodiment, determining the network situation may include also determining particular characteristics of the network situation. For example, a network situation may be an unwanted situation (such as a failure), or a wanted situation (such as an opportunity to reduce cost, for example, by turning off a network entity). A network situation may be determined for a network (or any part of a network), for a service (or any part of a service), for a network entity (such as network entities **218**), etc. For example, a network situation associated with an SLA may represent a situation where the network (or an associated service) does not perform according to the SLA. As such, the characteristics of the network situation may be any collection of parameters representing a fault or an opportunity (e.g., to reduce cost), etc. Such cause for the network situation may be associated with a load, or a load change.

At operation **404**, monitoring rules may be created and/or distributed. Such monitoring rules may be used to instruct a relevant network entity (of the network entities **218**) to measure and report one or more parameters that may be relevant to a network situation(s). Additionally, the monitoring rules may instruct the network entity when to measure each parameter, and how to report any measurement. In one embodiment, a rate of measuring a parameter may be different (such as being more frequent) than a rate of reporting. Further, the reporting may be conditioned by a value measured (or calculated), such as an average value, rate of change of value, etc. Moreover, the monitoring rule may include instructions to locally store unreported measurement(s) for a predetermined span of measurements and/or time.

In another embodiment, a monitoring rule may instruct one or more network entities **218** and/or the monitoring system **222** to report values of parameters and/or characteristics for a particular service in a particular temporal pattern. For example, the event log **220** the or log data **224**, may report a timely value of a parameter, or the time in which the value of a parameter crossed a predetermined threshold value, etc.

At operation **406**, event-log records are collected, including, log data which may be relevant to the network situation as determined by the characteristics of the network situation.

Additionally, a network situation in the log data is detected in the log data. See operation **408**. In one embodiment, the network situation may be detected based on characteristics of the network situation. At operation **410**, the network situation in the log data is labeled. Further information relating to the log data and/or the event-log data may be found in FIG. **4**.

At operation **412**, the log data (such as log data **224**) is scanned to detect a network situation classifier. In one embodiment, the log data may include training files used to determine a particular pattern of particular event-log records. Additionally, one or more training files may be created based on such log data. In one embodiment, the network situation classifier may include a particular sequence of parameter value(s) carried by log-data (such as log data **224**). Additionally, it may precede and/or predict, a network situation. Further, the particular sequence of parameter value(s) may be specific to a configuration of network entities (such as network entities **218**) and services, as well as to the set of monitoring rules (such as monitoring rules **248**) executed at that period.

At operation **414**, an AI model is created to detect the networks situation classifier. For example, in one embodiment, one or more RT-analysis rules **252** (e.g., a rule-base) may be created for detecting the particular networks situation classifier. In the context of the present description, this rule-base, when created by an AI learning system (such as the RT analysis system **226**), may be considered an "AI-model". It is to be appreciated that this network situation classifier and the respective AI-model (i.e., rule-base) may be particular to the network configuration for which the log data (such as log data **224**) is collected. In one embodiment, the one or more RT-analysis rules **252** may be implemented as AI models created by an AI learning system (such as RT-analysis rules **252** that may be used by the RT analysis system **226** to detect a classifier in the log data **224**).

Additionally, in the context of the present description, the term "particular rule-base" may refer to a rule-base derived from a data-set associated with a particular network configuration and/or topology, or a particular spectrum of network configurations and/or topologies. Further, a particular rule-base, especially in the context of an AI-learning system, may be equivalent to the term "AI-Model". AI-Model may therefore include any collection of rules generated by an AI-learning system, including a deep-learning system and/or a similar entity. The AI-Model may include data relating to a neural-network.

Further, the AI model may be tested to evaluate a confidence level. See operation **416**. For example, the AI model may be tested using testing files, including testing files created from log data (such as the log data **224**). The AI-model may be tested for a particular network situation classifier. Additionally, a measure of the confidence level may be calculated relating to the detection of a particular network situation classifier (such as an event-log pattern) by the particular AI-model. It is to be appreciated that this networks situation classifier and the respective AI-model may be particular to a specific network configuration for which the log data is collected.

In the context of the present description, the term "confidence level" may refer to any measure of confidence of detecting a classifier, and/or an event-log pattern, that may be associated with a particular suspected situation and/or predicted situation. For example, the confidence level may be measured/calculated according to a percentage of false-positive and/or false-negative detection of the particular classifier, and/or an event-log pattern. The measure of confidence level may represent a probability that, based on a particular suspected situation and/or predicted situation being detected, the particular suspected situation and/or predicted situation will develop. Further, confidence level may be represented simply by "confidence" particularly when associated with a confidence analysis such as a confidence analysis system and/or confidence analysis rules.

At operation **418**, a confidence may be assigned to the AI model. For example, the AI-model may be outputted with a specific confidence level to a database associated with the RT-analysis rules **252**. In one embodiment, the database may include RT-Analysis Rules **252** and thus may be accessed by the RT analysis system **226**. Further, the database may be linked to the RT analysis system **226** and may contain the RT-Analysis Rules **252**. After assigning a confidence to the AI model, method **400** may be repeated (starting back at operation **402**) for any number of network situations, and/or to amend the confidence of the AI model based on an updated network situation.

In one embodiment, the RT-analysis rules **252** for a particular predicted situation may include a rules-base (such as an AI model) for detecting a sequence of event-log data (such as log data **224**) preceding the predicted situation, and/or for reporting current values and corresponding near-future predictions of parameter value(s) changes in relation to any and/or all of the network entities **218** involved.

FIG. **4**B illustrates a method **401** of a run time process using an AI-model, in accordance with one embodiment. As an option, the method **401** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the method **401** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

In one embodiment, the method **401** may show a run-time process which may be used by the run-time module **214**. In one embodiment, the run-time module **214** may use the method **401** using an AI-model as may be created by the method **400**. Additionally, in another embodiment, the method **401** may be executed continuously as a main loop (without a start or end point). Further, the steps of the method **401** may be executed in parallel, or simultaneously, by various systems (such as but not limited to the monitoring system **222**, the RT analysis system **226**, the confidence analysis system **230**, the network optimizing system **234**, the orchestration system **238**) of the network management system **212**.

As shown at operation **420**, the monitoring system **222** may create and/or select and distribute the monitoring rules **248** to the network entities **218**. In one embodiment, the monitoring rules **248** may be distributed based on a current network configuration. The monitoring system **222** may receive the current network configuration from the orchestration system **238**. Further, the monitoring system **222** may continue to create and/or select and distribute the monitoring rules **248** to the network entities **218** as needed.

At operation **422**, the network entities **218**, using the monitoring rules **248**, may generate and send the event log **220** to the monitoring system **222**. The network entities **218** may generate and send the event log **220** continuously as needed.

At operation **424**, the monitoring system **222** may collect the event log **220** from the network entities **218** and may create the log data **224** (which may be run-time log data). The monitoring system **222** may continue to create the log data **224** continuously.

At operation **426**, the RT-Analysis system **226** may use the AI-Models of the RT-Analysis Rules **252** to analyze the log data **224** in real-time to detect the log-pattern/classifiers **304** and generate the respective data for the suspected one or more suspected situations **228**. Operation **426** may also be executed continuously, as RT-Analysis system **226** may receive from the monitoring system **222** new log-data **224**, detect more log-pattern/classifiers **304**, and generate more data for the one or more suspected situations **228**. Each of the one or more suspected situations **228** may be associated with a respective confidence level, which may indicate a probability of occurrence of the respective network situation within a particular time period (such as the time period **306**).

Additionally, at operation **428**, the confidence analysis system **230** may analyze the suspected situations **228** and their respective confidence levels to determine and adapt the RT appropriate analysis strategy. For example, the confidence analysis system **230** may request the monitoring system **222** to create and/or select and distribute the monitoring rules **248** to the network entities **218** to increase the probability of detecting a log-pattern/classifiers **304**, and/or to increase the confidence level of a respective suspected situation **228**. In one embodiment, the confidence analysis system **230** may generate respective data of the predicted situations **232**, such as where a respective confidence level reaches a predetermined threshold. The confidence analysis system **230** may process operation **428** continuously and/or repeatedly as the suspected situation **228** may be further received from the RT-Analysis system **226**.

At operation **430**, the network optimization system **234** may analyze the predicted situations **232** to determine a new network configuration **236**. The network optimization system **234** may process the RT-Analysis system **226** continuously and/or repeatedly as the predicted situations **232** may be further received from the confidence analysis system **230**.

Further, at operation **432**, the orchestration system **238** may receive from the network optimization system **234** a new network configuration **236** and implement it (at operation **434**) by modifying, migrating, installing and/or removing the network entities **218**. The orchestration system **238** may process operation **432** continuously and/or repeatedly as the network configuration **236** is further received from the network optimization system **234**. As a new network configuration is implemented, the monitoring system **222** may create and/or select and distribute the monitoring rules **248** to the respective network entities **218**, and the RT analysis system **226** may select and/or use the respective AI-models included in the RT-Analysis Rules **252**.

Additionally, the network optimizing system **234** may determine the network configuration **236** that the orchestration system **238** may then implement to avoid or exploit one or more of the predicted situations **232**. Implementing a new network configuration **236** may result in a configuration change or a network reconfiguration. The network optimizing system **234** may determine which of the pending predicted situations **232** should be treated (e.g., avoided or exploited) in the subsequent configuration change.

In one embodiment, the network optimizing system **234** may determine a new network configuration **236** while the orchestration system **238** may still be implementing another (e.g., previously instructed) configuration change (of a previously implement network configuration **236**). For example, the network optimizing system **234** may instruct parallel configuration changes affecting different parts of the communication network **202** and/or different network entities **218**, and/or different services.

As such, the network optimizing system **234** may consider several parameters that may affect a decision associated with a reconfiguration of the network. Such parameters may include cost, priority, severity, confidence level, death expectancy of the pending predicted situation, life expectancy of a new configuration, collision with another reconfiguration currently processed by the orchestration system **238**, etc. In the context of the present description, the term "minimal reconfiguration time" may refer to a minimal time required by an orchestration system (such as orchestration system **238**) to migrate one or more network entities (such as network entities **218**). In one embodiment, minimal reconfiguration time may be associated with a particular service and/or SLA, and, more particularly but not exclusively, with a particular network situation associated with the service and/or SLA.

In one embodiment, a configuration change (such as implemented via the network optimizing system **234** or the orchestration system **238**) may be tagged, identified, and/or associated with one or more particular causes and effects and/or result (such as a particular load-change, requirement, fault, cyber-attack, etc.). For example, the network optimizing system **234** and/or orchestration system **238** may tag and/or associate a configuration change with one or more of the causes for a particular configuration change. Additionally, each tag or association may be assigned a weighting factor representing the effect of a particular cause on determining the particular configuration change.

