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Grigoryan et al.

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(45) **Date of Patent: Nov. 26, 2019**

(54) **METHODS AND SYSTEMS TO DIAGNOSE ANOMALIES IN CLOUD INFRASTRUCTURES**

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(73) Assignee: **VMware, Inc.**, Palo Alto, CA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 362 days.

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(22) Filed: **Jun. 3, 2016**

(65) **Prior Publication Data**

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(51) **Int. Cl.**

G06F 13/00	(2006.01)
H04L 12/24	(2006.01)
H04L 29/08	(2006.01)

(52) **U.S. Cl.**
CPC ***H04L 41/064*** (2013.01); ***H04L 41/0677*** (2013.01); ***H04L 41/142*** (2013.01); *H04L 67/10* (2013.01)

(58) **Field of Classification Search**
CPC ... H04L 29/08072; H04L 29/06; H04L 43/00; H04L 12/2602; H04L 41/22; H04L 41/064; H04L 41/142; H04L 41/0677; H04L 67/10; G06F 13/00
USPC 709/224
See application file for complete search history.

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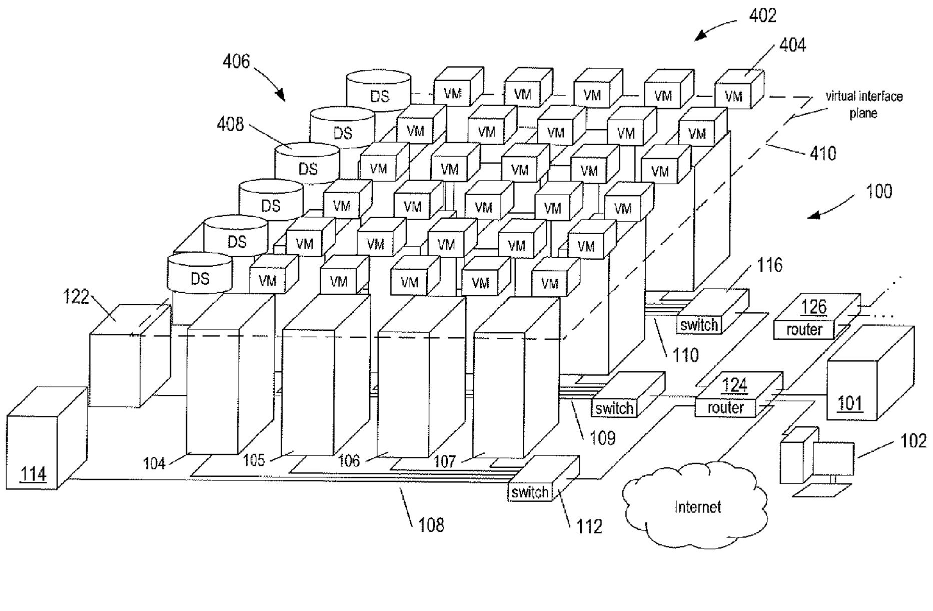
Primary Examiner — Robert B Harrell

(57) **ABSTRACT**

A problem in a cloud infrastructure may be identified when a server computer deviates from a normal level of operation based on anomaly scores, which generates an alert and an alert time that indicates when the alert is generated. Methods then determine which virtual machine ("VM") and other IT objects/resources or their pools contribute to the problem within a time window surrounding the estimated problem start time and calculate which objects show similar, related anomalous behavior. Methods also generate ranked remediation recommendations on an object level and server computer-to-object level. The methods generate results that enable a system administrator to identify the start time of the problem and identify the objects that are responsible for the problem.

27 Claims, 28 Drawing Sheets



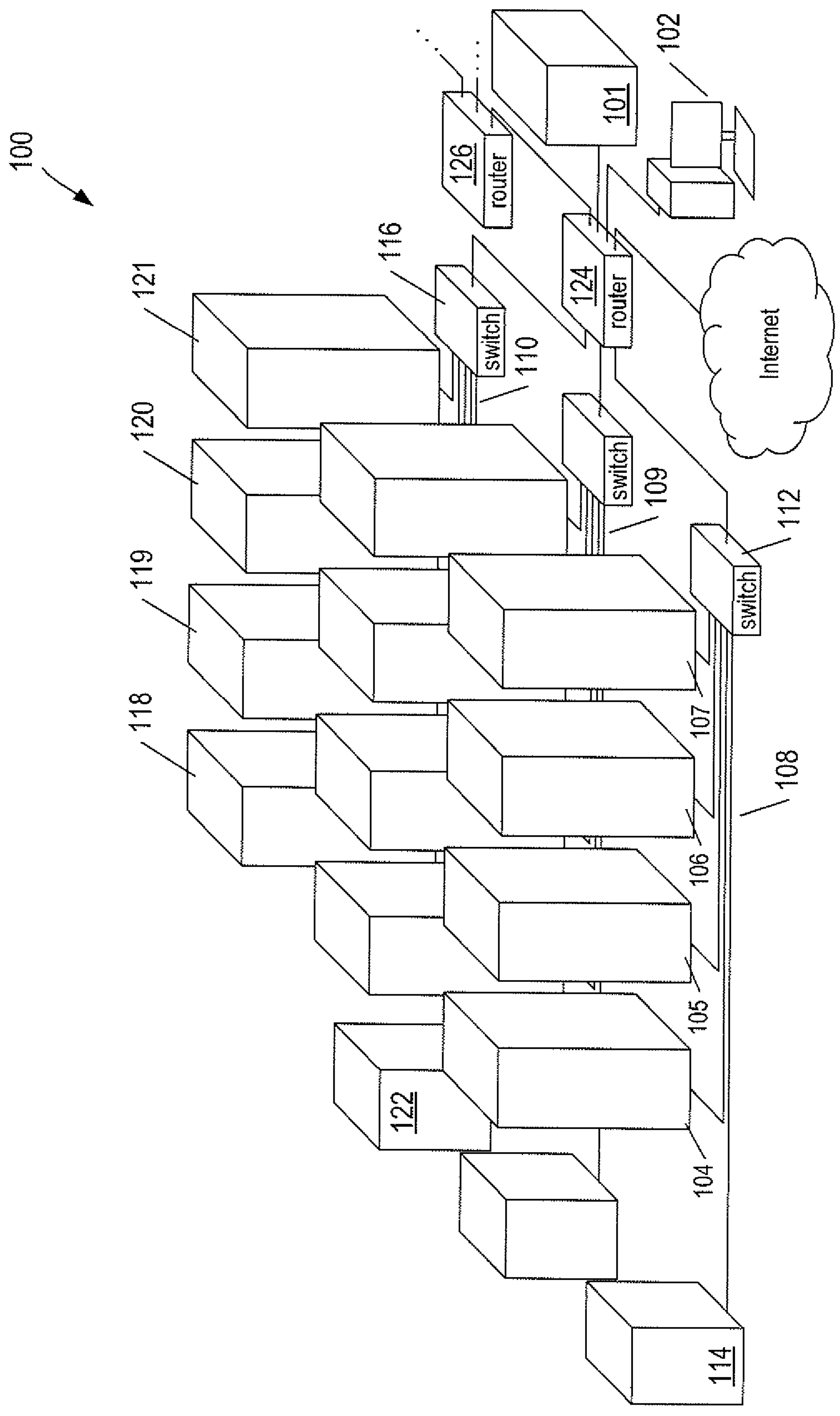

100
101
102
126
router
124
router
Internet
116
switch
110
121
120
switch
109
112
switch
119
118
107
106
108
105
122
104
114

FIG. 1

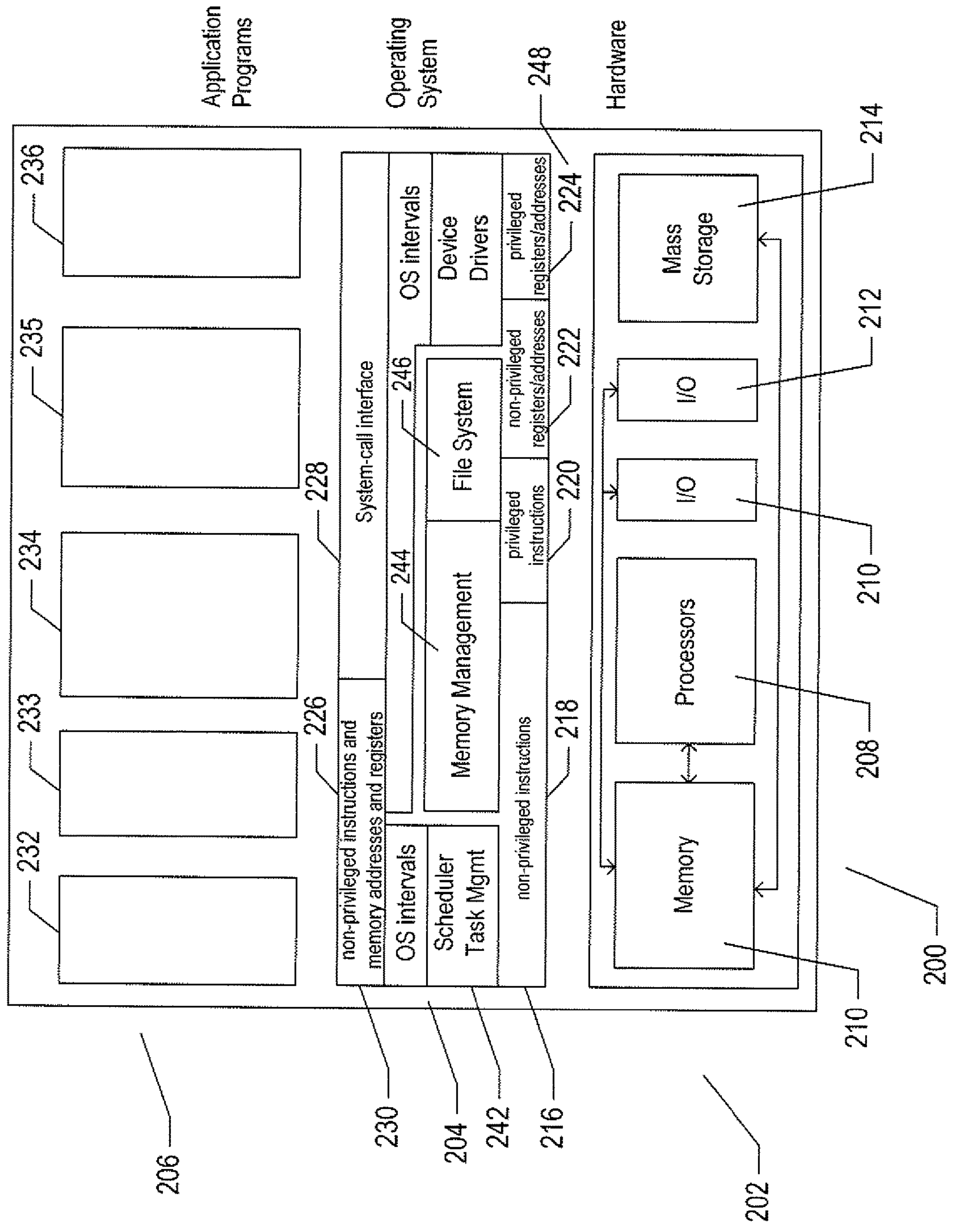
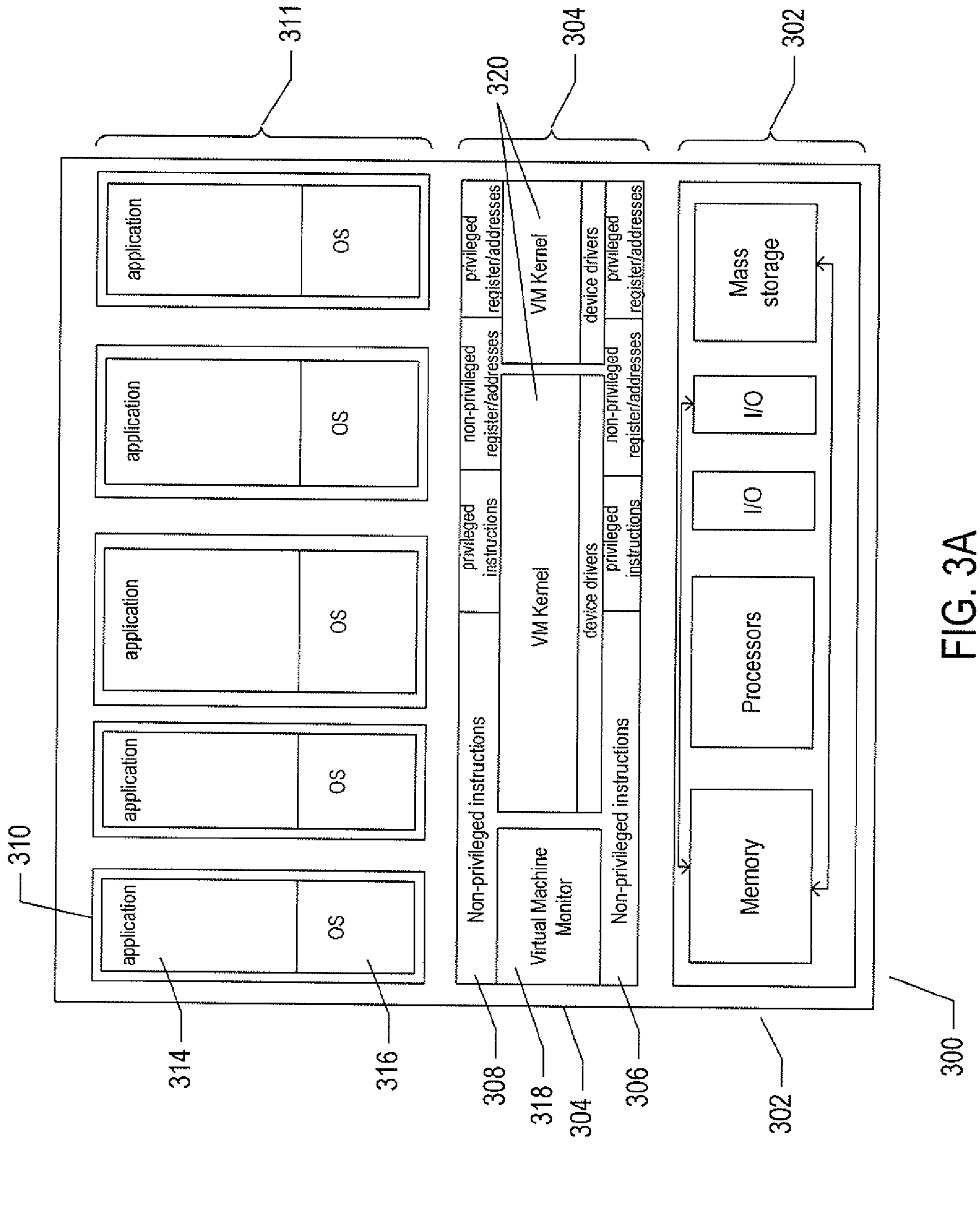
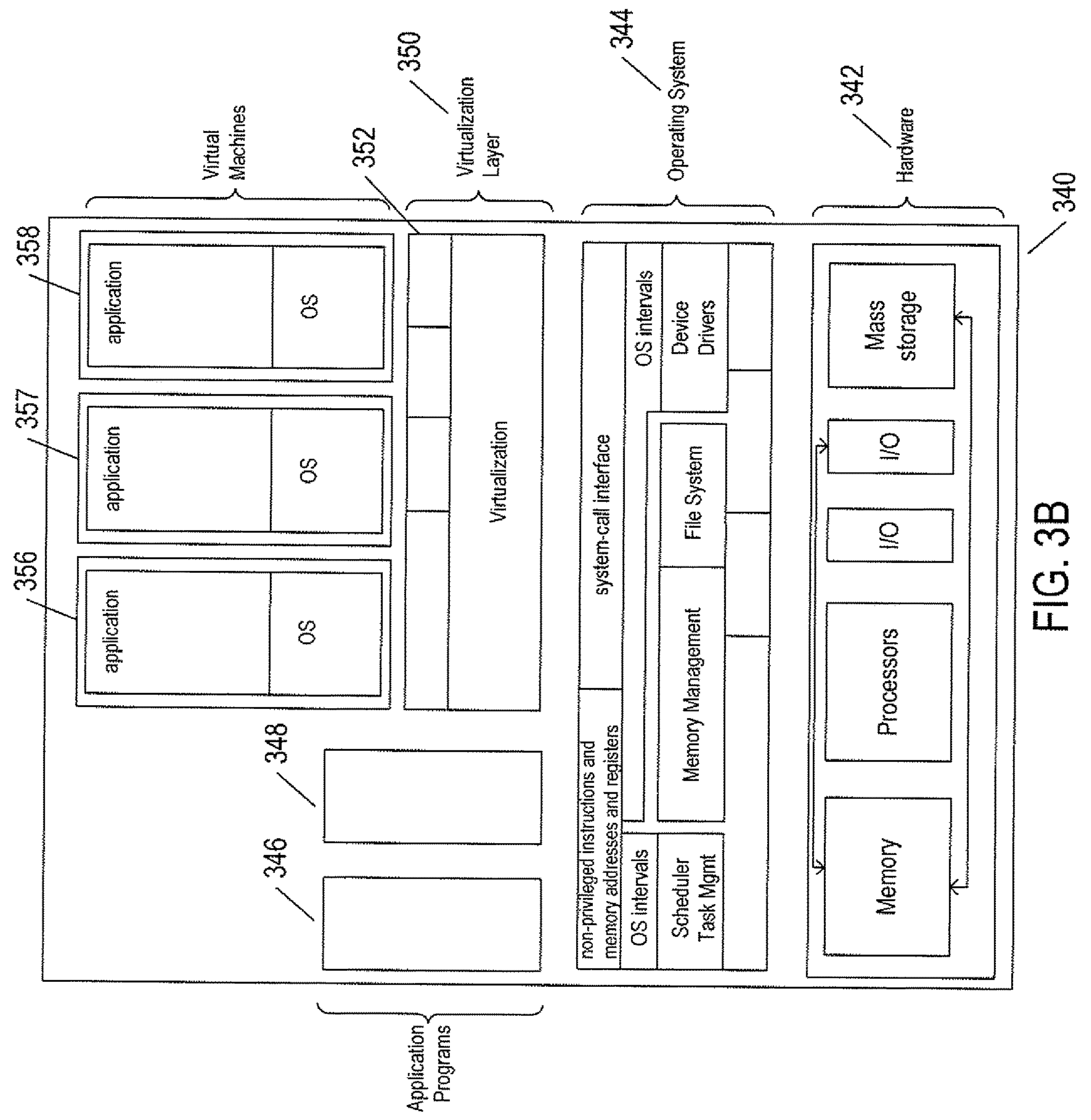