Further, configuration settings may be stored as a data record or a data field in a file or a database (such as a database associated with network optimizing system **234**). The data field or data record may include a start and stop time of the respective configuration, and the format of the data field or data record may enable a software package to identify the differences between two (or more) configurations represented by their respective data field or data record.

In the context of the present description, the term "difference measure" may refer to a value representing a difference between two (or more) configurations. Additionally, the term "dislocation" may refer to an entity located in a configuration which differs from the location noted in a reference configuration. A dislocation may refer to a missing entity, an added entity, and/or an entity located in a different place. Such entity may be any hardware component and/or a software component, such as a VNF instance, and/or a service, such as a micro-service.

In various embodiments, training and/or testing data may be derived from the same data-set (including log-data). Additionally, the training data may be used to train the AI-engine to produce a rule-base, and the testing data may be used to evaluate the effectiveness of the developed rule-base.

The network optimization system **234** may determine the network configuration **236** which the orchestration system **238** may then implement to avoid or exploit one or more predicted situations. In one particular situation, implementing a new network configuration may result in a configuration change or a network reconfiguration. As such, the network optimization system **234** may determine which of the pending predicted situations should be treated (e.g., avoided or exploited) during the next configuration change.

Additionally, the network optimization system **234** may determine a new network configuration while orchestration system **238** may still be implementing another (e.g., previously instructed) network configuration **236**. For example, network optimization system **234** may instruct parallel configuration changes affecting different parts of communication network **202**, network entities **218**, and/or different services.

In one embodiment, the network optimization system **234** may consider a variety of parameters which may affect a reconfiguration decision, including but not limited to, cost, priority, severity, confidence level, death expectancy of the pending predicted situation, life expectancy of the new configuration, collision with another reconfiguration currently processed by the orchestration system **238**, etc. These parameters may also be considered in the context of processing the reconfiguration decision points **264** by the network optimizing system **234**.

Additionally, it is to be appreciated that a configuration or reconfiguration change may directly affect cost. For example, a configuration change may involve migration of a software entity from one hardware entity to another. Such a migration may be executed in the form of "make before break", so as not to disrupt or adversely affect any service. This operation may mean that software entity B is installed, operated and updated in hardware entity B before software entity A is removed from hardware entity A. Therefore, software entity A and software entity B may be operative in parallel, and may each be implemented on a specific hardware entity, thereby increasing cost, including hardware, electricity, maintenance (including dissipating heat from hardware) costs, as well as third party costs including processing, storage, communication, licensing, etc. Furthermore, any additional costs (including extra hardware entities, etc.) may obviously affect the ability to generate income using the particular hardware entity.

Additionally, a configuration or reconfiguration change may be subject to priorities (such as due to limited resources). For example, migrating a first software entity from hardware entity A to hardware entity B may adversely affect the ability to migrate a second software entity to hardware entity A or to hardware entity B, as well as to any other hardware entity depending on a communication facility and/or hardware entity involved in the migration of the first software entity.

In one embodiment, the network optimization system **234** may use at least two sets of rules including configuration rules (which may determine how to resolve one or more predicted situations by an optimal reconfiguration) and reconfiguration decision points **264** (which may additionally determine when to resolve pending predicted situations).

In one embodiment, based on the processing of the reconfiguration decision points **264**, the network optimization system **234** may determine which of the pending predicted situations to process for the next network configuration and when to process such pending predicted situations. For example, the network optimization system **234** may determine based on a reconfiguration condition point (of the reconfiguration decision points **264**), whether to effect a reconfiguration immediately, or to delay a reconfiguration based on, for example, a combination of long death expectancy and low confidence level. In one embodiment, a reconfiguration may be delayed until a confidence level increases.

Additionally, the deep system module **216** may include processes (e.g., modules, systems) that may create and modify run-time rules. In one embodiment, the deep system module **216** may be construed as a -reverse analysis channel as it may use the output of the run-time module **214** to manage run-time rules. In other words, the deep system module **216** analyzes the behavior of the run-time module **214** so as to improve it by optimizing the rules controlling the behavior of the run-time module **214**, such as adaptive pattern recovery and/or behavioral patterns.

FIG. **5** illustrates a network management system **500**, in accordance with one embodiment. As an option, the network management system **500** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the network management system **500** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

As shown, an AI learning system **510** which may produce the RT-analysis rules **252** (or the AI-models, or predictors). The AI learning system **510** may analyze training data and/or testing data that is created from the log data **224** to produce RT-analysis rules **252**. Additionally, the AI learning system **510** may receive as input the log data **224**.

Additionally, the training and testing data preparation system **502** may include a monitoring design module **504** and a labeling system **506**. Labeling system **506** may convert log-data (such as the log data **224**) into training-data and testing-data for the AI learning system **510**. The labeling system **506** may label training-data and testing-data. In one embodiment, the labeling system **506** may determine where to properly mark network situations in the training-data and/or testing-data. In one embodiment, the labeling system **506** may receive as input the log-data **224** from the monitoring system **222**. In one embodiment, the log-data inputted to the labeling system **506** may be separate from the log data **224**. For example, in one embodiment, the monitoring system **222** may provide separate log-data to the labeling system **506**. The output of the labeling system **506** includes training data and testing data (based on log-data with labels of network situations). The output of the monitoring design module **504** includes monitoring rules adapted to particular network situations.

In one embodiment, the monitoring design module **504** may create and distribute monitoring rules to one or more relevant network entities such that that network situations and their respective classifiers can be detected. Additionally, a network situation may depend on a network configuration and/or the monitoring rules (such as the monitoring rules **248**) which may depend on the network situations and/the network configuration.

Additionally, the monitoring design module **504** may optimize monitoring rules to improve the log-data collected and provided to the training and testing data preparation system **502** such that predicted situations can be predicted more accurately and/or earlier, and to enable detection of more or new predicted situations. The output of the training and testing data preparation system **502** may be provided as training data **508**, which in turn, may be sent to the AI learning system **510**.

As shown, the configuration design system **518** may optimize configuration rules (such as configuration rules **260** and/or reconfiguration decision points **264**) to improve the results of the network configuration system. To that end, the configuration design system **518** may receive inputs from the run-time module, including the network configuration **236** and/or one or more predicted situations **232**, as well other network parameters, including SLAs **210**. Additionally, the configuration design system **518** may measure the quality of the computed network configuration, including a cost of a reconfiguration, time required to reconfigure the network, a length of time the configuration has lasted, etc. In one embodiment, the configuration design system **518** may include goals for the network reconfiguration.

Additionally, an AI model selection & pruning **516** system may receive the network configuration **236** and based on such, may select and prune network configurations, resulting in RT-analysis rules **252**. Further, testing analysis system **514**, may receive an output from the RT analysis system, and may provide such data as input to the training and testing data preparation system **502**.

FIG. **6** illustrates a network management system **600**, in accordance with one embodiment. As an option, the network management system **600** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the network management system **600** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

As shown, the network management system **600** builds upon the network management system **500**. In one embodiment, the network management system **600** may be used to simulate network behavior when there is no sufficient amount of log-data (which may result from network dynamics, including new network configurations). In such a situation, log-data may be simulated or synthesized. In particular, simulating log-data may include analyze the network behavior to produce primitives that may then be used as components from which training data is composed/synthesized/simulated.

A higher level of the deep system module **216** of the network management system **212** may include processes (e.g., modules, systems) that simulate a network behavior when there is not enough log-data (such as the log data **224**). Insufficient log data may result from network dynamics. As demand changes and shifts more rapidly and more frequently, particular network configurations may not produce sufficient log-data. Additionally, network configurations may be new (thereby having no history of log-data). As such, there may be a need to simulate (or synthesize) log-data. The simulation level (corresponding with the simulation module **602**) may include a collection of mechanisms that analyze the network behavior to produce "primitives". The primitives in turn may be used as a simulation of training-data and testing-data for a new configuration.

In one embodiment, the simulation module **602** may include a behavior analysis system **604**, which may produce several primitives, including behavioral patterns **606** and network conditions **608**. In one embodiment, the behavioral patterns may include sequences of event-log data (such as log data **224**) produced by a network entity (of the network entities **218**), or a particular virtual network function (or a similar entity), that are characteristic of a particular arrangement such as a timing to serve a particular service to a particular customer.

At simulation system **610**, log-data may be simulated or synthesized for a particular configuration, including arranging, interlinking, and interleaving, behavioral patterns. As such, the behavioral patterns **606** should be properly detected, defined, and characterized, such that they can be properly selected and combined in the process of simulating, or synthesizing, log-data as shown in simulated log data **612**.

Additionally, network conditions **608** include situations that may be predicted by the RT analysis system **226**. Additionally, the network conditions **608** may serve as labels for labeling (via the labeling system **506** of the training & testing data preparation system **502**) the training data **508** (or testing data) for the AI learning System **510**. As such, the network conditions **608** should be properly detected, defined, and characterized, such that they can be automatically detected and properly labeled in old and new simulated (synthesized) log-data, as shown in simulated log data **612**. For example, a network condition (of the network conditions **608**) may be characterized by one or more network parameter(s), and/or by a condition of one or more of particular type(s), including a network fault, a service fault, an SLA fault, a cyber-attack, a security breach, a cost-reduction opportunity, etc.

FIG. **7** illustrates a system **700**, in accordance with one embodiment. As an option, the system **700** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the system **700** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

As shown, a security module **702** and a coordination module **704** may relate to an exogenic level **701**. The exogenic level **701** may be separate from the network management system **212**, the run-time module **214**, and/or the deep system module **216**. In one embodiment, the exogenic level **701** may include any aspect foreign to the network management system **212**, including but not be limited to interaction with the outside world, other networks, other network management systems, cyber-attacks, and/or any other phenomena that is not intended as internal to the network management system **212**.

The system **700** may relate to systems and functions that interact with the environment of the communication network **202**. For example, coordination module **704** may include inter-network coordination **718** and service marketplace **720**. In one embodiment, inter-network coordination may include coordinating load and configuration matters with neighboring networks, automatically negotiating with other networks and customers, mitigating cyber attacks, etc. Additionally, the inter-network coordination **718** and the service marketplace **720** may communicate with one or more external entities **722**. For example, the external entities may include other networks, and/or network systems of customers.

The coordination module **704** therefore may involve computation(s) that depend on the current configuration of the network. In this manner, the coordination module **704** may relate to rules that apply to the current configurations, including current monitoring rules **248**, current RT-analysis rules **252**, current confidence analysis rules **256**, current configuration rules **260**, orchestration rules **266**, current behavioral patterns **606**, etc.