Application Programs
Operating System
Hardware
232
233
234
235
236
226
228
non-privileged instructions and memory addresses and registers
System-call interface
OS intervals
OS intervals
Scheduler Task Mgmt
Memory Management
File System
Device Drivers
244
246
non-privileged instructions
privileged instructions
non-privileged registers/addresses
privileged registers/addresses
218
220
222
224
248
Memory
Processors
I/O
I/O
Mass Storage
208
210
210
212
214
200
202
204
206
216
230
242

FIG. 2



311
304
302
320
application
OS
application
OS
application
OS
application
OS
application
OS
privileged register/addresses
VM Kernel
device drivers
privileged register/addresses
non-privileged register/addresses
non-privileged register/addresses
privileged instructions
VM Kernel
device drivers
privileged instructions
Non-privileged instructions
Virtual Machine Monitor
Non-privileged instructions
Mass storage
I/O
I/O
Processors
Memory
310
314
316
308
318
304
306
302
300

FIG. 3A



Virtual Machines
358
357
356
application
OS
application
OS
application
OS
352
350
Virtualization Layer
Virtualization
344
Operating System
system-call interface
OS intervals
Device Drivers
File System
Memory Management
non-privileged instructions and memory addresses and registers
OS intervals
Scheduler Task Mgmt
342
Hardware
Mass storage
I/O
I/O
Processors
Memory
340
346
348
Application Programs

FIG. 3B

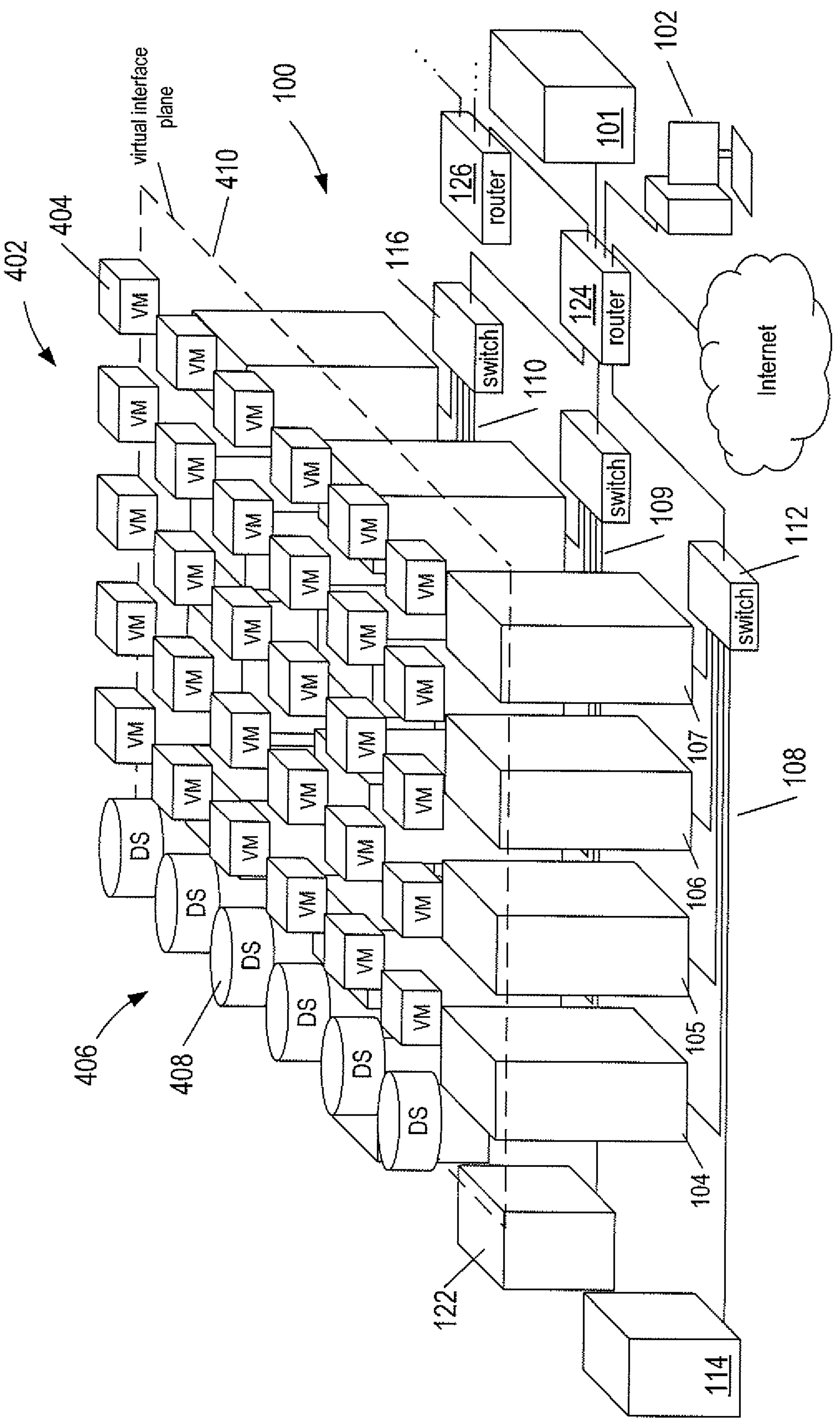

402
404
virtual interface plane
410
100
VM
DS
406
408
101
102
126
router
124
router
116
switch
110
switch
109
112
switch
Internet
107
106
105
104
108
122
114

FIG. 4

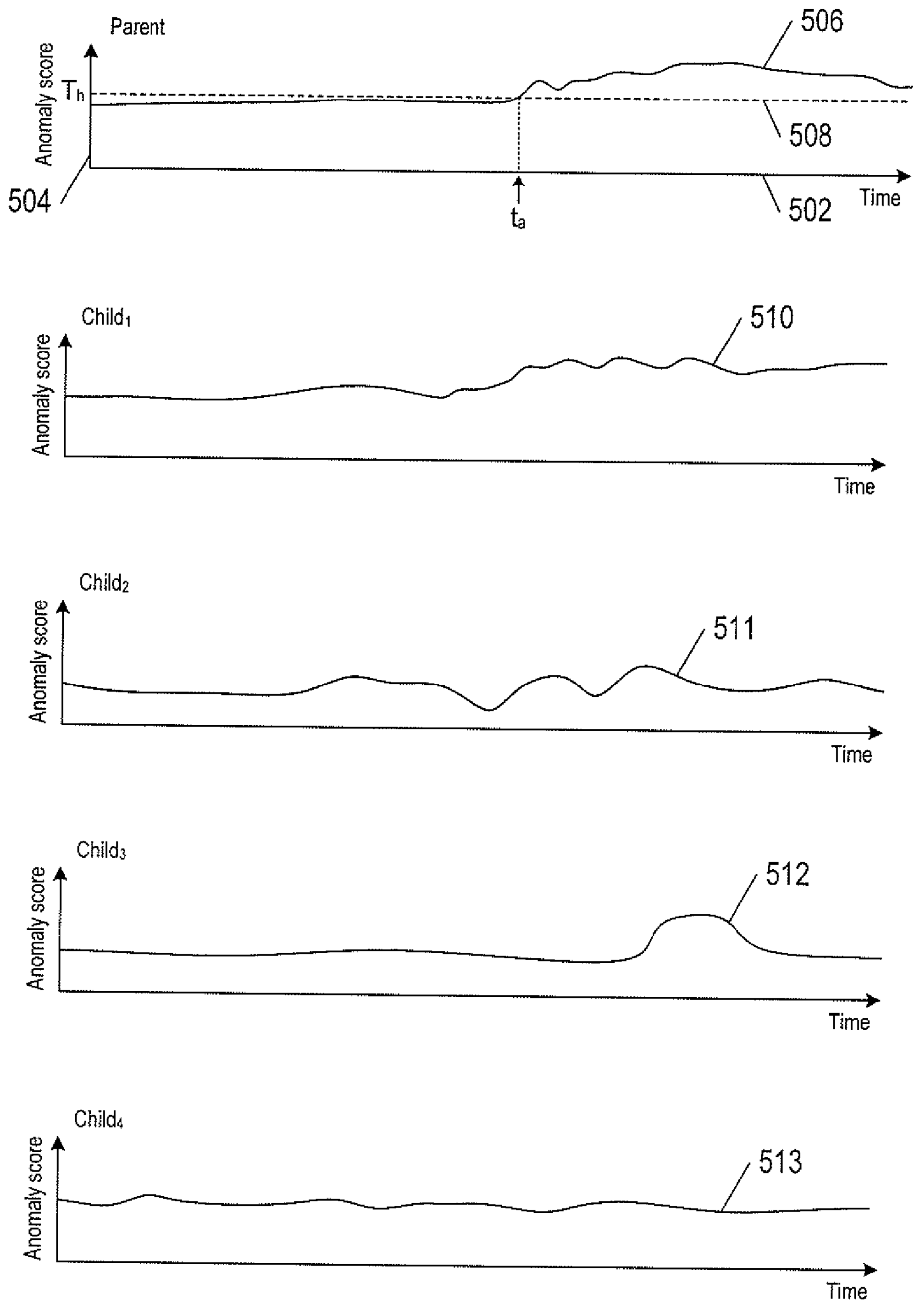

Parent
Anomaly score
T_h
506
508
504
502
Time
t_a
$Child_1$
Anomaly score
510
Time
$Child_2$
Anomaly score
511
Time
$Child_3$
Anomaly score
512
Time
$Child_4$
Anomaly score
513
Time

FIG. 5

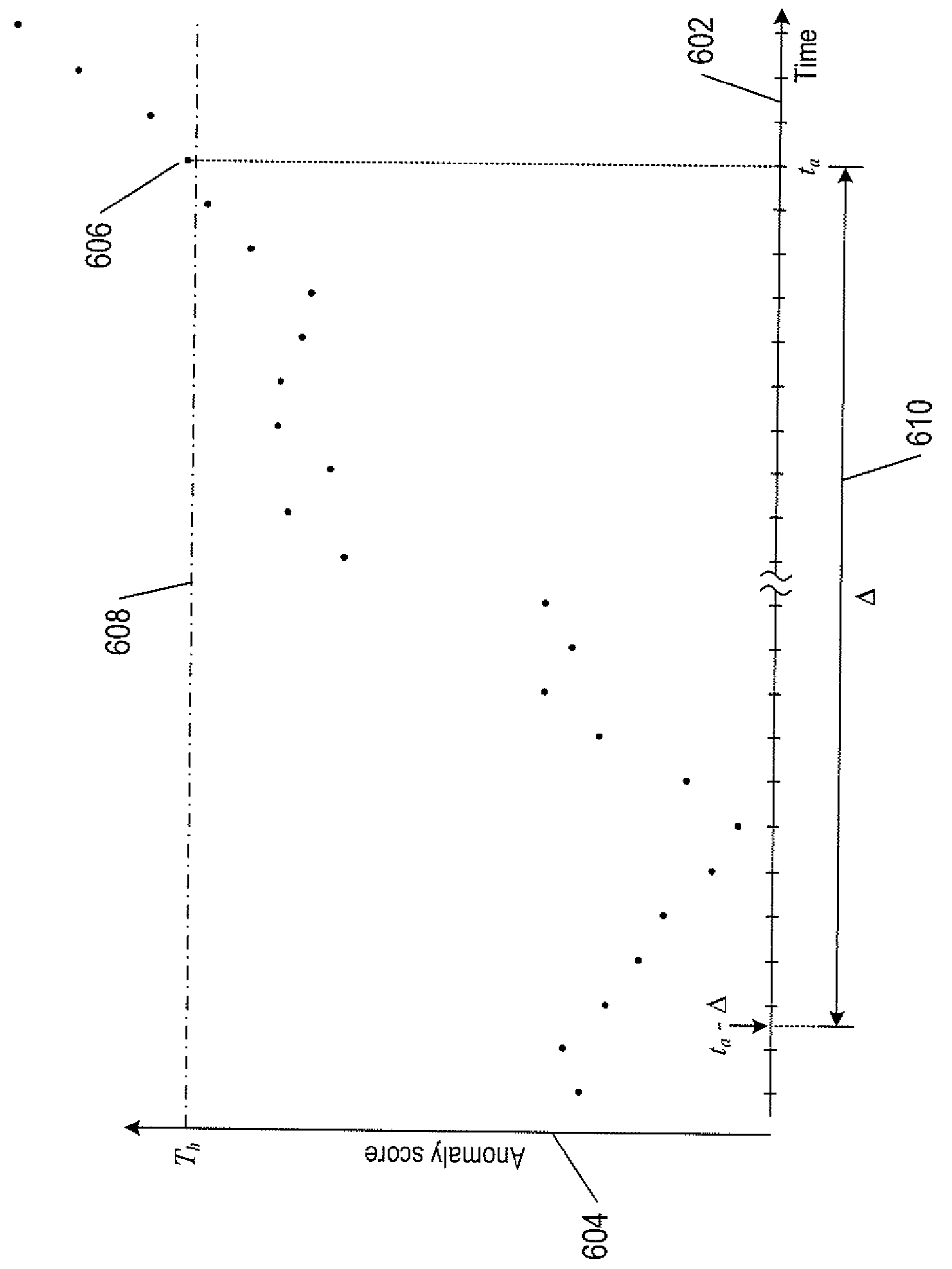


FIG. 6A

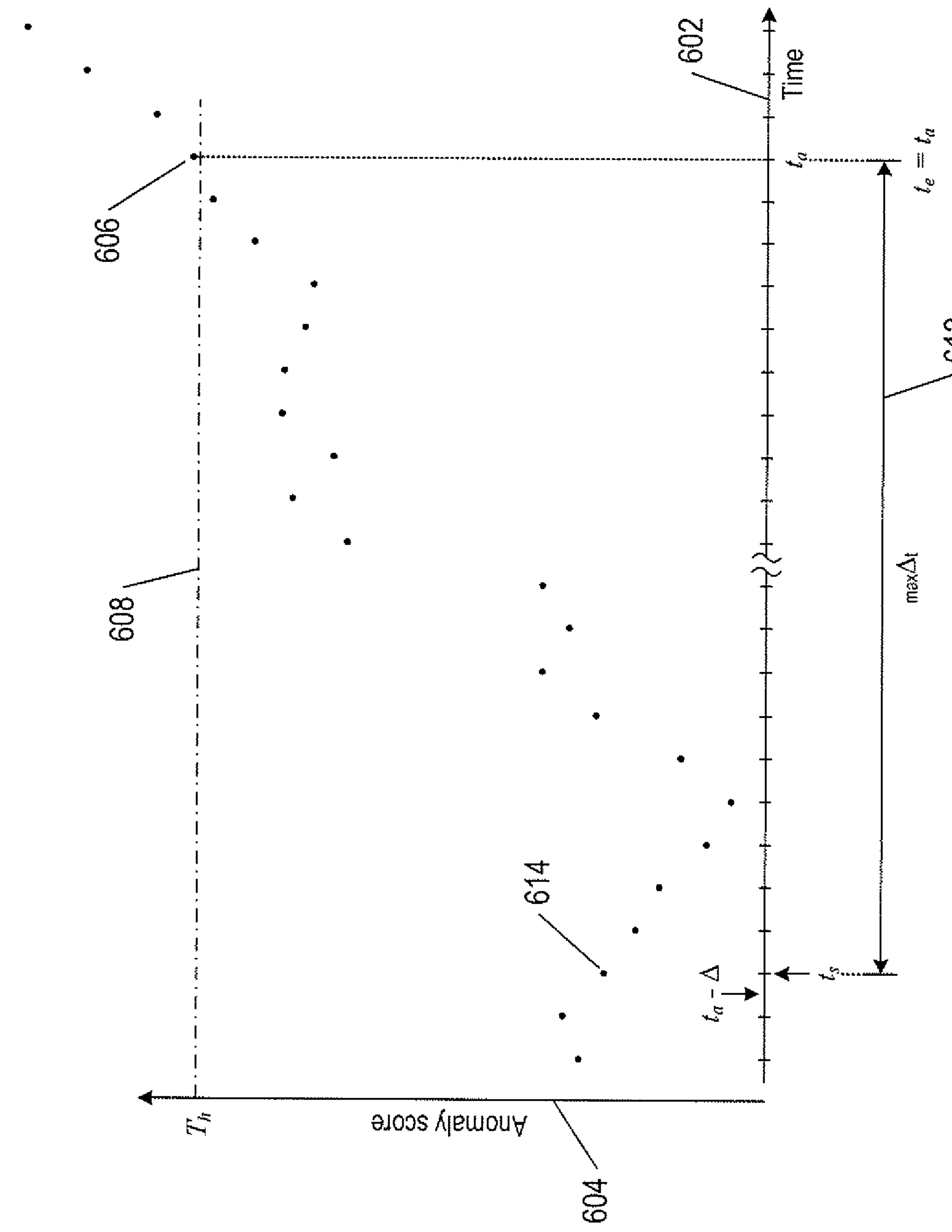

606
608
602
Time
t_a
$t_e = t_a$
612
$_{max}\Delta t$
614
$t_a - \Delta$
t_s
T_h
Anomaly score
604

FIG. 6B

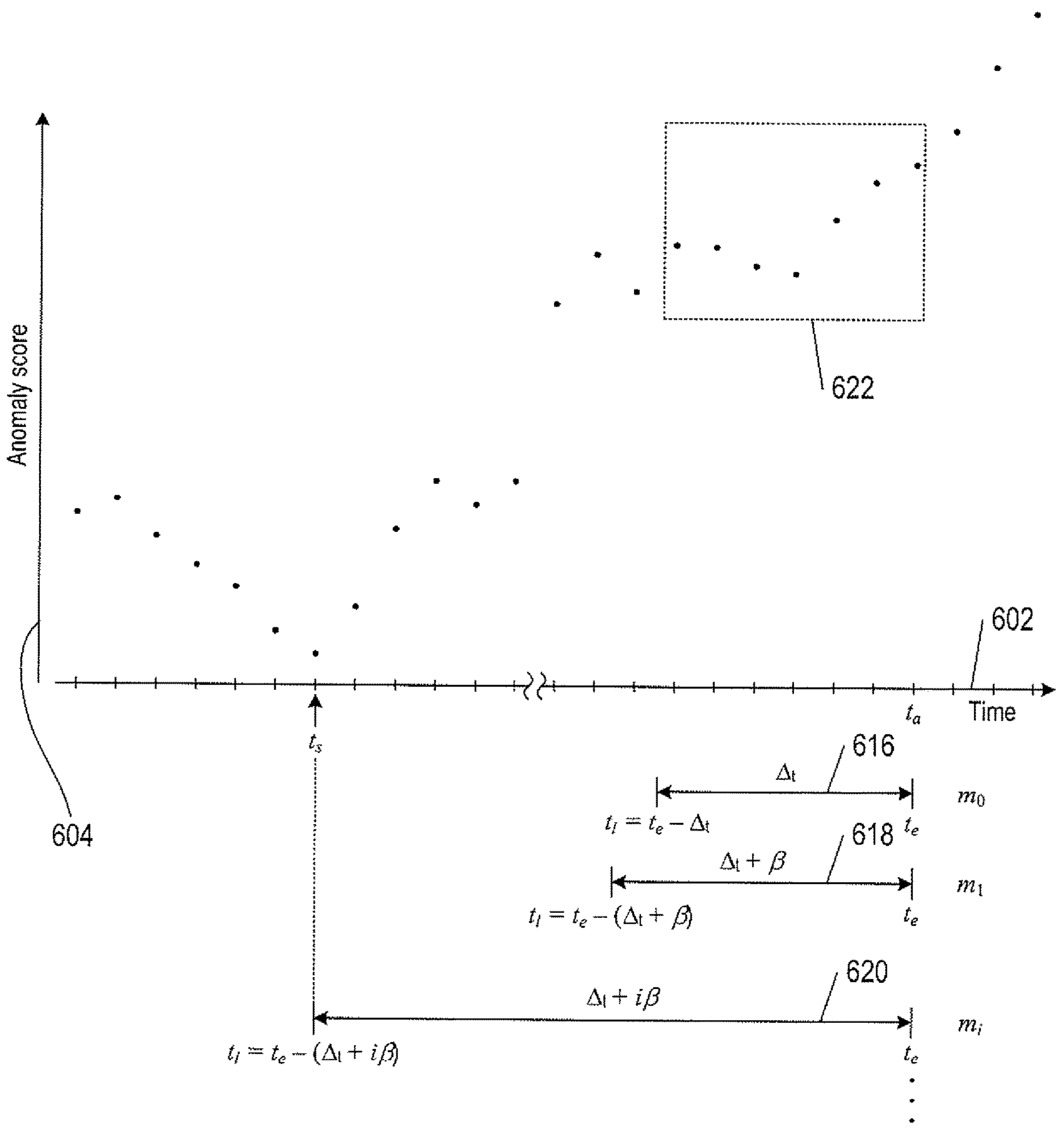

Anomaly score
622
602
t_a
Time
t_s
604
616
Δ_t
m_0
$t_l = t_e - \Delta_t$
t_e
618
$\Delta_t + \beta$
m_1
$t_l = t_e - (\Delta_t + \beta)$
t_e
620
$\Delta_t + i\beta$
m_i
$t_l = t_e - (\Delta_t + i\beta)$
t_e

FIG. 6C

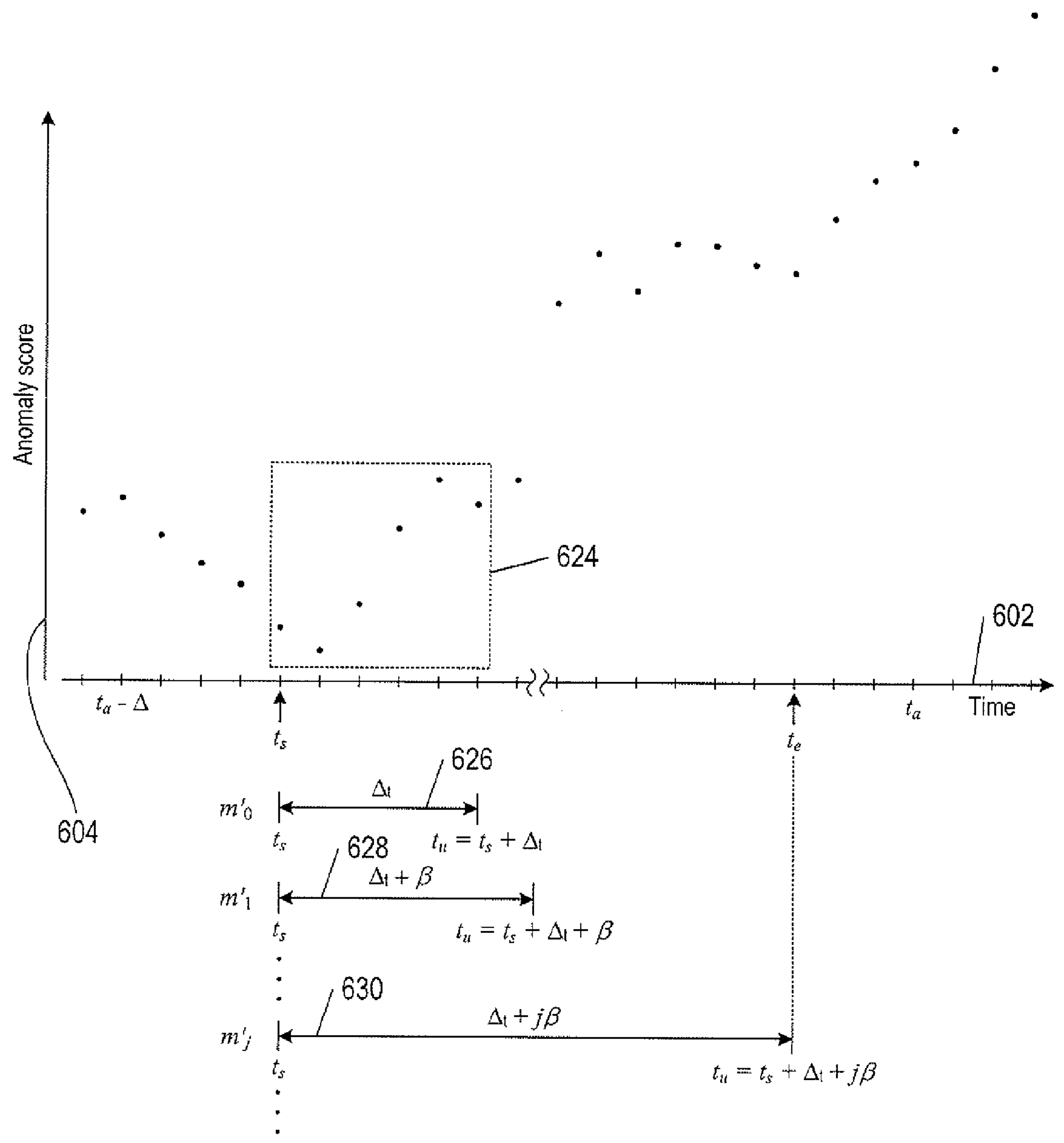

Anomaly score
624
602
$t_a - \Delta$
t_s
t_e
t_a
Time
604
626
Δ_t
m'_0
t_s
$t_u = t_s + \Delta_t$
628
$\Delta_t + \beta$
m'_1
t_s
$t_u = t_s + \Delta_t + \beta$
630
$\Delta_t + j\beta$
m'_j
t_s
$t_u = t_s + \Delta_t + j\beta$