Any such rules of any layer/module/component of the network management system **212** may be exchanged with any external party (such as another network operator, a service provider, and/or a consumer), and/or transmitted to or received from any external party. Additionally, when negotiating network information with a third party (or third parties) any rule may be encrypted and embedded in the negotiation information. In one embodiment, the negotiation information may include the configuration and associated rules that apply to the network condition.

As shown, security module **702** may include a cyber security system **706** which may receive input from critical parameter **710**, authenticate system **712**, and one or more predicted situations **232**. The security module **702** additionally includes an event-log source entities **714** which may be in communication with the monitoring rules **716**. In one embodiment, the monitoring rules **716** may include monitoring rules **248**. Further, the security module **702** may include a breach report **708** that receives an output from the cyber security system **706**. The cyber security system may additionally provide output to the simulation system **610**.

In various embodiments, although not shown in FIG. **7**, the system **700** may also interact with various components of the network management system **500** and/or the network management system **600**. For example, the inter-network coordination may interface with the behavior analysis system **604** and/or the configuration design system **518**. In like manner, the service marketplace **720** may interface with the behavior analysis system **604** and/or the configuration design system **518**.

Additionally, although the systems which control the network optimizing system **234** are not shown in FIG. **7**, it is to be understood that such control systems/aspects are specifically shown in FIG. **5** and/or FIG. **6**. Additionally, the training data **508** in FIG. **7** is not shown with an output, as the testing data **512** system is specifically not shown (but which is detailed in relation to FIG. **5** and/or FIG. **6**). It is to be appreciated that any omissions of flow of instructions and/or data in FIG. **7** may be supplemented through FIG. **5** and/or FIG. **6**. To simplify FIG. **7**, aspects of FIG. **5** and/or FIG. **6** were omitted in FIG. **7** to more clearly show the system **700**.

Further, data exchanged between systems and/or processes (such as exemplified in FIG. **7** and other figure) may be communicated indirectly, such as by memory, storage, data sharing facility, and/or a database system. A database system may be included within any of the modules, such as any component of the network management system **212**. Further, the database system may include network configuration records, network situations associated with their respective network configurations, network situations associated with their respect minimum configuration time values, monitoring rules associated with network situations to which each monitoring rule is applicable, AI-models associated with their respective network situations, confidence levels and/or time periods associated with their respective AI-models and/or network situations, etc.

FIG. **8** illustrates a block diagram **800**, in accordance with one embodiment. As an option, the block diagram **800** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the block diagram **800** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

As shown, block diagram **800** includes a computational device **802** which may be used for a network entity (such as network entities **218**) and/or any computing element such as the network management system **212**, the deep system module **216**, etc., according to one exemplary embodiment. Additionally, the computational device **802** may include at least one processor unit **806**, one or more memory units **808** (e.g., random access memory (RAM), a non-volatile memory such as a Flash memory, etc.), one or more storage units **810** (e.g. including a hard disk drive and/or a removable storage drive, representing a floppy disk drive, a magnetic tape drive, a compact disk drive, a flash memory device, etc.), one or more communication units **812**, and/or one or more peripheral units **814** (or peripheral control units). The communication unit **812** may use any type of communication technology. Additionally, the computational device **802** may also include one or more communication buses **804** connecting any of the units of the computational device **802**.

Further, the computational device **802** may also include one or more power supply units **816** providing power to any of the units of the computational device **802**.

The computational device **802** may also include one or more computer programs **818**, or computer control logic algorithms, which may be stored in any of the memory units **808** and/or storage units **810**. Such computer programs, when executed, may enable the computational device **802** to perform various functions. Additionally, the memory units **808** and/or storage units **810** and/or any other storage may be a tangible computer-readable media.

FIG. **9** illustrates a block diagram **900** of a software programs, in accordance with one embodiment. As an option, the block diagram **900** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the block diagram **900** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

In one embodiment, the block diagram **900** may be used by the computational device **802** such as part of the one or more computer programs **818** according to one exemplary embodiment. Additionally, computer programs **818** may operate over hardware **904**, which may include hardware components as shown and described with reference to FIG. **8**.

The computer programs **902** may include a first level of one or more firmware **912** software programs. The one or more firmware **912** may provide control of one or more hardware components (such as the storage unit **810**, communication unit **812**, and/or a peripheral unit **814**). The computational device **802** may also include a second level of a base operating system **910**. The base operating system **910** may provide control of memory units **808** and the hardware **904**, typically via firmware **912**, as well as communication and coordination between other components.

Additionally, the computer programs **902** may also include a third level **908** of a one or more virtual machines and/or containers. Each virtual machine may include one or more subordinate operating systems, as well as a library of functions. Each container may include subordinate operating systems as well as a library of functions.

The computer programs **902** may also include a fourth level **906** of one or more application software programs and/or probes. An application software program may be any of the software systems as herein described.

In one embodiment, a probe may include a software program that monitors and/or measures (and reports to a monitoring system such as the monitoring system **222**) one or more operational parameters of any of the lower levels (such as the third level **908**, the base operating system **910**, and/or the firmware **912** of a first level), the hardware **904**, and/or operating parameters of one or more applications. For example, an application or a probe may be executed over the base operating system **910** directly, over a virtual machine (typically executing a subordinate operating system), or embedded within a container (typically also embedding a subordinate operating system).

In various embodiments, the communication network and network management system of FIG. **2**A may orchestrate (and/or manage, control) any component of any level of the computational device **802**. Additionally, any component of any level of the computational device **802** may measure one or more operational parameters and report such within the event log **220**, typically according to a monitoring rule (such as the monitoring rules **248**), to the monitoring system **222**. Further, the operations associated with network configuration, configuration change, reconfiguration, and/or migration, may refer to any software component of any level shown of the block diagram **900**.

More illustrative information will now be set forth regarding various optional architectures and uses in which the foregoing method may or may not be implemented, per the desires of the user. It should be strongly noted that the following information is set forth for illustrative purposes and should not be construed as limiting in any manner. Any of the following features may be optionally incorporated with or without the exclusion of other features described.

In this respect, the SLA **210** or any similar descriptions of wanted and/or unwanted network behavior (e.g., cost saving, service fault, cyber-security attack/breech, etc.) may be used to define a corresponding one or more parametrized network situations. A network situation **1022** may be parametrized in the sense that it can be detected when the value of one or more operational parameters of the network reaches a particular threshold, etc.

The monitoring rules **248** may be devised and implemented in sufficient network entities **218** to report the pertinent parameters identifying the respective network situation. The network situation may be detected in the log data **224** of the communication network and properly labeled. The AI-learning system **510** may be used to detect a classifier (such as a log-pattern, or a pattern of event parameters reported by various network entities **218**, where the log-pattern predicts a following network situation). In one embodiment, the AI-learning system **510** may operate in two steps where an unsupervised AI learning may search for a classifier and the AI-learning system **510** may then create an AI-model **244** to automatically detect a particular single classifier instance.

In one embodiment, an unsupervised AI learning may search for a classifier, such as a correlated repetition of patterns in the log data **224** preceding the network situation within a particular time range, wherein the time range may be statistically significant. Additionally, this may include a statistical process where the AI-learning system **510** may investigate a large number of instances of a particular type of network situation (as labeled) to identify a repetitive pattern of the log data **224** (which may be found immediately preceding the network situation within a particular time range), which may be identified as lead-time. It should be noted that there may be any number of different patterns of the log data **224** preceding a network situation type. In this sense, ‘immediately’ may mean within a predefined time range.

In one embodiment, the AI-learning system **510** may create an AI-model (such as the run-time rules and/or AI models **244**) to automatically detect a particular single classifier instance wherein the classifier (or the associated network situation) may have a confidence level representing the probability that the detected classifier will indeed mature into a network situation within a time range about the lead-time.

It should be further noted that these two steps may be implemented as a single procedure performing these two steps as a combined iterative process of detecting the classifier and creating the AI-model.

In one embodiment, the product of the AI-learning system **510** may be an AI model that detects a particular classifier. Further, the classifier may be a pattern of data elements, and the AI-model is a piece of software (e.g., a neural network) that detects the particular pattern in a stream of log data, so that, although the classifier and the AI-model may be different, they may also be closely related. Thus, parameters associated with the classifier may be associated with the AI-model and vice versa.

In one embodiment, the classifier, and hence the respective AI-model, may include such parameters as the time of the classifier, an identification of a particular type of network situation that may follow the classifier, a lead-time, and possibly a time range, a confidence level, and parameter characterization. In the context of the present description, the term confidence level may refer to the probability that the identified network situation will mature within a predetermined time range. In one embodiment, the predetermined time range may be at the end of the lead-time following the time of the classifier. Other parameters may include parameters associated with a group of classifiers and/or AI-models, such as a resolution stage (level) and minimum reconfiguration time, which may be associated with the network situation, etc.

Although the classifier itself may be unknown, the AI-learning system **510** may provide some data about the classifier, such as the parameters that the AI-model may process to detect an identifier. Additionally, these parameters may form a parameter characterization data and, thus, the parameter characterization data of a particular AI-model may identify each such parameter by type, as well as the particular network entities reporting the particular parameter.

In one embodiment, while the AI-learning system **510** may scan for a lower resolution classifier, the AI-learning system **510** may be requested to look for a classifier with a lead-time longer than any higher resolution classifier. In another embodiment, while the AI-learning system **510** scans for a higher resolution classifier, the learning system may be requested to look for a classifier with higher confidence level than any lower resolution classifier. Therefore, the AI-learning system **510** may produce a multi-stage structure of AI-models with increasing resolution, increasing confidence level, and decreasing lead-time (and vice versa).

FIG. **10** illustrates a multi-stage analysis system **1000**, in accordance with one embodiment. As an option, the multi-stage analysis system **1000** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the multi-stage analysis system **1000** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

In one embodiment, the multi-stage analysis system **1000** may relate to the communication network **202** and, as shown, a network management system **212**, using the run time module **214** (which may include a multi-stage AI analysis system), with confidence analysis system **230**, in accordance with one embodiment.

In one embodiment, the communication network **202** may include a plurality of communication networks. Each (or a plurality of) communication network **202** may connect any number of devices associated with the customer **208** with any number of devices of the service operator **206**.

Communication network **202** may have several types of customers, such as clients and service providers. In one embodiment, a client (including the customer **208**) may consume a service provided by communication network **202** or by a third party service provider (including the service operator **206**).