FIG. 6D

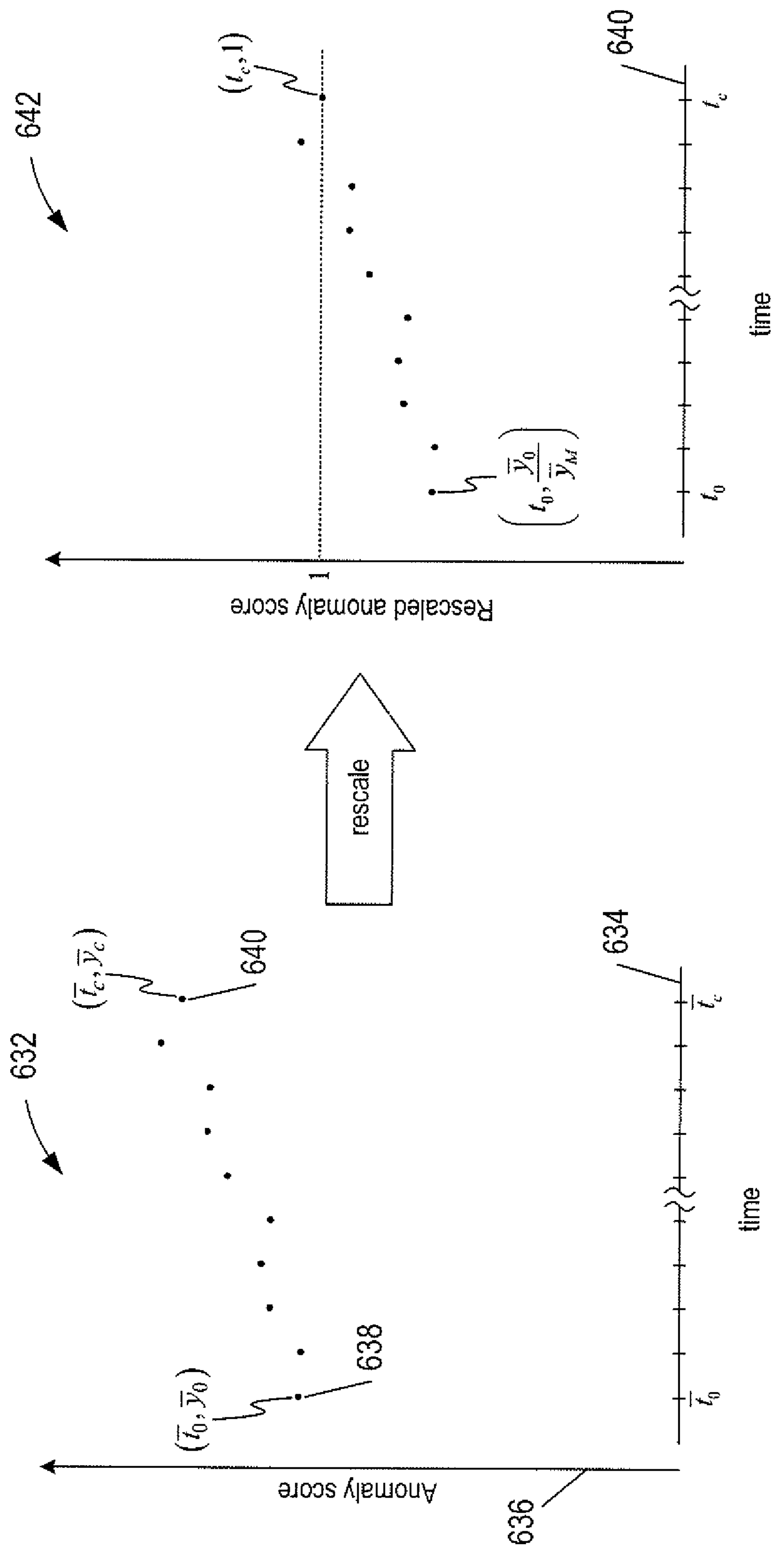

632
Anomaly score
636
$(\bar{t}_0, \bar{y}_0)$
638
$(\bar{t}_c, \bar{y}_c)$
640
634
$\bar{t}_0$
$\bar{t}_c$
time
rescale
642
Rescaled anomaly score
1
$(t_c, 1)$
$\left(t_0, \frac{\bar{y}_0}{\bar{y}_M}\right)$
640
t_0
t_c
time

FIG. 6E

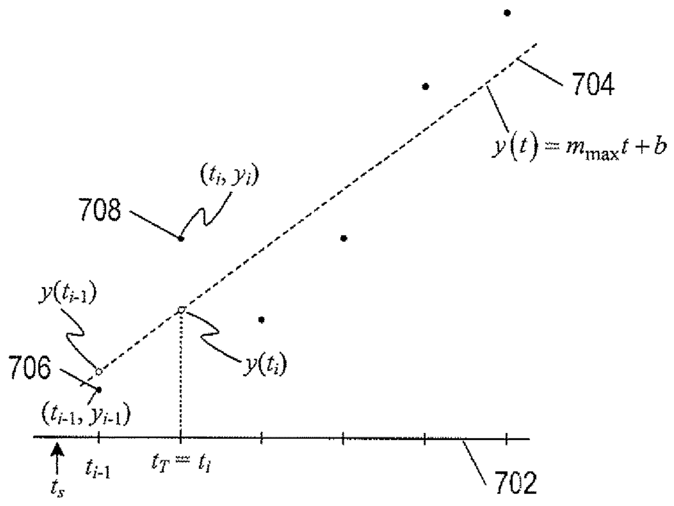


FIG. 7A

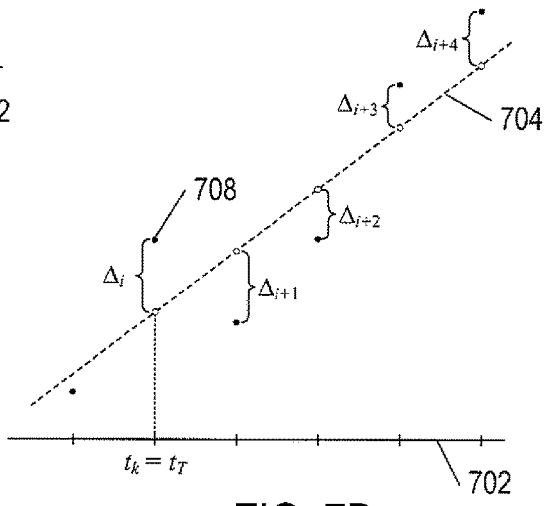


FIG. 7B

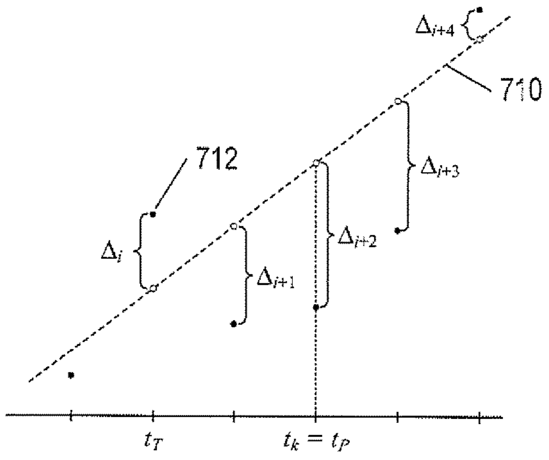


FIG. 7C

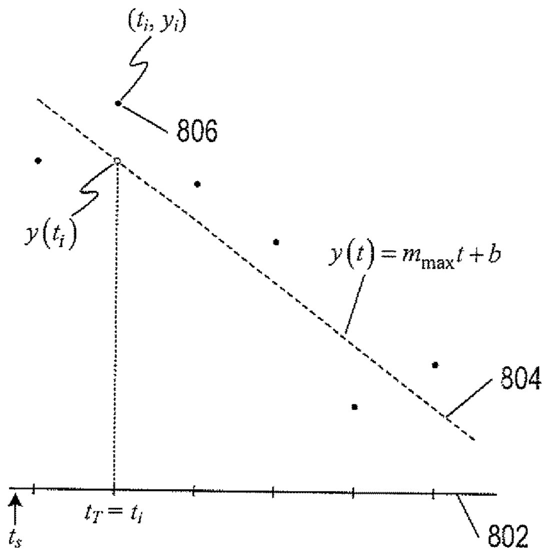


FIG. 8A

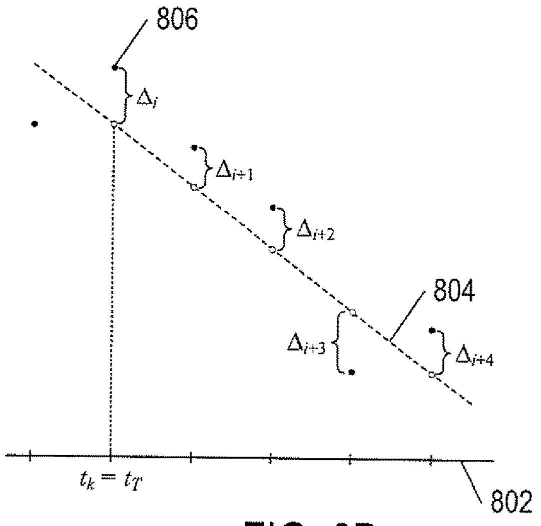


FIG. 8B

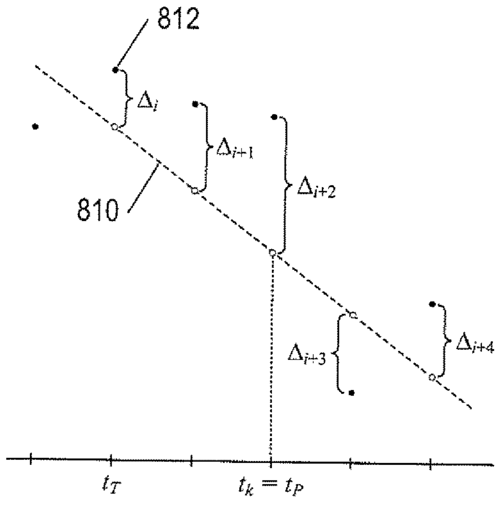


FIG. 8C

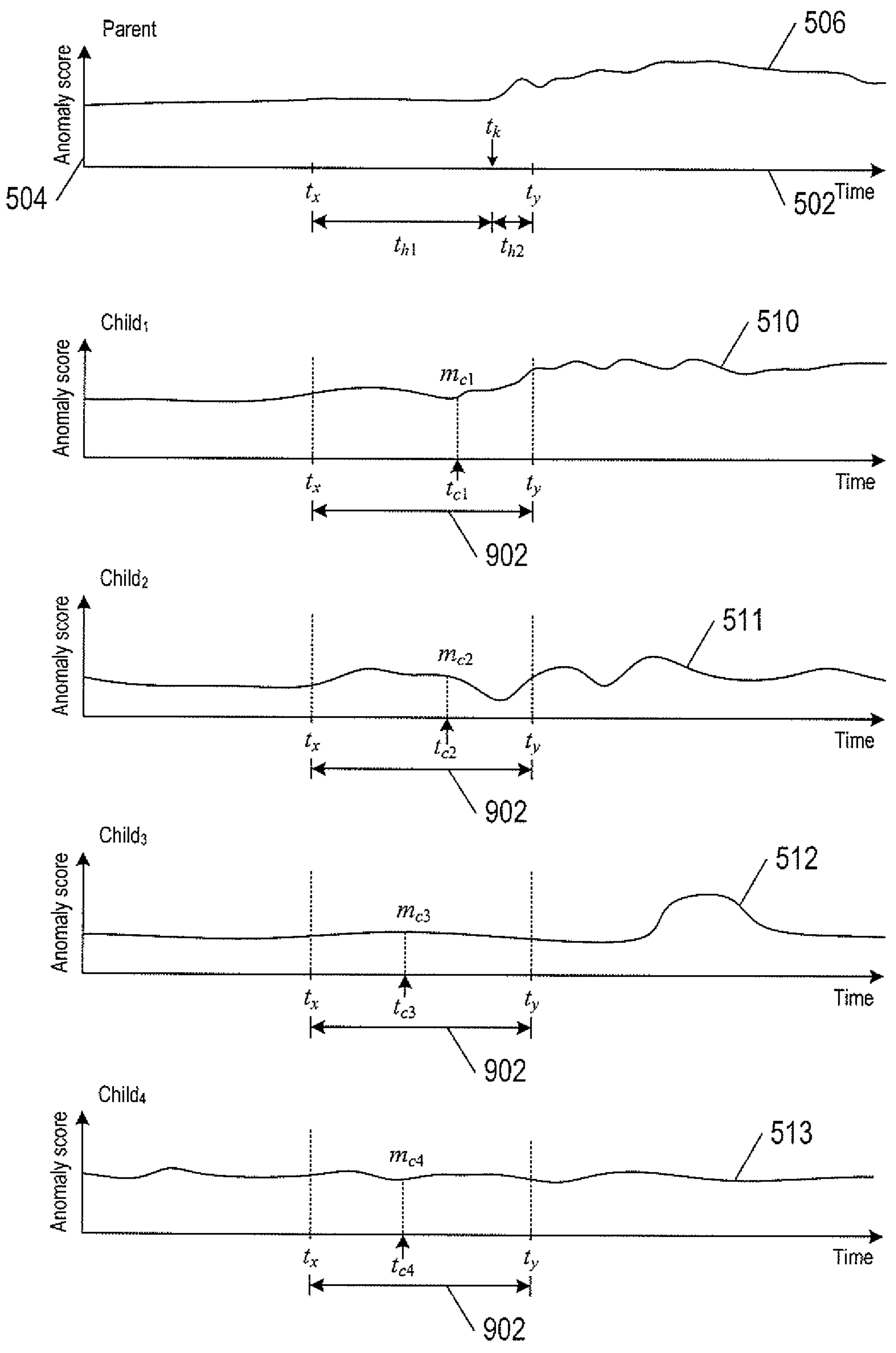

Parent
Anomaly score
506
504
t_k
t_x
t_y
502
Time
t_{h1}
t_{h2}
Child₁
510
m_{c1}
t_{c1}
902
Child₂
511
m_{c2}
t_{c2}
902
Child₃
512
m_{c3}
t_{c3}
902
Child₄
513
m_{c4}
t_{c4}
902

FIG. 9

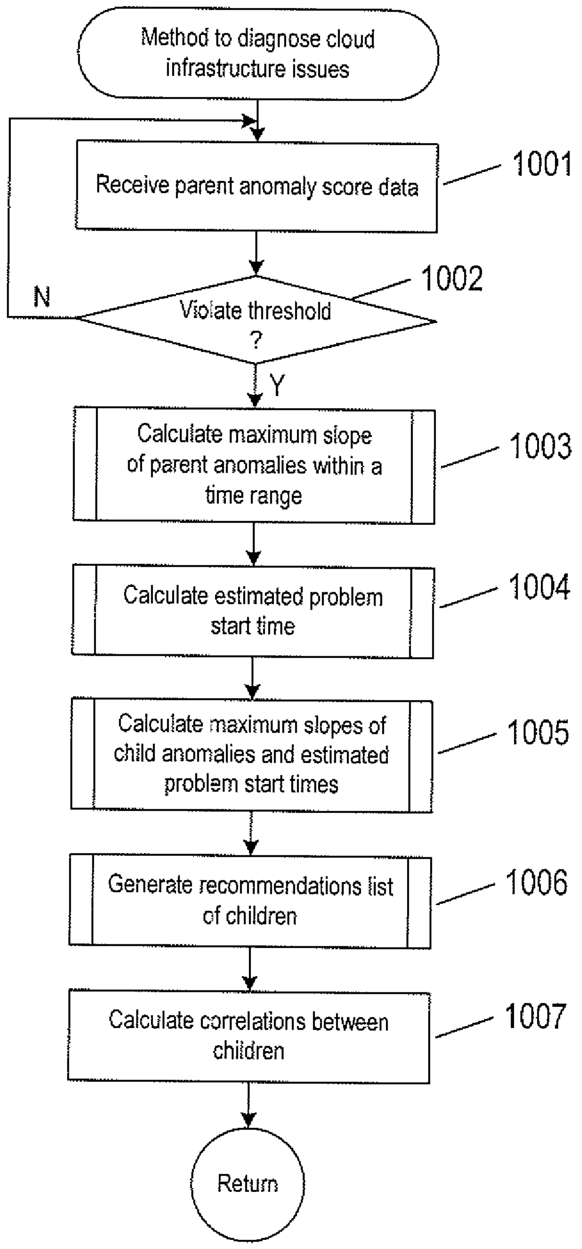
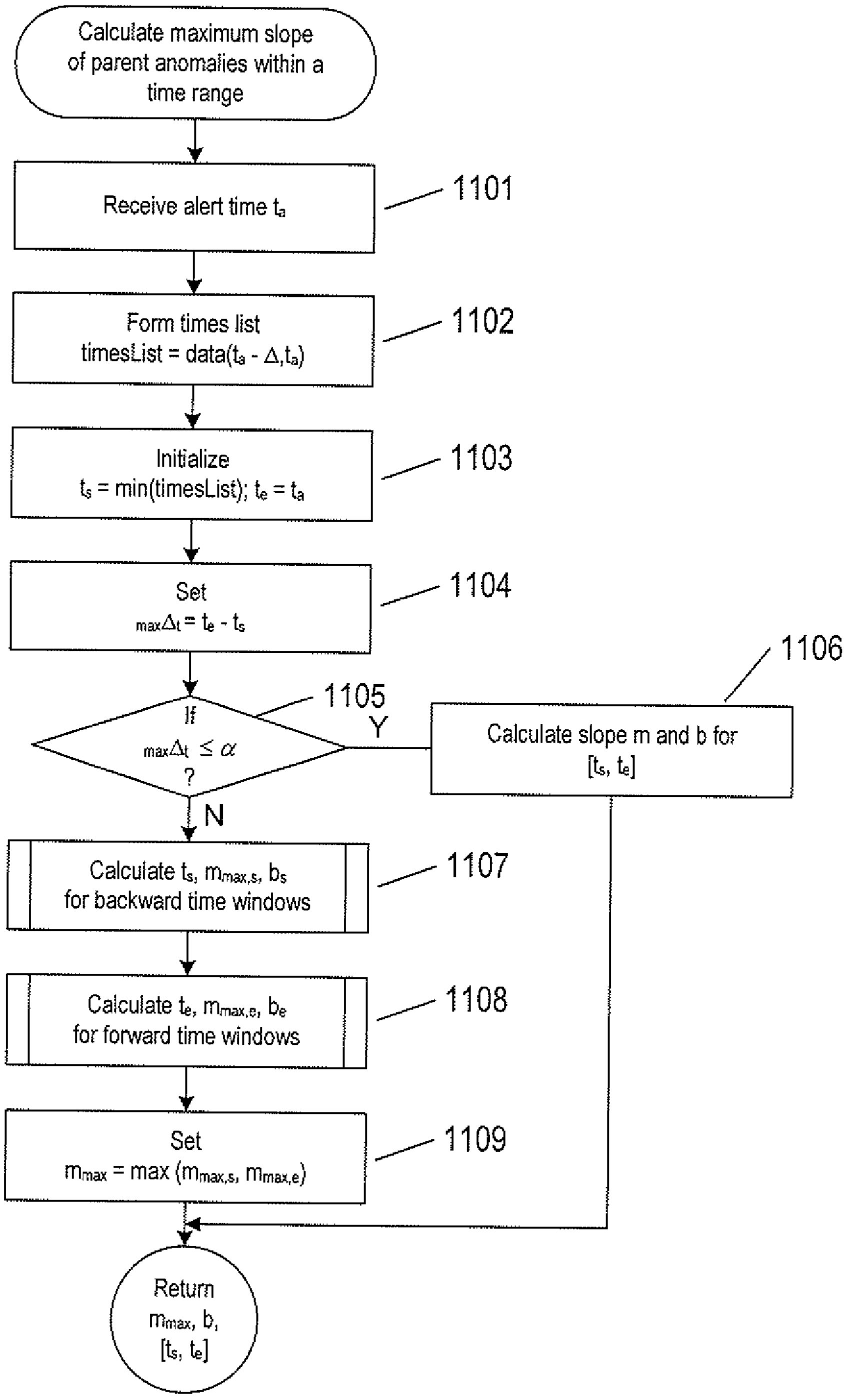

Method to diagnose cloud infrastructure issues
Receive parent anomaly score data
1001
Violate threshold ?
1002
N
Y
Calculate maximum slope of parent anomalies within a time range
1003
Calculate estimated problem start time
1004
Calculate maximum slopes of child anomalies and estimated problem start times
1005
Generate recommendations list of children
1006
Calculate correlations between children
1007
Return

FIG. 10



Calculate maximum slope of parent anomalies within a time range
Receive alert time t_a
1101
Form times list timesList = data(t_a - Δ,t_a)
1102
Initialize t_s = min(timesList); t_e = t_a
1103
Set ${}_{max}\Delta_t = t_e - t_s$
1104
1105
If ${}_{max}\Delta_t \leq \alpha$?
Y
N
Calculate slope m and b for $[t_s, t_e]$
1106
Calculate t_s, $m_{max,s}$, b_s for backward time windows
1107
Calculate t_e, $m_{max,e}$, b_e for forward time windows
1108
Set $m_{max} = \max(m_{max,s}, m_{max,e})$
1109
Return m_{max}, b, $[t_s, t_e]$

FIG. 11

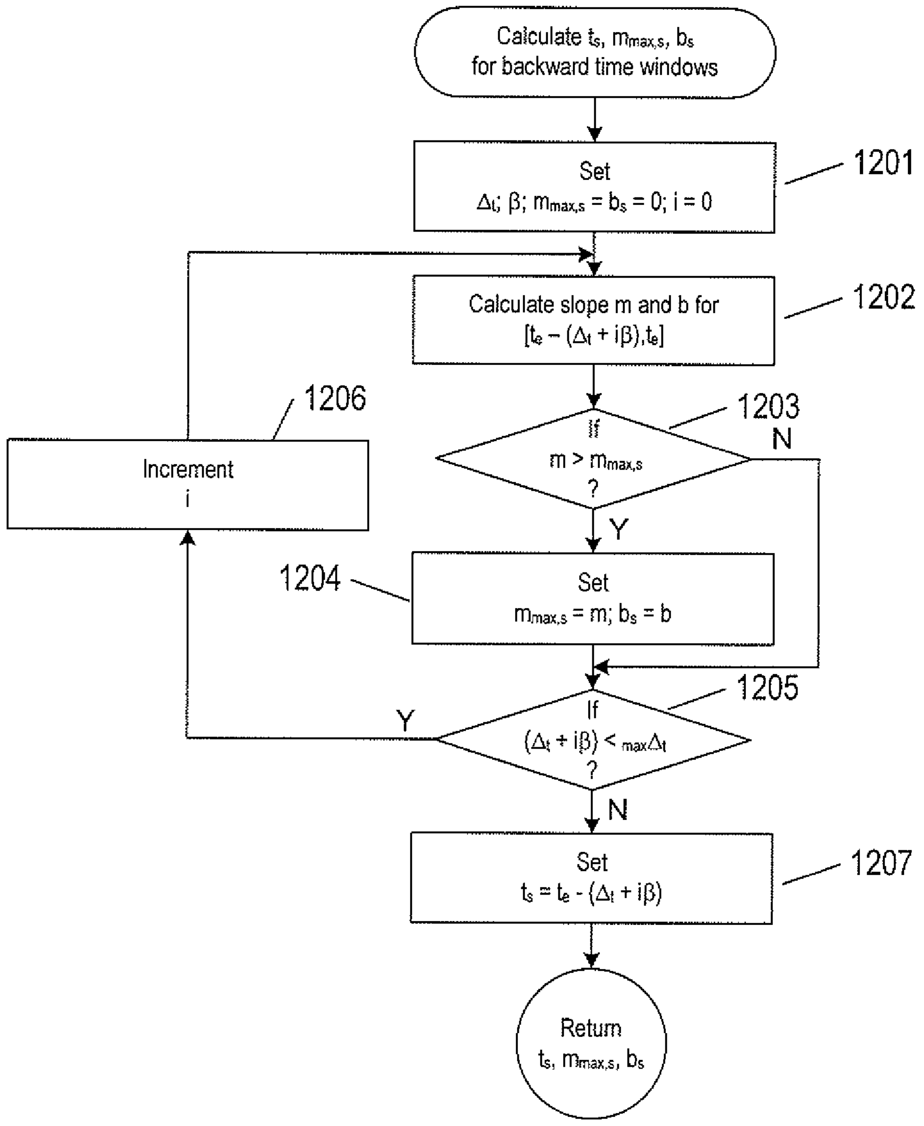

Calculate t_s, $m_{max,s}$, b_s for backward time windows
Set Δ_t; β; $m_{max,s} = b_s = 0$; $i = 0$
1201
Calculate slope m and b for $[t_e - (\Delta_t + i\beta), t_e]$
1202
If $m > m_{max,s}$?
1203
N
Y
Set $m_{max,s} = m$; $b_s = b$
1204
Increment i
1206
If $(\Delta_t + i\beta) < {}_{max}\Delta_t$?
1205
Y
N
Set $t_s = t_e - (\Delta_t + i\beta)$
1207
Return t_s, $m_{max,s}$, b_s

FIG. 12

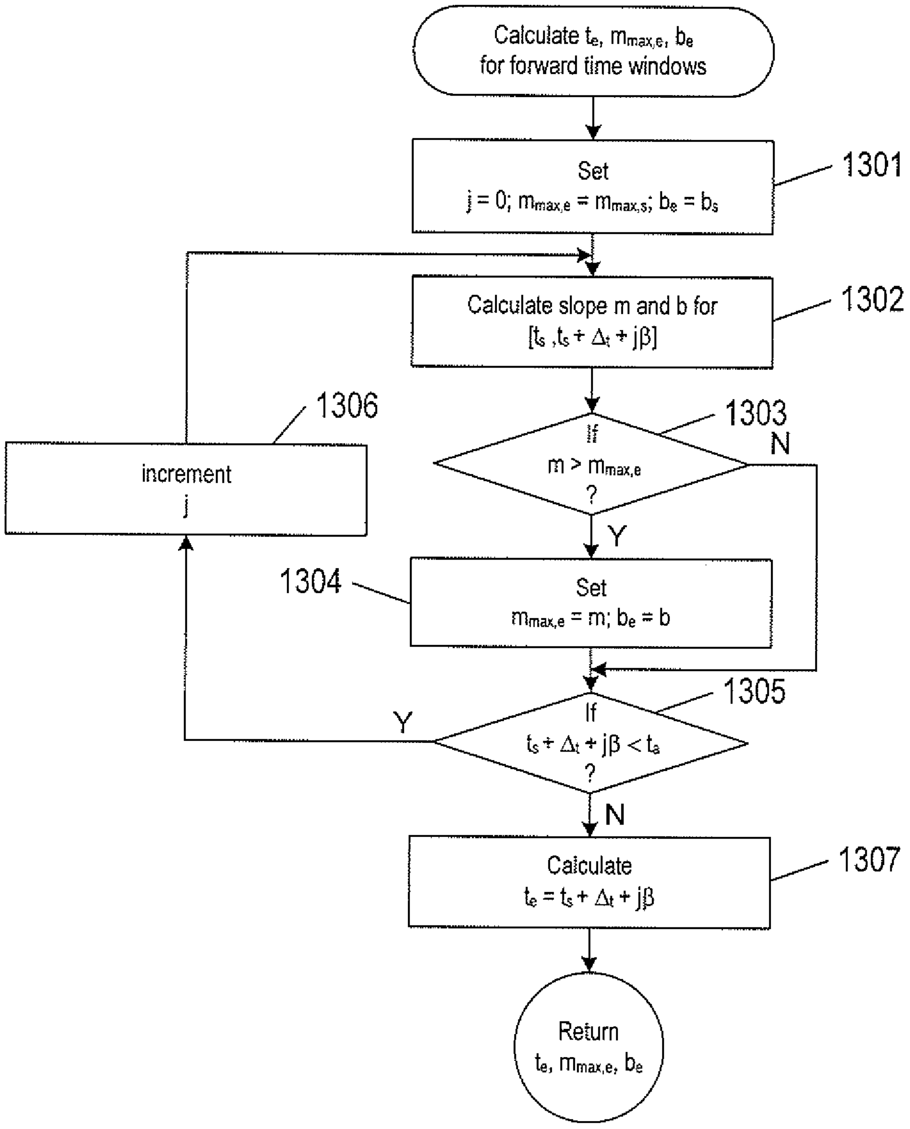
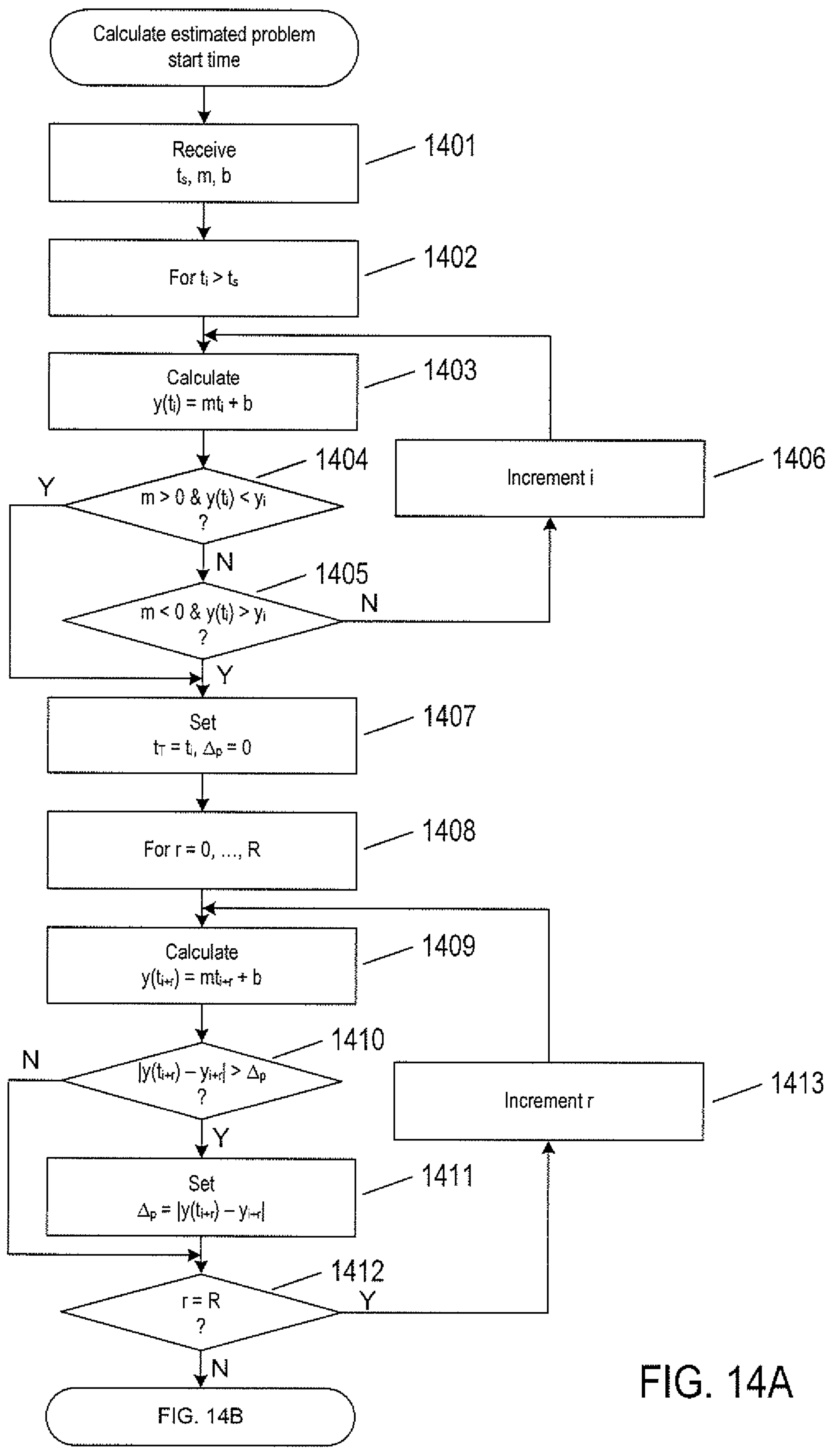