The customer **208** may execute any number of customer software packages. The service operator **206** may execute any number of service software packages. In one embodiment, the service software package may be provided by the same customer, by a different customer, and/or by a third party providing a software service (such as software-as-a-service (SaaS)). The service operator **206** may be operated by a customer's computing center, by a cloud operating entity, by a network operating entity such as being a part of the communication network, and/or by an edge computing operating entity, etc.

In another embodiment, the customers **208** and/or the service operator **206** may have one or more service level agreements (SLA) **210**. In one embodiment, the SLA **210** may include any definition of a type, level, and/or quality of network service(s) the communication network **202** should provide for each and any of the customer **208**, client, service, the service operator **206**, etc.

The communication network **202** may include any type and number of network entities **218** arranged and interconnected in any particular configuration and/or topology. A network entity **218** may be a communication device, a computing device (with processing power, memory, storage, etc.), and/or a software program executed by the communication device and/or the computing device.

The network entities **218** may be arranged to provide services to the customers **208**. The network entity **218** may be arranged to provide, or participate in, one or more services. A service may be provided by the network entity **218**.

In one embodiment, communication and/or processing functions (in association with the network management system **212**) may be provided as software executed by computing devices, such as Virtual Network Functions (VNFs) of a Network Function Virtualization (NFV).

The operation of the communication network **202**, including the communication devices, the computing devices, the VNFs, etc. may be managed by the orchestration system **238** executing orchestration software. The orchestration system **238** may deploy software packages, such as micro-services and/or VNFs, in various communication devices and/or computing devices within the communication network.

The operation of the communication network, including the communication devices, the computing devices, the VNFs, etc. may be monitored by the monitoring system **222** executing monitoring software. The monitoring system **222** may collect the event log **220** data from the network entities **218** and produce the log data **224**. The log data **224** may include a log database as well as a real time log stream. The monitoring system **222** may collect the event log **220** data and produce the log data **224** according to the monitoring rules **248**.

The monitoring system **222** may manage the monitoring activity as well as the contents of the log data **224**. For example, the management may be accomplished by communicating one or more of the monitoring rules **248** to the one or more network entities **218**, or by instructing the one or more network entities **218** to report a status or events according to the one or more monitoring rules **248**.

Additionally, the monitoring system **222** may also use the monitoring rules **248** to determine how to collect the event log **220** data. The monitoring system **222** may also use the monitoring rules **248** to determine how to compute statistical log data based on a plurality of data for a particular event log **220**. Further, the monitoring system **222** may also use the monitoring rules **248** to determine how to structure the contents of log data **224** (including a log database and/or a real-time log stream). In various embodiments, the log data **224** may be divided into two streams, including a first stream that may be used by the AI learning system **510**, and a second real-time stream that may be used by the RT analysis system **226**. In this manner, therefore, the log data **224** may be divided into any number of streams. In other embodiments, a first stream may be used by the learning system, and may function as a database, from which training and testing log-data is derived. Additionally, a second stream may include RT log-data analyzed in real-time as it is provided by the monitoring system. This RT log-data may be provided as a number of streams, subject to the implementation of the multi-feed system.

The network orchestration system **238** may install and/or initiate one or more network entities **218** (such as a probe) to track and/or to analyze a behavior of the communication network **202** and to provide event log **220** according to the one or more monitoring rules **248**.

In one embodiment, the RT analysis system **226** may integrate an artificial intelligence (AI) analysis system. Additionally, the RT analysis system **226** may process the log data **224** to detect a network situation that may require changing the network configuration **236** (and/or a reconfiguration of the network as provided by the network optimizing system **234**). Upon detecting a network situation, the RT analysis system **226** may produce a predicted situation **232** data item and communicate it to the network optimizing system **234**.

Based on the one or more of the received predicted situation **232** data items, the one or more SLAs **210**, and/or any other information affecting configuration requirements of the network, the network optimizing system **234** may determine a new network configuration **236** (or a network reconfiguration) and communicate it to the orchestration system **238**.

Based on new network configuration **236**, the orchestration system **238** may deploy software packages. For example, the software packages may include micro-services, VNFs, and/or configuration-change data. Additionally, the software packages may be provided by a network analysis and configuration system executing network analysis and configuration software (including but not be limited to the network optimizing system **234** and/or the orchestration system **238**).

In one embodiment, the configuration change may shift a processing load or communication load from one part of the communication network to another, so as to balance the processing or communication load and provide adequate service level. Additionally, the configuration may change based on near continual changing requirements of the network, and/or the network customer(s) **208**. Alternatively, a configuration change may involve moving loads out of a particular (or group of) network entity **218** to enable orchestration system **238** to shut-down any of the network entities **218** to reduce a cost of operation.

Additionally, the configuration change may involve migration of one or more network entities **218**. In one embodiment, the migration may occur without adversely affecting the continuity, and/or quality, etc., of the service provided by the migrated network entity **218**. Further, migrating a network entity **218** may involve migrating a software network entity between hardware network entities. In one embodiment, the migration may involve installing a new copy of the migrated software network entity **218** in another hardware network entity, updating the new software network entity and verifying coherent operation, and discontinuing (e.g., removing) old, migrated, software network entity. These configuration changes may also involve splitting, joining, mirroring, etc., one or more network entities **218**. As such, the term "migration" may include to any type of shifting processing and/or service throughout the network.

In one embodiment, the monitoring rules **248** may include rules communicated to the relevant network entities **218**. For example, the monitoring rules **248** may include values of parameters and/or characteristics for a particular service, including a service with a particular temporal pattern. The event log **220** may report a value of a parameter, and/or a time in which the value of a parameter crossed a predetermined threshold value, etc.

The SLA **210** may include one or more threshold values for characteristics or parameters that a relevant network entity **218** may measure and report. The network orchestration system **238** may set the monitoring rules **248**, according to the relevant SLA **210**, and instruct the appropriate network entity **218** to measure and report (such as the event log **220**) a particular parameter in an appropriate frequency. The network orchestration system **238**, and/or the monitoring system **222** may instruct a network entity **218** to execute and report such measurements. Additionally, the network orchestration system **238** and/or the monitoring system **222** may install a special network entity **218**, including but not be limited to a probe, to execute and report such measurements.

An SLA **210** may include one or more statistical threshold values, including for one or more characteristics or parameters. The statistical threshold value may refer, for example, to the number of occurrences of a value (or range of values) of a characteristic or parameter in a predefined period. In some embodiments, if a particular network entity **218** cannot calculate and/or report such statistical measure, the monitoring rule **248**, as may be set by the orchestration system **238**, may be applied by the monitoring system **222**, which may compute the value, generate the event log **220**, and add it to the log data **224**.

As shown in FIG. **10**, the RT analysis system **226** may be associated with several sub-systems. For example, in one embodiment, a run-time part may include the RT analysis system **226** and the confidence level **230**.

The network management system **212**, and/or any of its systems and sub-systems, may include human-interface(s) to enable an operator to supervise and/or intervene in, the operation of the network management system **212**. In one embodiment, the human-interface(s) may enable an operator to induce reinforced learning. For example, the reinforced learning may be achieved by approving an automatic decision of the system, disapproving an automatic decision of the system, and/or enforcing a human decision.

The deep system module **216** may include a training and testing data preparation system **502** and an AI learning system **510**. The training and testing data preparation system **502** may convert the log data **224** into the training data **508** and the testing data **512**. For example, the training and testing data preparation system **502** may label or mark the log data **224**, or a part of log data **224**, with data-fields (or data-records) identifying a particular network situation.

The AI learning system **510** may then use the training data **508** (and the testing data **512**) to create an AI model which may be found in the RT-analysis rules **252**. In one embodiment, the AI model may be used to predict one or more network situations in the training data **508**. Additionally, the AI model may include or be a predictor, which may be used to determine a particular pattern of log data **224** elements or records. Further, the log data **224** elements or records may precede a network situation early enough to initiate network reconfiguration.

In one embodiment, the AI model may detect a particular pattern of values, value ranges, and/or thresholds, etc. for parameters reported by particular network entities **218**. Additionally, the AI model may detect values of parameters computed by the monitoring system **222**, and which may be provided in the log data **224** (including as well a log database and/or a real-time log stream). The pattern of log data elements may be considered as a classifier for a particular network predicted situation **232**. As such, a classifier may include at least one value of a parameter(s) of the event log **220** which may precede the network situation by a predetermined time period.

The AI run-time system **1002** may then use the AI model to analyze the log data **224** (including real-time log-data stream) to produce a predicted situation **232**.

Additionally, the run-time system **1002** may be associated with the network management system **212** including the run time module **214** which may include the RT analysis system **226** and a confidence analysis system **230**. The RT analysis system **226** may analyze the log data **224** (including but not be limited to a log database or a real-time log stream) to detect a suspected situation and produce a suspected situation **228** data. Each suspected situation **228** may indicate a cause and may be accompanied with one or more values representing a level of confidence of the validity of the particular situation.

The confidence analysis system **230** may process one or more suspected situation **228** data, produce a pattern recovery data **1006**, and communicate the pattern recovery data **1006** to the monitoring system **222**, to the orchestration system **238**, and/or to the RT analysis system **226**.

The confidence analysis system **230** may produce the pattern recovery data **1006** based, for example, on a confidence history **1004**. The confidence history **1004** may record statistical parameters of a confidence level (or the development thereof) relating to a variety of suspected situations. These statistical parameters may include the probability that the confidence level of a particular suspected situation will increase, the time rate in which the confidence level of a particular suspected situation may increase, etc.

In one embodiment, the pattern recovery data **1006** may instruct the monitoring system **222** to use one or more particular monitoring rules **248**. For example, the monitoring rule **248** may require the monitoring system **222** to investigate the event log **220** received from one or more particular network entities **218** and compare parameter values with a predetermined condition (such as a threshold value or range). If such condition is met, the monitoring system **222** may request any one or more particular network entities **218** to report measurement(s) of a parameter(s) for a particular time. As such, the pattern recovery **1006** may effect a particular predetermined synchronization between measurements of different various network entities **218**. The synchronizing monitoring rules **248** may also be processed by network entities **218**.

The orchestration system **238** may deploy software packages (including but not be limited to micro-services and/or VNFs) in various communication devices and/or computing devices within the network management system **212**. The orchestration system **238** may deploy the software packages according to configuration data and/or configuration-change data, provided by a network analysis and configuration system (such as the network optimizing system **234** and/or the orchestration system **238**) executing network analysis and configuration software. The configuration change may shift processing load and/or communication load from one part of the communication network to another so as to balance the load and provide adequate service level according to the ever changing requirements of the network customers.