Calculate t_e, $m_{max,e}$, b_e for forward time windows
Set $j = 0$; $m_{max,e} = m_{max,s}$; $b_e = b_s$
1301
Calculate slope m and b for $[t_s, t_s + \Delta_t + j\beta]$
1302
1303
If $m > m_{max,e}$?
N
Y
Set $m_{max,e} = m$; $b_e = b$
1304
1306
increment j
1305
If $t_s + \Delta_t + j\beta < t_a$?
Y
N
Calculate $t_e = t_s + \Delta_t + j\beta$
1307
Return t_e, $m_{max,e}$, b_e

FIG. 13



Calculate estimated problem start time
Receive t_s, m, b
1401
For $t_i > t_s$
1402
Calculate $y(t_i) = mt_i + b$
1403
$m > 0$ & $y(t_i) < y_i$?
1404
Y
N
Increment i
1406
$m < 0$ & $y(t_i) > y_i$?
1405
N
Y
Set $t_T = t_i$, $\Delta_p = 0$
1407
For r = 0, ..., R
1408
Calculate $y(t_{i+r}) = mt_{i+r} + b$
1409
$|y(t_{i+r}) - y_{i+r}| > \Delta_p$?
1410
N
Y
Increment r
1413
Set $\Delta_p = |y(t_{i+r}) - y_{i+r}|$
1411
r = R ?
1412
Y
N
FIG. 14B

FIG. 14A

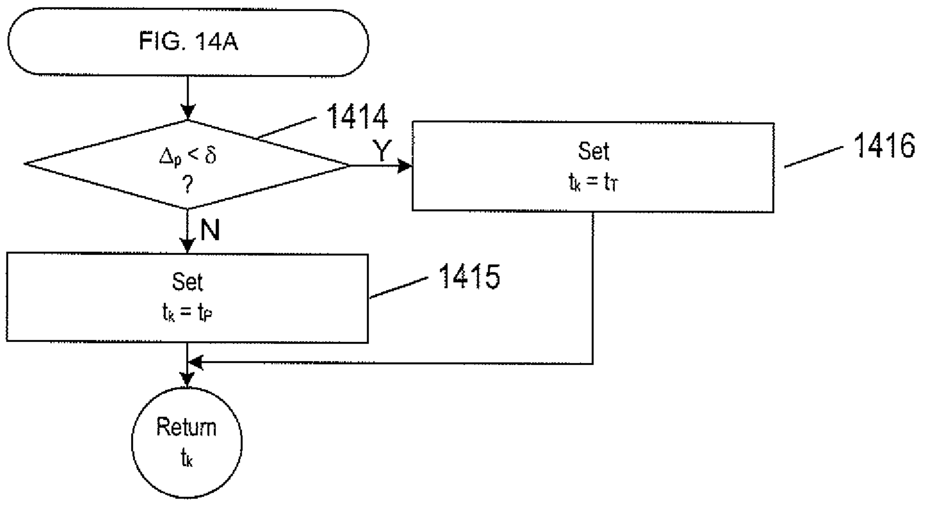


FIG. 14B

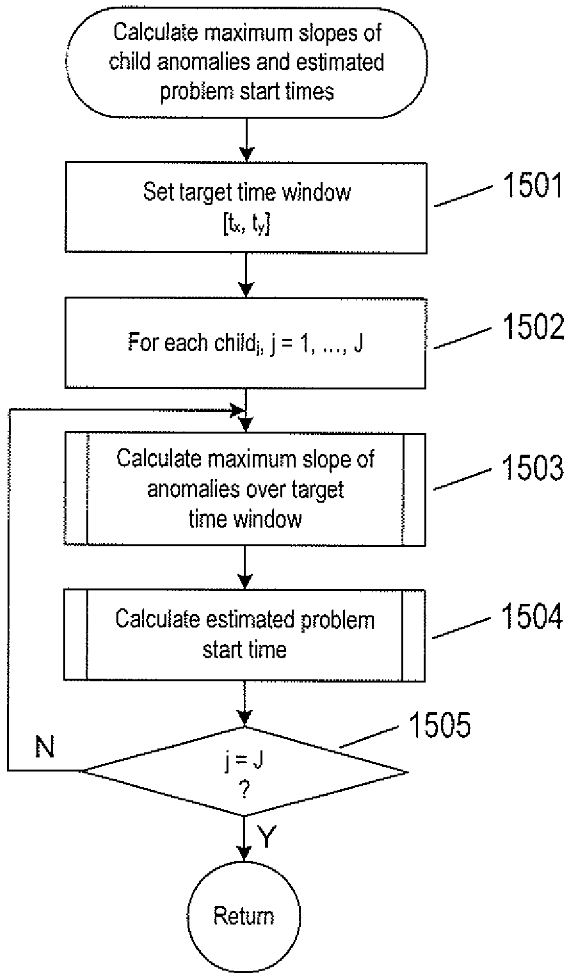

Calculate maximum slopes of child anomalies and estimated problem start times
Set target time window $[t_x, t_y]$
1501
For each $child_j$, j = 1, ..., J
1502
Calculate maximum slope of anomalies over target time window
1503
Calculate estimated problem start time
1504
j = J ?
1505
N
Y
Return

FIG. 15

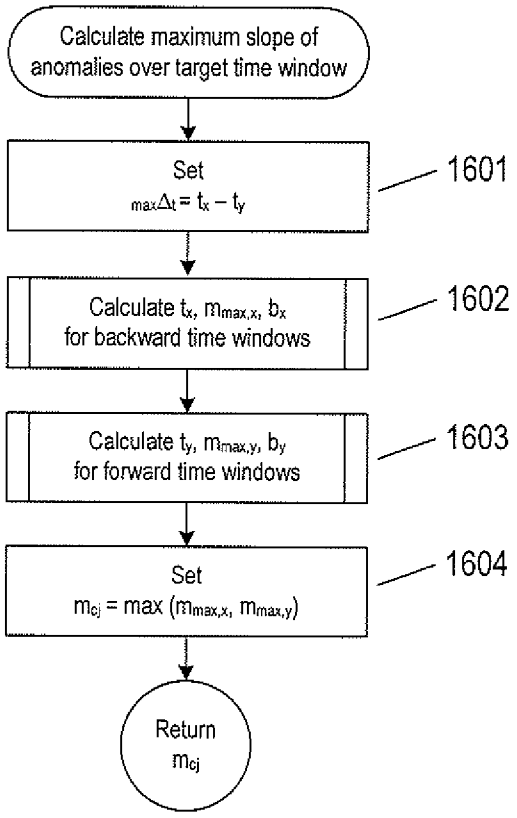

Calculate maximum slope of anomalies over target time window
Set $_{max}\Delta_t = t_x - t_y$
1601
Calculate t_x, $m_{max,x}$, b_x for backward time windows
1602
Calculate t_y, $m_{max,y}$, b_y for forward time windows
1603
Set $m_{cj} = \max(m_{max,x}, m_{max,y})$
1604
Return m_{cj}

FIG. 16

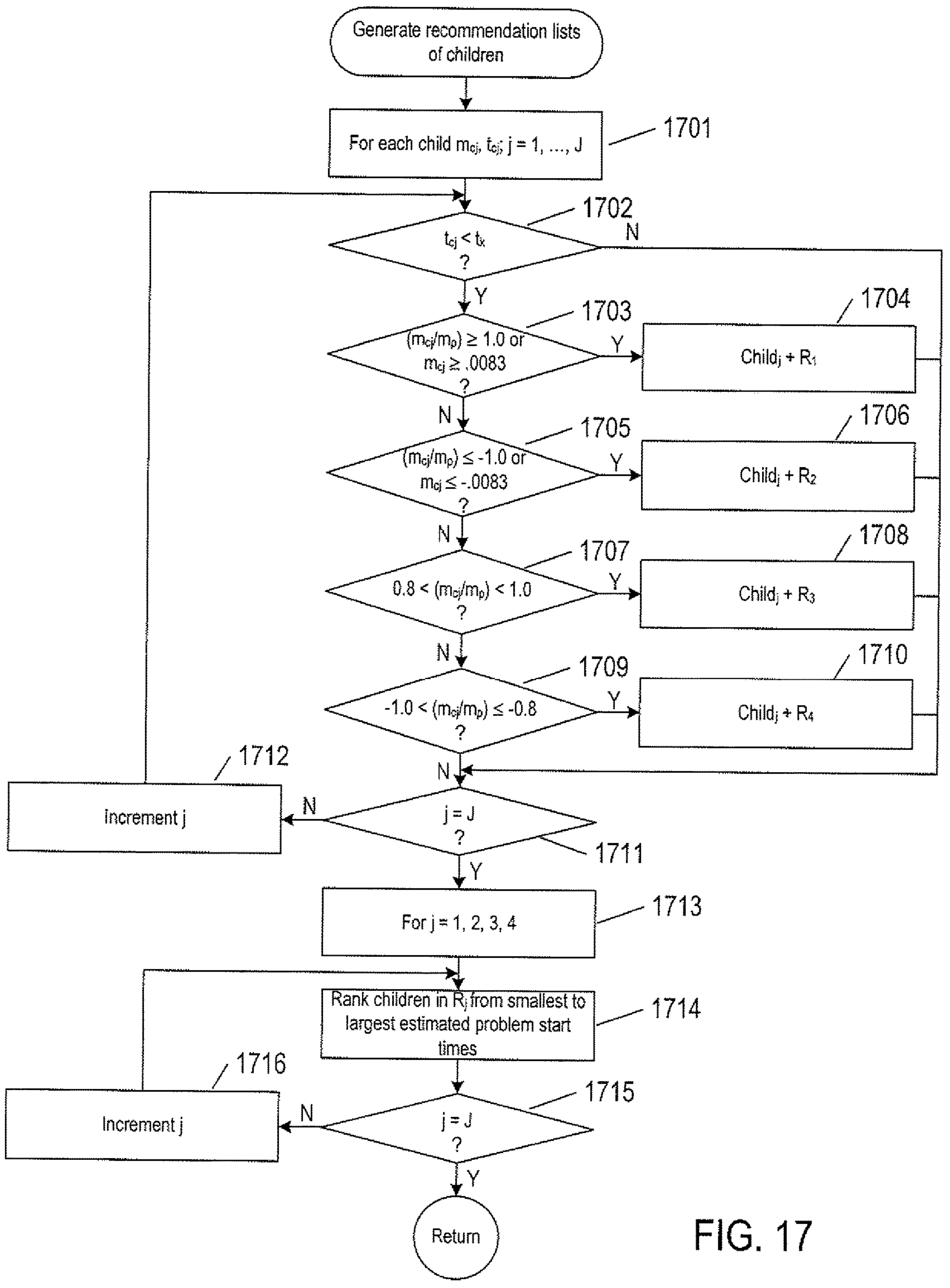

Generate recommendation lists of children
For each child m_{cj}, t_{cj}; j = 1, ..., J
1701
$t_{cj} < t_x$?
1702
N
Y
$(m_{cj}/m_p) \geq 1.0$ or $m_{cj} \geq .0083$?
1703
Y
$Child_j \rightarrow R_1$
1704
N
$(m_{cj}/m_p) \leq -1.0$ or $m_{cj} \leq -.0083$?
1705
Y
$Child_j \rightarrow R_2$
1706
N
$0.8 < (m_{cj}/m_p) < 1.0$?
1707
Y
$Child_j \rightarrow R_3$
1708
N
$-1.0 < (m_{cj}/m_p) \leq -0.8$?
1709
Y
$Child_j \rightarrow R_4$
1710
N
Increment j
1712
N
j = J ?
1711
Y
For j = 1, 2, 3, 4
1713
Rank children in R_j from smallest to largest estimated problem start times
1714
Increment j
1716
N
j = J ?
1715
Y
Return

FIG. 17

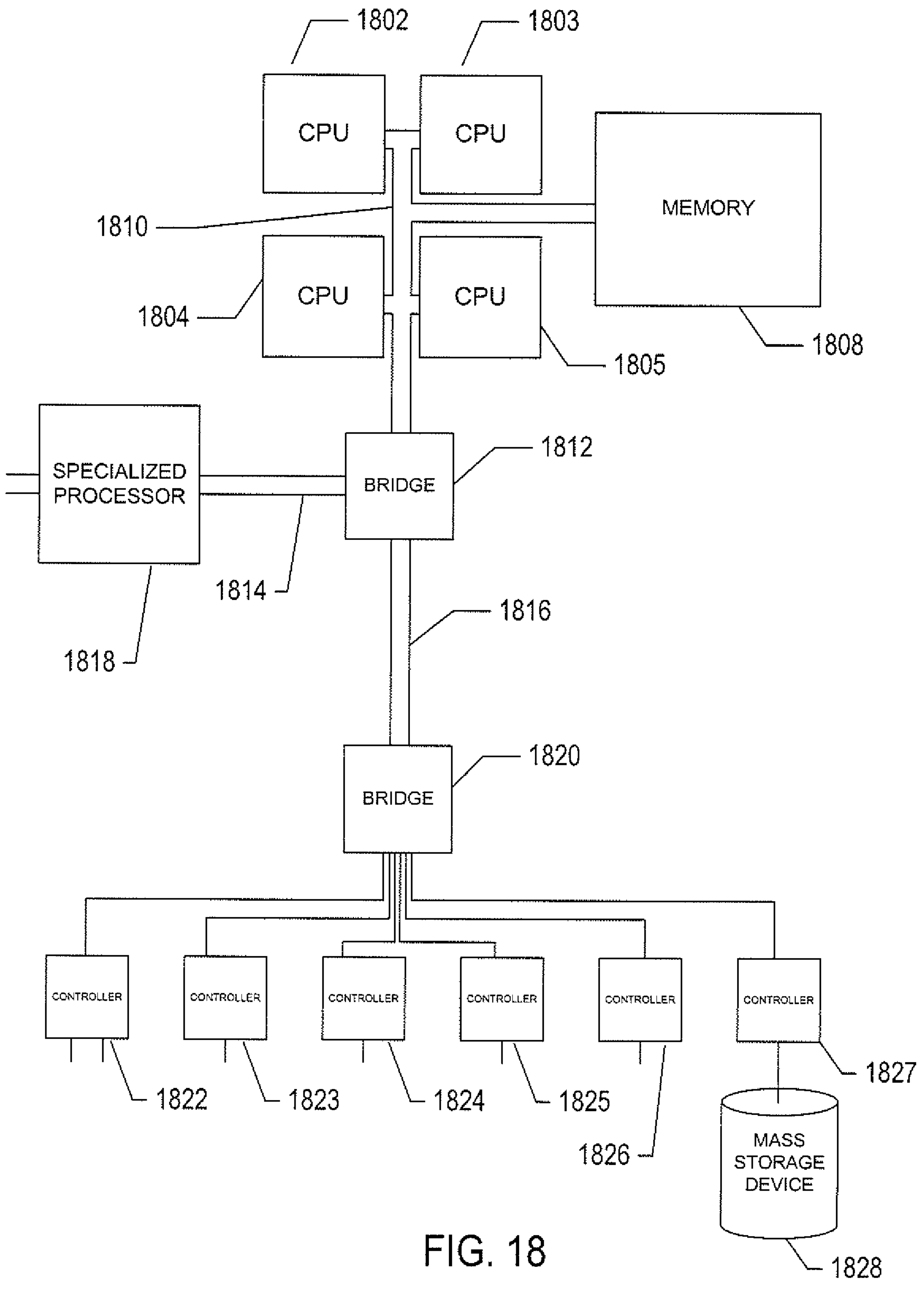

1802
1803
CPU
CPU
MEMORY
1810
CPU
CPU
1804
1805
1808
SPECIALIZED PROCESSOR
BRIDGE
1812
1814
1816
1818
BRIDGE
1820
CONTROLLER
CONTROLLER
CONTROLLER
CONTROLLER
CONTROLLER
CONTROLLER
1822
1823
1824
1825
1826
1827
MASS STORAGE DEVICE
1828

FIG. 18

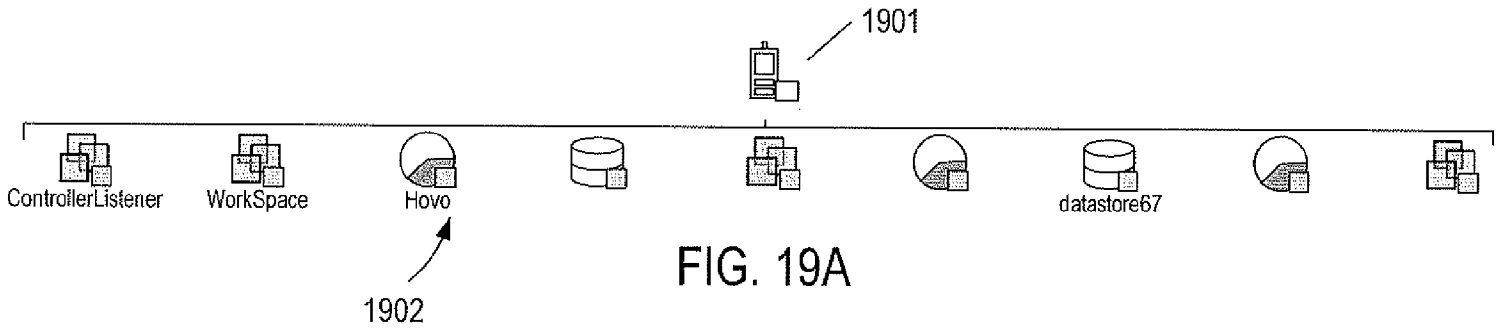


FIG. 19A

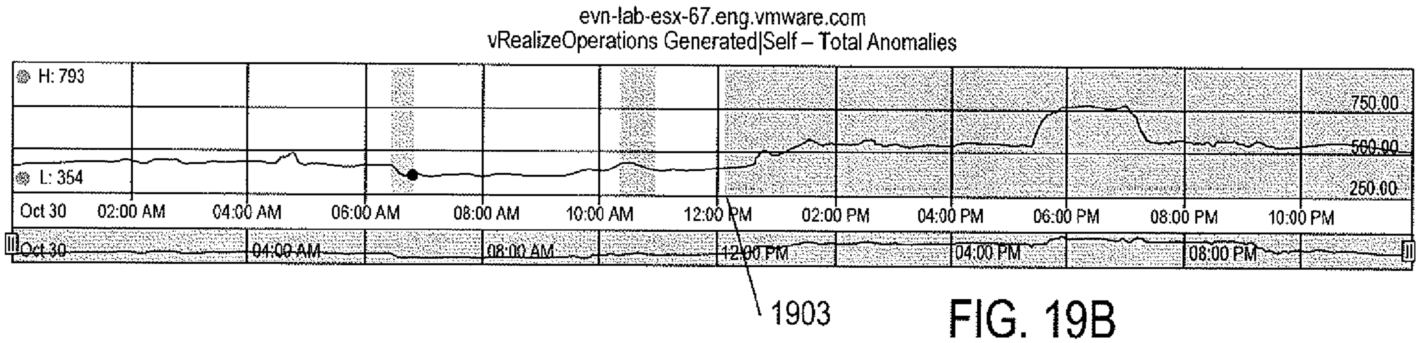


FIG. 19B

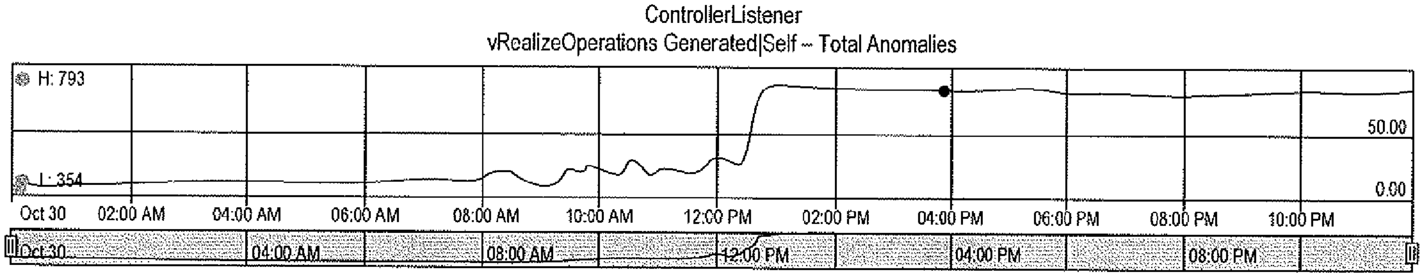


FIG. 19C

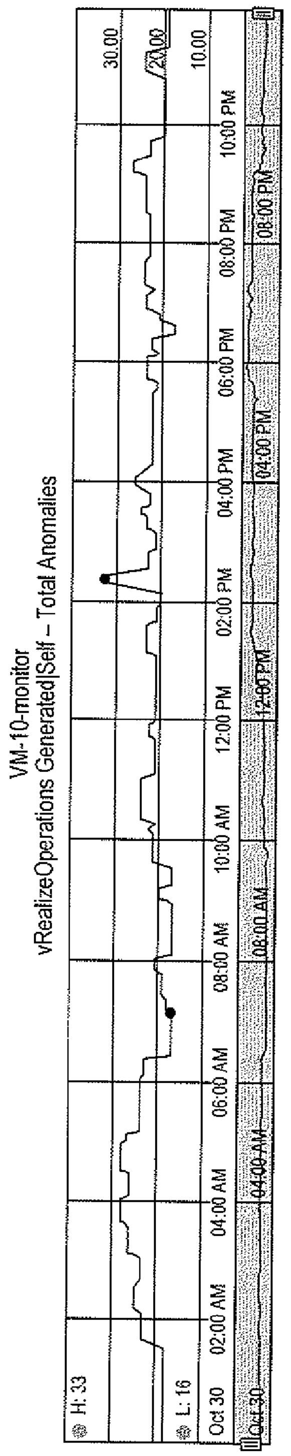


FIG. 19D

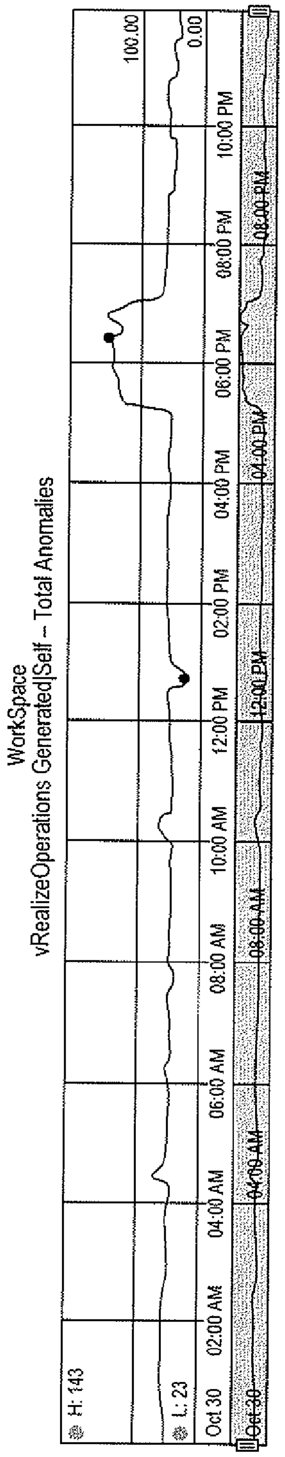


FIG. 19E

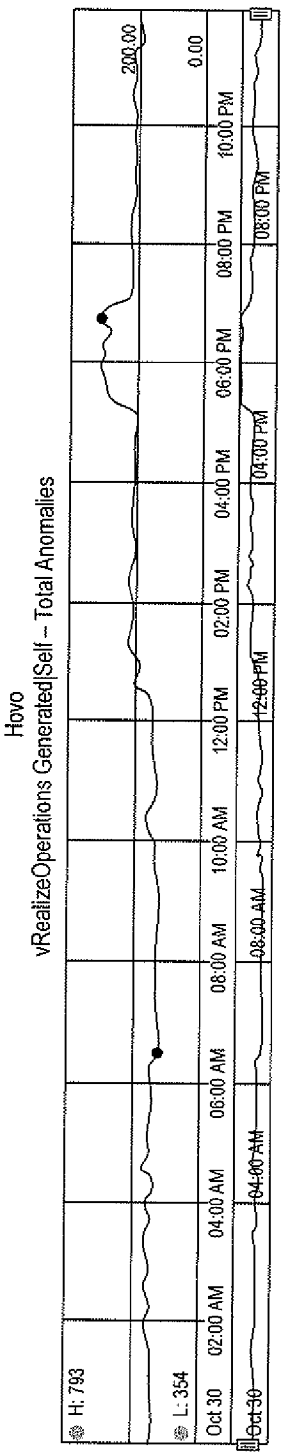
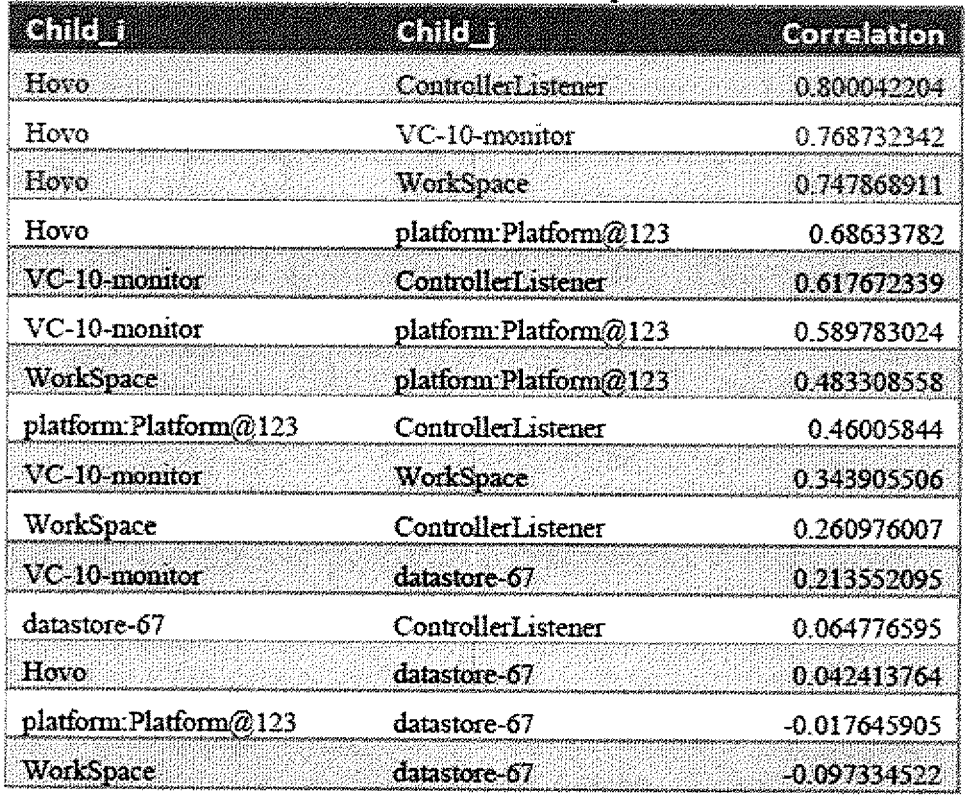


FIG. 19F

Table I: Child-to-child correlations for problem interval.