The RT analysis system **226**, the network optimizing system **234**, and/or the network orchestration system **238** may create a new monitoring rule **248**, delete the monitoring rule **248**, and/or modify a parameter of the monitoring rule **248**. The modifications to the monitoring rules **248** may be associated and/or follow a predicted situation **232**, and or a new network configuration **236**, and or a configuration change. For example, the run-time system **1002** of the network management system **212** may modify one or more monitoring rules **248** to obtain more detailed log data **224** so as to increase (or decrease) a level of confidence of a predicted situation **232**.

To improve the ability of the network management system **212** to detect or predict load-changes, the RT analysis system **226** and/or the orchestration system **238** may make changes to the monitoring rules **248**, for example, by changing a rate of monitoring a function, and/or by changing a threshold for reporting a change of a particular parameter monitored, etc.

As such, the deep system module **216** may amend the monitoring rules **248**, and/or produce new monitoring rules **248**, to have more detailed patterns leading to a fault situation and/or fault events. In this manner, one or more predictors of network situations may be more effectively and accurately generated.

FIG. **11** illustrates a data structure **1100**, in accordance with one embodiment. As an option, the data structure **1100** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the data structure **1100** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

As shown, the data structure **1100** includes three levels, including level **1 1118**A, level **2 1118**B, and level N **1118**C. Of course, it to be appreciated that any number of levels may be implemented. In one embodiment, level **1 1118**A, level **2 1118**B, and level N **1118**C may correspond with three levels of resolution of the log data **224** and corresponding AI-models.

In one embodiment, a data structure may include a data record representing a particular configuration, such as the network configuration **236**. Additionally, any number of network configuration **236** records may be included in the data structure, where each network configuration **236** may represent a particular network configuration **236**.

As shown, a network configuration **236** record may be associated with a configuration change **1106** representing a change of the network configuration from a previous network configuration **236**.

The network configuration **236** may also be associated with a set of monitoring rules **1128** and with a set of network situations **1102**. In one embodiment, the monitoring rules **1128** may include the monitoring rules **248**. Additionally, the monitoring rules **1128** may instruct the network entities **218** and/or the network monitoring system **222** how to measure and report event logs **1126** and create log data **224**. In one embodiment, the event log **1126** may include the event log **220**.

The training and testing data preparation system **502** may use a record describing a particular type of network situation to detect the network situations **1102** in the log data, and label the log data **224** to train the AI learning system **510** to create an AI model **1120** to detect the development of the network situations **1102** in the log data **224**. The RT analysis system **226** may then use one or more AI models **1120** to identify a respective suspected situation **1110** and assign it with a particular confidence level **1112**. In one embodiment, the suspected situation **1110** may include the suspected situation **228**.

In one embodiment, the AI model **1120** may identify the network situations **1102** by detecting a corresponding classifier **1122** in the log data **1126**. In one embodiment, the classifier **1122** may include but not limited to an event pattern or a log pattern. Additionally, the log data **1124** may include the log data **224**. The confidence level **1112** may be computed based on values of the parameters of the corresponding classifier **1122** (including an event pattern). If the confidence level **1112** is above a predefined threshold value, the confidence analysis system **230** may produce a predicted situation **1114** record. In one embodiment, the predicted situation **1114** may include the predicted situation **232**.

A communication network may have millions of network entities **218**. Each network entity **218** may measure a variety of parameters each minute (or for any amount of time). These parameters may be communicated to the monitoring system **222** and properly stored in the log data **224**, and then processed (analyzed) by the RT analysis system **226**. In one embodiment, such flow of events may occur in real-time.

In one embodiment, each of the customers **208** of the communication network may have an SLA **210** (or a similar entity defining communication and/or processing requirements) with a network operator as well as SLAs **210** between the customers **208** and (third party) the service operators **206**. Each of the SLA **210** may affect one or more of the network situations **1102**. Additionally, each network situation **1102** may affect several classifiers **1122**. In turn, the classifier **1122** may affect at least one AI model **1120**.

As such, the RT analysis system **226**, when analyzing the log data **1124**, may operate a very large number of AI-models **1120**, and which may occur in parallel or near in parallel. Each of the AI model **1120** may scan the log data **1124** (including the log data stream) for a particular pattern of data of several parameters within respective value ranges or thresholds. In one embodiment, this scan may be repeated. Additionally, it may occur in parallel and may be processed in real-time.

Measuring, communicating, storing and processing such large amounts of data in real-time may be highly impractical. Therefore, as shown in the data structure **1100**, applying a multi-stage monitoring and multi-stage analysis may assist in processing such large amounts of data. In one embodiment, each stage may represent a different resolution of the amount and type of data measured, and/or communicated, and/or stored, and/or processed.

As shown, each level (corresponding with the level **1** **1118**A, the level **2** **1118**B, and the level N **1118**C) may include the monitoring rules **1128**, which may be used to collect the event log **1126**, which in turn creates the log data **1124**, which in turn, creates a classifier **1122** (including an event pattern), which in turn may be used to create an AI model **1120**.

Additionally, there may be N levels (or stages) of resolution, which may correspond with any number of "N" levels. Further, each stage may have a particular set of monitoring rules **1128**, which in turn may produce a different set of event log **1126** records. Each stage may then produce a different log data **1124** (including a data log stream), which in turn may carry a different set of event patterns classifiers **1122**. In this manner, each level (or stage) may use a different set of AI models **1120** to detect the respective classifier **1122** (and/or event patterns).

In one embodiment, a default stage used by the network management system **212** may be level **1** **1118**A. Additionally, the stage **1** may include the lowest resolution (especially in comparison to the level **2** **1118**B and/or the level N **1118**C). Additionally, the low resolution may imply that the network **202** may produce less event log **220** records per time unit (e.g., a second). This may in turn cause each network entity **218** to perform fewer measurements, which in turn may result in fewer measurements being reported and/or stored in the log data **224**.

For example, fewer measurements may be made because the corresponding monitoring rule **248** may instruct a lower measurement frequency (repetition rate), a less sensitive reporting threshold, and/or a storage of a particular average of some measurements rather than the measurements themselves.

The monitoring rules **1128** for the level **1** **1118**A may be arranged to produce the classifier **1122** for each and every network situation **1102**. In another embodiment, the monitoring rules **1128** for the level **1** **1118**A may be arranged to produce the training data **508** and testing data **502** labeled with the network situation **1102**. In this manner, the AI learning system **510** may produce AI models **1120**, where each AI model **1120** may detect at least one classifier **1122** for each corresponding network situation **1102**.

In one embodiment, the AI model **1120** for the level **1** **1118**A may detect a corresponding network situation **1102** with relatively low confidence level **1112**, which may be insufficient to determine a predicted situation **1114**. In another embodiment, the AI learning system **510** may have produced an AI model **1120** that detects two or more network situations **1102**. For example, the AI model **1120** may detect a classifier **1122** (or an event pattern) representing the two or more network situations **1102**. In this embodiment, additional monitoring data may be needed to properly determine particular network situations **1102** with a sufficient confidence level **1112**.

If the confidence analysis system **230** detects a suspected situation with a confidence level **1112** lower than a threshold value required to determine a predicted situation **232**, the confidence analysis system **230** may produce a pattern recovery record **1006** and communicate it to the monitoring system **222**, to the orchestration system **238**, to the RT analysis system **226**, and/or to any similar entity. In various embodiments, the pattern recovery record **1006** may affect a number of actions, as follows.

Action 1

In one embodiment, in response to the pattern recovery record **1006**, the monitoring system **222** may resend the log data **224** with additional measurements. Additionally, these additional measurements may be reported and collected by the monitoring system **222**. However, in one embodiment, the additional measurements may not be provided in the level **1** **1118**A log-data **1124** so as to reduce an amount of data and the respective processing load. For example, the monitoring system **222** may compute a particular parameter that may have been included in the level **1** **1118**A log-data **1124** including a combination of a plurality of parameters (including, for example, an average). Additionally, the combination may be computed based on a plurality of parameters of different types.

Action 2

In another embodiment, responsive to the pattern recovery record **1006**, the monitoring system **222** may send to one or more network entities **218** one or more monitoring rules **248** requesting to report measurements that were collected by the network entity **218** and stored. Additionally, the report measurements may have been not reported but possibly used by the network entity **218** to compute a particular parameter that was reported to the monitoring system **222**.

Action 3

Still yet, in one embodiment, responsive to the pattern recovery record **1006**, the monitoring system **222** may request one or more network entities **218** to measure, collect, and/or report additional parameters, particular parameters in a higher frequency, particular parameters within a more sensitive threshold (or a range of parameters).

Action 4

In another embodiment, responsive to the pattern recovery record **1006**, the monitoring system **222** may cause an effect of a synchronization between measurements of different types of parameters, or between measurements by different network entities **218**. The synchronization may be simultaneous, in the sense that a plurality of parameters may be measured at the same time by the same network entity **218** or by different network entities **218**. Additionally, the synchronization may be coincidental, in the sense that a particular parameter measurement (such as measuring a particular value like a threshold or range) may trigger the measurement of another parameter, or a sequence of such measurements, by the same network entity **218** or by different network entities **218**. In this sense, the initiating measurement may be a combination of measurements.

As such, the pattern recovery record **1006** may include an identification of the one or more suspected situations **1110** for which the monitoring system **222** should initiate a respective higher level (such as moving from the level **1** **1118**A to the level **2** **1118**B) of monitoring rules **1128**. Consequently, the RT analysis system **226** may use a respective higher level AI modules **1120**.

The network management system **212** may therefore move from the level **1** **1118**A monitoring and analyzing to the level **2** **1118**B monitoring and analyzing. Of course, it is to be appreciated that there may be several different level **2** **1118**B schemes, where a level **2** **1118**B scheme may apply to one or more particular network situations **1102** that have been detected as a respective suspected situation **1110** with insufficient confidence level **1112**. For any of such suspected situation **1110** with insufficient confidence level **1112** the confidence analysis system **230** may produce a respective pattern recovery record **1006** (shown in particular as pattern recovery **1→2 1130**) which may transform respective monitoring rules **1128** into level **2 1118**B monitoring and analysis. Additionally, in one embodiment, pattern recovery N−1>N **1132** may be additionally used as more than one level is used.

As such, the RT analysis system **226** may use one or more level **2 1118**B AI models **1120** corresponding to the pattern recovery record(s) **1130** (and/or **1132**), the new monitoring rules **1128**, and/or the updated log data **1124**.

Further stages of monitoring and analysis can be determined and escalated as needed to detect a suspected situation **1110** with sufficient confidence level **1112** while minimizing the burden of measuring, reporting, storing, and processing.

In one embodiment, the confidence analysis system **230** may be used to determine which suspected situation **1110** has a higher probability to develop a sufficient confidence level **1112**, which level should be used to attain the sufficient confidence level **1112**, and when to put into effect the required level.

The confidence analysis system **230** may determine a probability based on, for example, confidence history **1116**. The confidence history **1116** may record statistical parameters of the development of confidence level **1112** of various suspected situations **1110** with respect to the levels (such as the level **1 1118**A, the level **2 1118**B, and/or the level N **1118**C) used. The statistical parameters may include, for example, a probability that the confidence level **1112** of a particular suspected situation **1110** may increase, and/or a time rate in which the confidence level **1112** of a particular suspected situation **1110** may increase with respect to a particular level (such as the level **1 1118**A, the level **2 1118**B, and/or the level N **1118**C) used.

FIG. **12** illustrates a method for multi-stage monitoring and learning **1200**, in accordance with one embodiment. As an option, the method **1200** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the method **1200** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

Additionally, FIGS. **13**A, **13**B, and **13**C each illustrate a timeline **1301**, **1303**, and **1305**, respectively, of log data as processed by a multi-stage monitoring and learning system, in accordance with one embodiment. As an option, the timeline **1301**, **1303**, and **1305** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the timeline **1301**, **1303**, and **1305** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

Further, FIG. **14** illustrates a data structure **1400** produced by a multi-stage monitoring and learning system, in accordance with one embodiment. As an option, the data structure **1400** may be implemented in the context of any one or more of the embodiments set forth in any previous and/or subsequent figure(s) and/or description thereof. Of course, however, the data structure **1400** may be implemented in the context of any desired environment. Further, the aforementioned definitions may equally apply to the description below.

In one embodiment, the method **1200** may create a plurality of log data versions, then train an AI learning system **510** such that the AI learning system **510** may create a plurality of AI models **1122** for detecting the classifier(s) **1122** of the one or more network situations **1102**. It is to be appreciated that any number of log versions may be possible. Additionally, while the log data versions **1301**, **1303**, and **1305** have one network situation and one classifier, any number of network situations and any number of classifiers associated with the log data may be possible. Further, each network situation **1102** and/or each classifier **1122** may have a respective number of log data versions with a respective number of AI models **1120**.

As shown in FIG. **14**, the data structure **1400** may include a plurality of network situations, monitoring rules, classifiers, and AI-models (as herein explained in reference to FIG. **11**). For example, each network situation **1102** may associated with a plurality of sets of monitoring rules **1128**, where each set of monitoring rules **1128** may produce a log data version of a different resolution, including at least one classifier **1122**. The at least one classifier **1122** may have one or more AI models **1120** detecting the classifier **1122** in the respective log data version.

It is to be appreciated that a particular set of monitoring rules **1128** may accommodate a plurality of classifiers **1122** of a plurality of network situations **1102**. Additionally, a classifier **1122** such as A1 may be associated with a same network situation **1102** labeled as the network situation A **1402**. Of course, other classifiers **1122** may be associated with the network situation **1102** in the sense that a log pattern or event-pattern may be different due to different monitoring resolutions.

For example, a resolution **1** may indicate high resolution, a resolution **2** may indicate medium resolution, and a resolution N may indicate lowest resolution of respective log data versions **21**, **22**, and **23**. In the context of the present description, a resolution refers to a density of event logs, and/or a number of event logs per a predetermined space of time. Additionally, log data version **21** of FIG. **14** may correspond with log data versions **1301**, log data version **22** of FIG. **14** may correspond with log data version **1303**, and log data version **23** of FIG. **14** may correspond with log data version **1305**.

In particular, the network situation A **1402** may lead to monitoring rules A with resolution **1 1404**A, monitoring rules A with resolution **2 1404**B, and/or monitoring rules A with resolution N **1404**C. Next, the monitoring rules may capture the log data **21** version A with resolution **1 1406**A, log data **22** version A resolution A **1406**B, and/or log data **23** version A with resolution A **1406**C.

The log data version may then lead to a classifier. In particular, the log data **21** version A with resolution **1 1406**A may lead to classifier A1 with resolution **1 1408**A, and classifier AM with resolution A **1410**A. The log data **22** version A resolution A **1406**B may lead to classifier A1 with resolution **2 1408**B, and classifier AM resolution **2 1410**B. Further, the log data **23** version A with resolution A **1406**C may lead to classifier A1 with resolution N **1408**C, and classifier AM with resolution N **1410**C.

The classifier may in turn lead to an AI model. In particular, the classifier A1 with resolution **1 1408**A may lead to AI model A1 with resolution **1 1412**A, which in turn may lead to a confidence level A1A **1416**A and a lead-time A1A **1418**A. The classifier AM with resolution **1 1410**A may lead to AI model AM with resolution **1 1414**A, which in turn may lead to a confidence level A1B **1416**B, and a lead-time A1B **1418**B.

The classifier A1 with resolution **2 1408**B may lead to AI model A1 with resolution **2 1412**B, which in turn may lead to a confidence level A2A **1416**C and a lead-time A2A **1418**C. The classifier AM with resolution **2 1410**B may lead to AI model AM with resolution **2** **1414**B, which in turn may lead to a confidence level A2B **1416**D, and a lead-time A2B **1418**D.

Additionally, the classifier A**1** with resolution N **1408**C may lead to AI model A**1** with resolution N **1412**C, which in turn may lead to a confidence level ANA **1416**E and a lead-time ANA **1418**E. The classifier AM with resolution N **1410**C may lead to AI model AM with resolution N **1414**C, which in turn may lead to a confidence level ANB **1416**F, and a lead-time ANB **1418**F.

With respect to FIG. **13**A, timeline **1301** includes a plurality of event log **1302**A data and a label **1304** of a particular network situation. The particular network situation may be associated with a minimal time period representing the time to reconfigure the network per the particular network situation. The timeline **1301** may include a data version (such as the log data version **21** version A with resolution **1** **1406**A). Additionally, the timeline **1301** may include a classifier **1308** of one or more event log **1302**A data, with a respective lead-time **1306** between the end of the classifier (time of a last log event of the classifier) and label **1304**. In one embodiment, the timeline **1301** may represent the highest resolution, and the AI-model detecting the classifier **1308** may have the highest confidence level. Typically, a lead-time **1306** of the classifier **1308** may include a shorter lead-time, as the density of the event log **1302**A is higher (in comparison to the timeline **1303** and the timeline **1305**). In one embodiment, the timeline **1301** may include log data of a particular version.

In another embodiment, FIG. **13**C includes the timeline **1305** with the lowest resolution (in comparison to the timeline **1301** and the timeline **1303**). Consequently, log data of the timeline **1305** may include a smaller number or density, per time, of event log **1300** data. The event log **1302**C may be different than the event log data of the other versions, carrying less, or different data. The classifier **1316** may have less data objects, such as event log **1302**C data records. The AI-model for the classifier **1316** may also include a lower confidence level. However, the classifier **1316** may include the longest lead-time **1314** from the label **1304** of the same particular network situation. In one embodiment, the timeline **1305** may include log data of a separate particular version from the log data associated with the timeline **1301** and/or the timeline **1303**.

Still yet, FIG. **14**B includes the timeline **1303** where log data may have a median resolution, corresponding with a medium density of event log **1302**B data carrying a medium amount of data. A classifier **1312** (or classifiers) may have a medium number of data objects. The AI-model for classifier **1312** may have a medium confidence level and a medium lead-time **1310**.

With respect to FIG. **12**, the method **1200** may include a multi-stage monitoring and learning process. In one embodiment, the method **1200** may start with an arbitrary medium resolution version of the log data **224** and then work towards a higher resolution and/or lower resolution version as needed to reach predetermined goals. In one embodiment, the predetermined goals may include predetermined values, and/or value ranges of confidence levels and respective lead-time periods. It is to be appreciated that the method **1200** may be an iterative and/or repetitive process. Additionally, the method **1200** may optimize the data structure **1400**, for example, with respect to a confidence level and a lead-time produced by the AI-modules of the respective resolution level(s).

For example, the method **1200** may include creating a set of monitoring rules for a particular network situation A having a particular minimum reconfiguration time. This set of monitoring rules may be used to generate log data of a particular version at a specific resolution. The AI learning system **510** may then create one or more AI models **1120** detecting respective classifiers **1122** that predict a network situation A with a particular confidence level (CL), and a lead-time (LT) that is equal or greater than the minimum reconfiguration time (MRT) of the network situation A.

If, for example, the confidence level is less than a predetermined upper goal, or the lead-time is less than the minimum reconfiguration time, the method **1200** may include creating, for the same network situation A, a second set of monitoring rules having a higher resolution. The method **1200** may include repeating this process until the confidence level reaches the predetermined upper goal, and the lead-time is at least the minimum reconfiguration time.

Additionally, the method **1200** may also work down the resolution. For example, another set of monitoring rules having lower resolution may be created for the same network situation A, which may be used to work down the resolution. The AI learning system **510** may then create one or more AI-models **1120** detecting respective classifiers **1122** that predict network situation A with a particular confidence level and lead-time. In one embodiment, the confidence level may be lower than the confidence level of any higher resolution log data, but higher than a minimal predetermined value of the confidence level. Additionally, the lead time may be at least a value of the longest lead time for any of the higher-resolution log data versions.

In one embodiment, the method **1200** may define a first set of monitoring rules, where the first set of monitoring rules is used by at least one network entity of the communication network to create event log data of activity of the network. In one embodiment, the first set of monitoring rules may generate higher-resolution event log data, collect the event log data as log data of the activity of the network, define at least one network situation to be detected in the log data, and compute at least one AI-model, using the AI learning system **510**. In one embodiment, the AI-model may enable the AI-analysis system **510** to detect the network situation in the log data.

Additionally, the method **1200** may define a second set of monitoring rules, where the second set of monitoring rules is used by at least one network entity of the communication network to create event log data of activity of the network. In one embodiment, the second set of monitoring rules may generate lower-resolution event log data than the first set of monitoring rules, collect the event log data as log data of the activity of the network, define at least one network situation to be detected in the log data, and compute at least one AI-model, using the AI learning system **510**. In one embodiment, the AI-model may enable the AI-analysis system **510** to detect the network situation in the log data. The log data collected with the second set of monitoring rules may include less data elements than the log data collected with the first set of monitoring rules.

Further, the method **1200** may also compute a confidence level for the AI-model typically representing a probability that the respective classifier is within a predetermined time range. After computing a confidence level, the method **1200** may repeat in the form of defining a set of monitoring rules, collecting the event log data as log data, defining at least one network situation to be detected in the log data, and computing at least one AI model. Such steps may be repeated until the confidence level is more than a predetermined value. In a separate embodiment, such steps may be repeated as well until the confidence level is less than another predetermined value.

Still yet, the method **1200** may include comparing lead time periods, and accepting an AI model for lower-resolution log data if the respective lead-time period is larger than the lead-time period for a respective AI model of a higher-resolution log-data. The AI-models may detect a classifier preceding the network situation, where the classifier includes at least one value of at least one parameter of at least one event log preceding the network situation by a first time period.

As shown, operation **1202** includes selecting a particular network situation designated here as "network situation A". In the present embodiment, network situation A may be one of the network situations characterized for the current network configuration. The characteristics of network situation A may enable the creation of respective monitoring rules that measures relevant parameters and report them as event-log records (see operation **1204**), which may be collected to form log data (see operation **1206**). In one embodiment, the log data may be collected at a specific resolution, such as resolution medium ("M"). The characteristics of network situation A may enable the creation of one or more rules, or a similar mechanism, for detecting network situation A in log data of the network in the current configuration (see operation **1208**). The characteristics of network situation A may also enable the formation of a label to designate an occurrence of network situation A in the log data (see operation **1210**). The characteristics of network situation A may also enable the evaluation of the minimum reconfiguration time for repairing or exploiting the network situation A.

In one embodiment, the method **1200** may, for example, execute operations **1202**, **1204**, **1206**, **1208**, and **1210** for an arbitrary set of monitoring rules that may be considered as medium resolution and designated as log data M (such as, for example, the log data displayed in timeline **1303** of FIG. **13**B). As such, the method **1200** may create training data (as well as testing data) for AI-learning system.

As shown, operation **1212** includes scanning log data M to detect a classifier for network situation A, and in turn, creating create an AI-model to detect the classifier (see operation **1214**). Next, at operation **1216**, confidence level and lead time of the detectable classifier with respect to network Situation A may be determined. Further, the confidence level and lead time are assigned to the AI model. See operation **1218**. In one embodiment, such AI model may be used to detect the classifier.

At decision **1220**, it is determined if the lead-time (LT) is less than the minimum reconfiguration time (MRT) for repairing or exploiting network situation A, and/or if the confidence level satisfies a predetermined minimum criterion.

If the lead-time is smaller than the minimum reconfiguration time, or if the confidence level is less than the minimum criterion (Lower Goal), the method **1200** may proceed to operation **1224** where monitoring rules are created and distributed for resolution N−1 where the resolution N−1 is greater than the resolution N. As such, the resolution level is increased. Additionally, operations **1206-1218** are then repeated for resolution N−1. See operation **1226**.

If the lead-time is not smaller than the minimum reconfiguration time, or if the confidence level is not less than the minimum criterion, the method **1200** proceeds to decision **1222**, where if the lead-time is greater than the minimum reconfiguration time, and/or if the confidence level is less than the maximum criterion (Upper Goal), then the method **1200** proceeds again to operation **1224**, and then operation **1226**.

However, if the upper goal of confidence level is achieved per decision **1222**, the method **1200** may proceed to reduce the level of resolution per operation **1228**. In particular, operation **1228** includes creating and distributing monitoring rules for resolution N+1 where resolution N+1 is less than a resolution N. Then, operations **1206** through **1218** may be repeated until a lower confidence level goal is reached, as shown in decision **1232**. In particular, the decision **1232** may include determining whether the lead-time is greater than the minimum reconfiguration time and if the confidence level is less than a minimum criterion (Lower Goal). Additionally, decision **1232** may discard lower resolution systems (monitoring rules and AI-models) and may produce a lead-time shorter than the maximum lead-time being the longest lead-time of any of the higher resolution systems.

At operation **1234**, the network situation B (or the following network situation) may be selected. In this manner, the method **1200** may be repeated for all network situations that may be characterized for the current network configuration.

In this respect, the SLA **210** or any similar descriptions of wanted and/or unwanted network behavior (e.g., cost saving, service fault, cyber-security attack/breech, etc.) may be used to define a corresponding one or more parametrized network situations of the network situation **1102**. The network situation **1102** may be parametrized in the sense that it can be detected by one or more communication parameters, where the one or more communication parameters reached a particular threshold or value range, etc.

The monitoring rules **1128** may then be devised and implemented in sufficient network entities **218** to report the respective parameters identifying the respective network situation **1102**. The network situation **1102** may then be detected in the log data **1124** of the communication network and properly labeled. The AI learning system **510** may then be used to detect a classifier **1122**, namely a log-pattern, or a pattern of event parameters reported by various network entities **218**, where the log-pattern happens to predict a following network situation. The AI learning system **510** may operates in two steps.

In step 1, —unsupervised AI learning may search for a classifier **1122**, such as a correlated repetition of log-patterns preceding the network situation **1102** within a particular time range, which may be statistically significant. This may be a statistical process where the AI learning system **510** may investigate a large number of instances of the particular type of network situation **1102** (as labeled) to identify a repetitive log-pattern typically preceding the network situation **1102** within a particular time range, which may be identified as lead-time. There may be any number of different log-patterns preceding a network situation type.

In step 2, the AI learning system **510** may create an AI-model **1120** to automatically detect a particular single classifier instance. The classifier **1122** (or the associated network situation **1102**) may have a confidence level **1112** representing a probability that the detected classifier **1122** may mature into a network situation within a time range about the lead-time.

It is to be appreciated that step 1 and step 2 may be implemented as a single procedure performing these two steps as a combined iterative process of detecting the classifier and creating the AI model **1120**.

Additionally, in one embodiment, a product of the learning system is the AI model **1120** that detects the particular classifier **1122**. The classifier **1122** may be a pattern of data elements, and the AI model **1120** may be a piece of software (e.g., a neural network) that detects the particular pattern in a stream of the log data **1124**, so although the classifier **1122** and the AI model **1120** may be different, they may be closely related. Therefore, parameters associated with the classifier **1122** may be associated with the AI model **1120** and vice versa.

The classifier **1122**, and hence the respective AI-model **1120** may have but not be limited to the following parameters: time of the classifier, an identification of a particular type of network situation that may follow the classifier, a lead-time, a time range, a confidence level, and/or parameter characterization. A configuration level may represent a probability that the identified network situation may mature within the time range at the end of the lead-time following the time of the classifier. Further parameters may include parameters associated with a group of classifiers and/or AI models, such as but not limited to resolution stage (level), minimum reconfiguration time (which may be associated with the network situation), etc.

Though the classifier **1122** may be unknown, the AI learning system **510** may provide some data about the classifier **1122**, such as the parameters that the AI model **1120** may process to detect the identifier. These parameters may form the parameter characterization data. Therefore, the parameter characterization data of a particular AI model may identify each such parameter by type, as well as the particular network entities **218** reporting the particular parameter.

When the AI learning system **510** scans for a lower resolution classifier, the AI learning system **510** may be requested to look for a classifier with a lead-time longer than any higher resolution classifier. When the AI learning system **510** scans for a higher resolution classifier, the AI learning system **510** may be requested to look for a classifier with higher confidence level than any lower resolution classifier. Therefore, the AI learning system **510** may produce a multi-stage structure of the AI models **1120** with increasing resolution, increasing confidence level, and decreasing lead-time (and vice versa).

In one embodiment, the RT analysis system **226** may detect a lower-resolution classifier, and at such detection, there may be a higher-resolution classifier associated with a higher confidence level and sufficient lead-time. Therefore, if the higher resolution AI-model detects a respective classifier it may have lead time longer than the minimum reconfiguration time for the particular network situation in the particular configuration.

Additionally, for a particular type of network situation **1102**, there is a multi-stage structure of stratified resolutions, where within each resolution level/stage, there may be any number of AI models/classifiers (to be processed in parallel). In one embodiment, each of the AI models may have a respective lead-time and confidence level. However, in another embodiment, lower resolution AI models may have lower confidence level (to ensure low probability of false negative detection) and longer lead-time (to enable operating the higher resolution AI model in time).

Each of the network situation **1102** may have its own multi-stage resolution structure having a plurality of levels of resolution. Each resolution level may include one or more AI models **1120**, and one or more monitoring rules **1128** to produce the log data **1124** that the respective AI model **1120** may process to identify the respective classifiers **1122** to predict the network situation **1102** with a respective confidence level **1112** (probability of occurrence within a respective time range).

FIG. **15** illustrates a network architecture **1500**, in accordance with one possible embodiment. As shown, at least one network **1502** is provided. In the context of the present network architecture **1500**, the network **1502** may take any form including, but not limited to a telecommunications network, a local area network (LAN), a wireless network, a wide area network (WAN) such as the Internet, peer-to-peer network, cable network, etc. While only one network is shown, it should be understood that two or more similar or different networks **1502** may be provided.

Coupled to the network **1502** is a plurality of devices. For example, a server computer **1512** and an end user computer **1508** may be coupled to the network **1502** for communication purposes. Such end user computer **1508** may include a desktop computer, lap-top computer, and/or any other type of logic. Still yet, various other devices may be coupled to the network **1502** including a personal digital assistant (PDA) device **1510**, a mobile phone device **1506**, a television **1504**, etc.

FIG. **16** illustrates an exemplary system **1600**, in accordance with one embodiment. As an option, the system **1600** may be implemented in the context of any of the devices of the network architecture **1500** of FIG. **15**. Of course, the system **1600** may be implemented in any desired environment.

As shown, a system **1600** is provided including at least one central processor **1602** which is connected to a communication bus **1612**. The system **1600** also includes main memory **1604** [e.g. random access memory (RAM), etc.]. The system **1600** also includes a graphics processor **1608** and a display **1610**.

The system **1600** may also include a secondary storage **1606**. The secondary storage **1606** includes, for example, a hard disk drive and/or a removable storage drive, representing a floppy disk drive, a magnetic tape drive, a compact disk drive, etc. The removable storage drive reads from and/or writes to a removable storage unit in a well-known manner.

Computer programs, or computer control logic algorithms, may be stored in the main memory **1604**, the secondary storage **1606**, and/or any other memory, for that matter. Such computer programs, when executed, enable the system **1600** to perform various functions (as set forth above, for example). Memory **1604**, storage **1606** and/or any other storage are possible examples of non-transitory computer-readable media. It is noted that the techniques described herein, in an aspect, are embodied in executable instructions stored in a computer readable medium for use by or in connection with an instruction execution machine, apparatus, or device, such as a computer-based or processor-containing machine, apparatus, or device. It will be appreciated by those skilled in the art that for some embodiments, other types of computer readable media are included which may store data that is accessible by a computer, such as magnetic cassettes, flash memory cards, digital video disks, Bernoulli cartridges, random access memory (RAM), read-only memory (ROM), and the like.

As used here, a “computer-readable medium” includes one or more of any suitable media for storing the executable instructions of a computer program such that the instruction execution machine, system, apparatus, or device may read (or fetch) the instructions from the computer readable medium and execute the instructions for carrying out the described methods. Suitable storage formats include one or more of an electronic, magnetic, optical, and electromagnetic format. A non-exhaustive list of conventional exemplary computer readable medium includes: a portable computer diskette; a RAM; a ROM; an erasable programmable read only memory (EPROM or flash memory); optical storage devices, including a portable compact disc (CD), a portable digital video disc (DVD), a high definition DVD (HD-DVD™), a BLU-RAY disc; and the like.

It should be understood that the arrangement of components illustrated in the Figures described are exemplary and that other arrangements are possible. It should also be understood that the various system components (and means) defined by the claims, described below, and illustrated in the various block diagrams represent logical components in some systems configured according to the subject matter disclosed herein.

For example, one or more of these system components (and means) may be realized, in whole or in part, by at least some of the components illustrated in the arrangements illustrated in the described Figures. In addition, while at least one of these components are implemented at least partially as an electronic hardware component, and therefore constitutes a machine, the other components may be implemented in software that when included in an execution environment constitutes a machine, hardware, or a combination of software and hardware.

More particularly, at least one component defined by the claims is implemented at least partially as an electronic hardware component, such as an instruction execution machine (e.g., a processor-based or processor-containing machine) and/or as specialized circuits or circuitry (e.g., discreet logic gates interconnected to perform a specialized function). Other components may be implemented in software, hardware, or a combination of software and hardware. Moreover, some or all of these other components may be combined, some may be omitted altogether, and additional components may be added while still achieving the functionality described herein. Thus, the subject matter described herein may be embodied in many different variations, and all such variations are contemplated to be within the scope of what is claimed.

In the description above, the subject matter is described with reference to acts and symbolic representations of operations that are performed by one or more devices, unless indicated otherwise. As such, it will be understood that such acts and operations, which are at times referred to as being computer-executed, include the manipulation by the processor of data in a structured form. This manipulation transforms the data or maintains it at locations in the memory system of the computer, which reconfigures or otherwise alters the operation of the device in a manner well understood by those skilled in the art. The data is maintained at physical locations of the memory as data structures that have particular properties defined by the format of the data. However, while the subject matter is being described in the foregoing context, it is not meant to be limiting as those of skill in the art will appreciate that various of the acts and operations described hereinafter may also be implemented in hardware.

To facilitate an understanding of the subject matter described herein, many aspects are described in terms of sequences of actions. At least one of these aspects defined by the claims is performed by an electronic hardware component. For example, it will be recognized that the various actions may be performed by specialized circuits or circuitry, by program instructions being executed by one or more processors, or by a combination of both. The description herein of any sequence of actions is not intended to imply that the specific order described for performing that sequence must be followed. All methods described herein may be performed in any suitable order unless otherwise indicated herein or otherwise clearly contradicted by context.

The use of the terms "a" and "an" and "the" and similar referents in the context of describing the subject matter (particularly in the context of the following claims) are to be construed to cover both the singular and the plural, unless otherwise indicated herein or clearly contradicted by context. Recitation of ranges of values herein are merely intended to serve as a shorthand method of referring individually to each separate value falling within the range, unless otherwise indicated herein, and each separate value is incorporated into the specification as if it were individually recited herein. Furthermore, the foregoing description is for the purpose of illustration only, and not for the purpose of limitation, as the scope of protection sought is defined by the claims as set forth hereinafter together with any equivalents thereof entitled to. The use of any and all examples, or exemplary language (e.g., "such as") provided herein, is intended merely to better illustrate the subject matter and does not pose a limitation on the scope of the subject matter unless otherwise claimed. The use of the term "based on" and other like phrases indicating a condition for bringing about a result, both in the claims and in the written description, is not intended to foreclose any other conditions that bring about that result. No language in the specification should be construed as indicating any non-claimed element as essential to the practice of the invention as claimed.

The embodiments described herein included the one or more modes known to the inventor for carrying out the claimed subject matter. Of course, variations of those embodiments will become apparent to those of ordinary skill in the art upon reading the foregoing description. The inventor expects skilled artisans to employ such variations as appropriate, and the inventor intends for the claimed subject matter to be practiced otherwise than as specifically described herein. Accordingly, this claimed subject matter includes all modifications and equivalents of the subject matter recited in the claims appended hereto as permitted by applicable law. Moreover, any combination of the above-described elements in all possible variations thereof is encompassed unless otherwise indicated herein or otherwise clearly contradicted by context.

What is claimed is:

1. A computer program product comprising computer executable instructions stored on a non-transitory computer readable medium that when executed by a processor instruct the processor to:

define a first set of monitoring rules used by at least one network entity of a communication network, wherein the first set of monitoring rules cause event log data to be collected with a first level of detail;

collect first event log data of first network activity of the communication network based on the first monitoring rules, the first event log data having the first level of detail;

define a first network situation corresponding to the network activity;

compute a first artificial intelligence (AI) model based on the first event log data having the first level of detail and the first network situation, wherein the first AI model is configured to predict the first network situation from the first event log data with:

a first confidence level that the first network situation will be correctly predicted, and

a first lead-time;

determine that the first confidence level achieves an upper confidence level goal;

determine that a second AI model with a lead-time longer than the first lead-time is to be computed, as a result of determining that the first confidence level achieves the upper confidence level goal;

responsive to determining that the second AI model with the lead-time longer than the first lead-time is to be computed, define a second set of monitoring rules used by the at least one network entity, wherein the second set of monitoring rules cause event log data to be collected with a second level of detail that is lower than the first level of detail;

collect second event log data of the first network activity of the communication network based on the second monitoring rules, the second event log data having the second level of detail; and

compute the second AI model based on the second event log data having the second level of detail and the first network situation, wherein the second AI model is configured for detecting the first network situation in the second event log data with:

a second confidence level that is lower than the first confidence level and that is higher than a minimal predetermined confidence level, and

a second lead-time that is longer than the first lead-time.

2. The computer program product of claim **1**, wherein the computer program product is configured to use the first AI model to detect the first network activity.

3. The computer program product of claim **1**, wherein the computer program product is configured to use the second AI model to detect the first network activity.

4. The computer program product of claim **1**, wherein the first AI model detects a first classifier preceding the first network situation, where the first classifier includes at least one first parameter found in first prior event log data collected before the first network situation by a first time period.

5. The computer program product of claim **4**, wherein the second AI model detects a second classifier preceding the first network situation, where the second classifier includes at least one second parameter found in second prior log data collected before the first network situation by a second time period.

6. The computer program product of claim **5**, wherein the first time period is smaller than the second time period.

7. A method, comprising:

defining a first set of monitoring rules used by at least one network entity of a communication network, wherein the first set of monitoring rules cause event log data to be collected with a first level of detail;

collecting first event log data of first network activity of the communication network based on the first monitoring rules, the first event log data having the first level of detail;

defining define a first network situation corresponding to the network activity;

computing a first artificial intelligence (AI) model based on the first event log data having the first level of detail and the first network situation, wherein the first AI model is configured to predict the first network situation from the first event log data with:

a first confidence level that the first network situation will be correctly predicted, and

a first lead-time;

determining that the first confidence level achieves an upper confidence level goal;

determining that a second AI model with a lead-time longer than the first lead-time is to be computed, as a result of determining that the first confidence level achieves the upper confidence level goal;

responsive to determining that the second AI model with the lead-time longer than the first lead-time is to be computed, defining a second set of monitoring rules used by the at least one network entity, wherein the second set of monitoring rules cause event log data to be collected with a second level of detail that is lower than the first level of detail;

collecting second event log data of the first network activity of the communication network based on the second monitoring rules, the second event log data having the second level of detail; and

computing the second AI model based on the second event log data having the second level of detail and the first network situation, wherein the second AI model is configured for detecting the first network situation in the second event log data with:

a second confidence level that is lower than the first confidence level and that is higher than a minimal predetermined confidence level, and

a second lead-time that is longer than the first lead-time.

8. A device, comprising:

a non-transitory memory storing instructions; and

one or more processors in communication with the non-transitory memory, wherein the one or more processors execute the instructions to:

define a first set of monitoring rules used by at least one network entity of a communication network, wherein the first set of monitoring rules cause event log data to be collected with a first level of detail;

collect first event log data of first network activity of the communication network based on the first monitoring rules, the first event log data having the first level of detail;

define a first network situation corresponding to the network activity;

compute a first artificial intelligence (AI) model based on the first event log data having the first level of detail and the first network situation wherein the first AI model is configured to predict the first network situation from the first event log data with:

a first confidence level that the first network situation will be correctly predicted, and

a first lead-time;

determine that the first confidence level achieves an upper confidence level goal;

determine that a second AI model with a lead-time longer than the first lead-time is to be computed, as a result of determining that the first confidence level achieves the upper confidence level goal;

responsive to determining that the second AI model with the lead-time longer than the first lead-time is to be computed, define a second set of monitoring rules used by the at least one network entity, wherein the second set of monitoring rules cause event log data to be collected with a second level of detail that is lower than the first level of detail;

collect second event log data of the first network activity of the communication network based on the second monitoring rules, the second event log data having the second level of detail; and

compute the second AI model based on the second event log data having the second level of detail and the first network situation, wherein the second AI model is configured for detecting the first network situation in the second event log data with:

a second confidence level that is lower than the first confidence level and that is higher than a minimal predetermined confidence level, and

a second lead-time that is longer than the first lead-time.

9. The computer program product of claim **1**, further comprising:

determine whether the second confidence level reaches a lower confidence level goal and whether the second lead-time is greater than a minimum reconfiguration time; and

determine that a third AI model is to be computed, as a result of determining that the second confidence level does not reach the lower confidence level goal and that the second lead-time is greater than the minimum reconfiguration time.

10. The computer program product of claim **9**, further comprising:

responsive to determining that the third AI model with the lead-time longer than the first lead-time is to be computed, define a third set of monitoring rules used by the at least one network entity, wherein the third set of monitoring rules cause event log data to be collected with a third level of detail that is lower than the second level of detail;

collect third event log data of the first network activity of the communication network based on the third monitoring rules, the third event log data having the third level of detail; and

compute the third AI model based on the third event log data having the third level of detail and the first network situation, wherein the third AI model is configured for detecting the first network situation in the third event log data with:

a third confidence level that is lower than the second confidence level and that is higher than the minimal predetermined confidence level, and

a third lead-time that is longer than the first lead-time.

11. The computer program product of claim **1**, wherein the lead-time includes a time period between a first time of a detection of a classifier in event log data and a second time that the first network situation is predicted to occur.

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