Child_i	Child_j	Correlation
Hovo	ControllerListener	0.800042204
Hovo	VC-10-monitor	0.768732342
Hovo	WorkSpace	0.747868911
Hovo	platform:Platform@123	0.68633782
VC-10-monitor	ControllerListener	0.617672339
VC-10-monitor	platform:Platform@123	0.589783024
WorkSpace	platform:Platform@123	0.483308558
platform:Platform@123	ControllerListener	0.46005844
VC-10-monitor	WorkSpace	0.343905506
WorkSpace	ControllerListener	0.260976007
VC-10-monitor	datastore-67	0.213552095
datastore-67	ControllerListener	0.064776595
Hovo	datastore-67	0.042413764
platform:Platform@123	datastore-67	-0.017645905
WorkSpace	datastore-67	-0.097334522

FIG. 19G

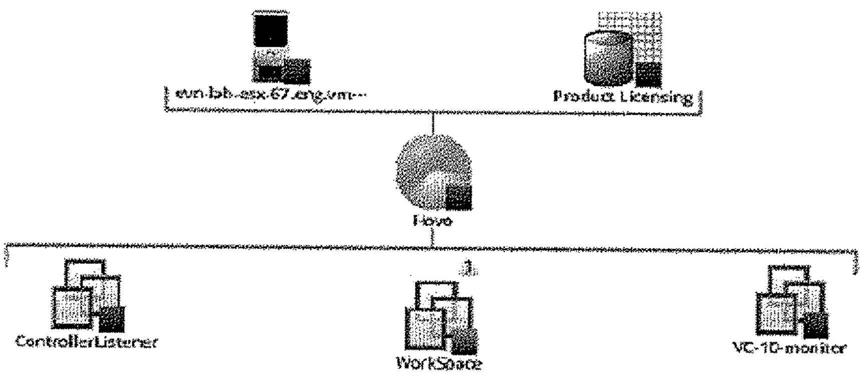


FIG. 19H

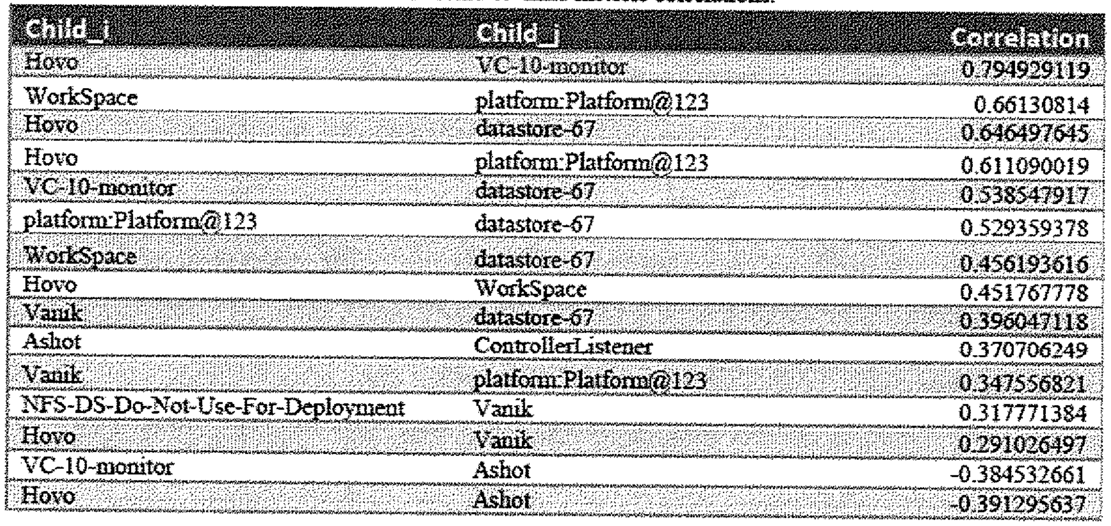


Table II: Child-to-child historic correlations.

Child_i	Child_j	Correlation
Hovo	VC-10-monitor	0.794929119
WorkSpace	platform:Platform@123	0.66130814
Hovo	datastore-67	0.646497645
Hovo	platform:Platform@123	0.611090019
VC-10-monitor	datastore-67	0.538547917
platform:Platform@123	datastore-67	0.529359378
WorkSpace	datastore-67	0.456193616
Hovo	WorkSpace	0.451767778
Vanik	datastore-67	0.396047118
Ashot	ControllerListener	0.370706249
Vanik	platform:Platform@123	0.347556821
NFS-DS-Do-Not-Use-For-Deployment	Vanik	0.317771384
Hovo	Vanik	0.291026497
VC-10-monitor	Ashot	-0.384532661
Hovo	Ashot	-0.391295637

FIG. 19I

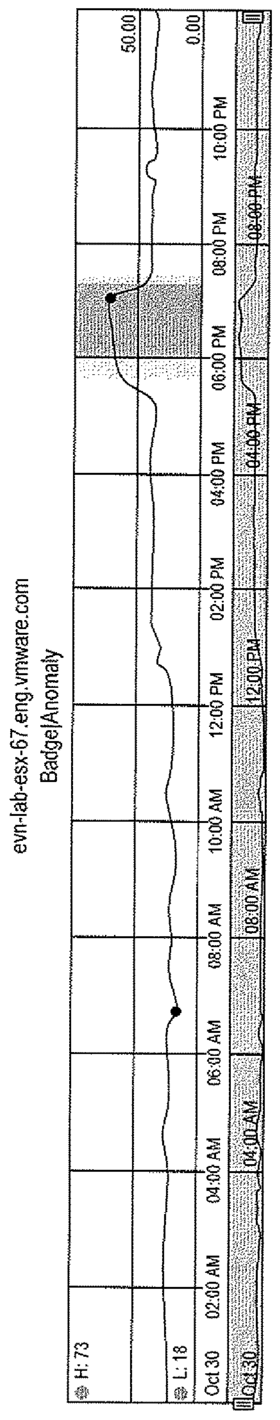


FIG. 19J

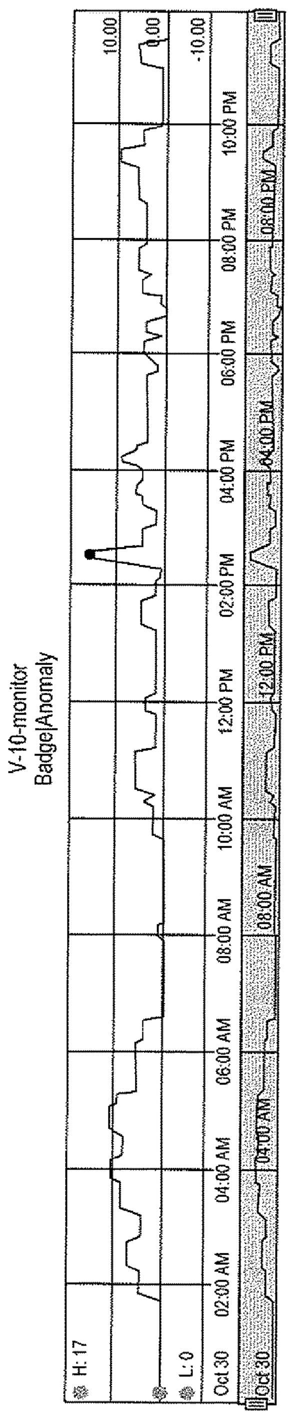


FIG. 19K

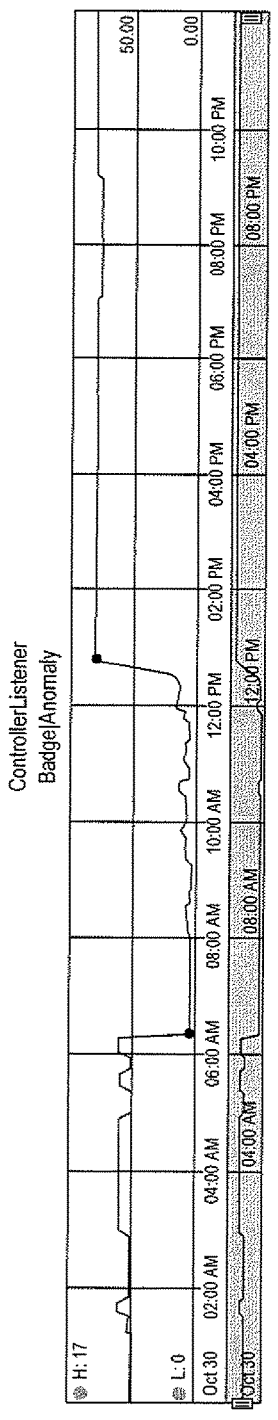


FIG. 19L

METHODS AND SYSTEMS TO DIAGNOSE ANOMALIES IN CLOUD INFRASTRUCTURES

TECHNICAL FIELD

The present disclosure is directed to methods and systems of detecting anomalies in cloud infrastructures.

BACKGROUND

In recent years, cloud computing has emerged as a preferred place for organizations to deploy their applications, store data, and enable remotely located employees and customers to access applications and data storage via the Internet. Cloud computing has also enabled independent cloud computing provides to sell cloud computing services, which enables organizations that purchase these services to decrease time to market while eliminating a heavy investment in information technology ("IT") resources and operating expenses. For example, organizations that choose to run their applications and store data in a cloud computing infrastructure maintained by a cloud computing provider may scale resources according to changing computing and data storage demands and reduce costs by paying only for the resources and workloads they use.

Physical and virtual cloud computing resources are typically monitored to determine how certain resources perform with respect to different operations. The physical resources include server computers, data-storage devices, networks, and load balancers, and the virtual resources include virtual machines ("VMs"), virtual data-storage devices, and virtual resource pools, such as a specific combination of VMs and virtual data-storage devices. Each resource generates one or more metrics that indicate how often, or how much of, the resource is used over time. For example, typical metrics collected over time include number of buffer accesses, physical and virtual CPU usage, physical and virtual memory usage, physical and virtual data-storage availability, and electrical power consumption. After multiple metrics have been collected, the metrics may be evaluated to assess and track resource performance. Of particular interest to system administrator is the ability to identify anomalies that occur within the cloud infrastructure based on the metrics. When a metric exceeds or falls below an associated threshold, an alert is typically generated. However, the system administrator may not be able to identify when the problem started and identify which resource is, or group of resources are, responsible for the problem in order to isolate and terminate the resource or group of resources before catastrophic problems occur. For example, a metric associated with a server computer that violates a threshold may be a good indicator of server computer failure, slowdown, and other problems with the server computer. However, the system administrator does not know if the problem is with the server computer itself or is a problem created by one or more of the VMs running on the server computer.

SUMMARY

A problem in a cloud infrastructure may be identified when a server computer deviates from a normal level of operation, which generates an alert and an alert time that indicates when the alert is generated. Based on the alert time, methods determine a more accurate estimate of a start time of the problem. Methods then determine which virtual machine ("VM") and other IT objects/resources or their pools contribute to the problem within a time window surrounding the estimated problem start time and calculate which objects show similar, related anomalous behavior. Method also generate ranked remediation recommendations on an object level and server computer-to-object level. The methods generate results that enable a system administrator to identify the start time of the problem and identify the objects that are responsible for the problem.

DESCRIPTION OF THE DRAWINGS

FIG. **1** shows an example of a cloud-computing facility.

FIG. **2** shows generalized hardware and software components of a server computer.

FIGS. **3**A-**3**B show two types of virtual machines and virtual-machine execution environments.

FIG. **4** shows an example set of thirty and datastores above a virtual interface plane in a cloud-computing facility.

FIG. **5** shows a plot of an anomaly score data for a parent and children associated with the parent.

FIGS. **6**A-**6**E show calculation of a maximum slope of anomaly score data.

FIG. **7**A shows a plot of anomaly score data with a positive slope in a time window.

FIG. **7**B shows a plot of vertical distances to a least-squares line calculated for the anomaly score data shown in FIG. **7**A.

FIG. **7**C shows a plot of vertical distance to a least-squares line fit to a set of positively sloped anomaly score data in a time window.

FIG. **8**A shows a plot of anomaly score data with a negative slope in a time window.

FIG. **8**B shows a plot of vertical distances to a least-squares line calculated for the anomaly score data shown in FIG. **8**A.

FIG. **8**C shows a plot of vertical distance to a least-squares line fit to a set of negatively sloped anomaly score data in a time window.

FIG. **9** show plots of the anomaly score data for the parent and children and anomaly score data in target time window.

FIG. **10** shows a control-flow diagram of a method to diagnose anomalies in a cloud infrastructure.

FIG. **11** shows a control-flow diagram of a method "calculate maximum slope of parent anomalies within a time range" called in FIG. **10**.

FIG. **12** shows a control-flow diagram of the routine "calculate t_s, $m_{max,s}$, b_s for backward time windows" called in FIG. **11**.

FIG. **13** shows a control-flow diagram of the routine "calculate t_e, $m_{max,e}$, b_e for forward time windows" called FIG. **11**.

FIG. **14**A-B shows a control-flow diagram of the routine "calculate estimated problem start time" called in FIG. **10**.

FIG. **15** shows a control-flow diagram of the routine "calculate maximum slopes of child anomalies and estimated problem start times" called in FIG. **10**.

FIG. **16** shows a control-flow diagram of the routine "calculate maximum slope of anomalies over the target time window" called in FIG. **15**.

FIG. **17** shows a control-flow diagram of the routine "generate recommendations list of children" called in FIG. **10**.

FIG. **18** shows an architectural diagram for various types of computers.

FIGS. **19**A-**19**L show experimental results for a prototype.

DETAILED DESCRIPTION

Cloud-computing facilities provide computational bandwidth and data-storage services much as utility companies provide electrical power and water to consumers. Cloud computing provides enormous advantages to small organizations without the devices to purchase, manage, and maintain in-house data centers. Such organizations can dynamically add and delete virtual computer systems from their virtual data centers within public clouds in order to track computational-bandwidth and data-storage needs, rather than purchasing sufficient computer systems within a physical data center to handle peak computational-bandwidth and data-storage demands. Moreover, small organizations can completely avoid the overhead of maintaining and managing physical computer systems, including hiring and periodically retraining information-technology specialists and continuously paying for operating-system and database-management-system upgrades. Furthermore, cloud-computing interfaces allow for easy and straightforward configuration of virtual computing facilities, flexibility in the types of applications and operating systems that can be configured, and other functionalities that are useful even for owners and administrators of private cloud-computing facilities used by a single organization.

FIG. **1** shows an example of a cloud-computing facility **100**. The cloud-computing facility **100** consists of a virtual-data-center management server **101** and a PC **102** on which a virtual-data-center management interface may be displayed to system administrators and other users. The cloud-computing facility **100** additionally includes a number of hosts or server computers, such as server computers **104-107**, that are interconnected to form three local area networks **108-110**. For example, local area network **108** includes a switch **112** that interconnects the four servers **104-107** and a mass-storage array **114** via Ethernet or optical cables and local area network **110** includes a switch **116** that interconnects four servers **118-1121** and a mass-storage array **122** via Ethernet or optical cables. In this example, the cloud computing infrastructure **100** also includes a router **124** that interconnects the LANs **108-110** and interconnects the LANS to the Internet, the virtual-data-center management server **101**, the PC **102** and to a router **126** that, in turn, interconnects other LANs composed of server computers and mass-storage arrays (not shown). In other words, the routers **124** and **126** are interconnected to form a larger network of server computers.

FIG. **2** shows generalized hardware and software components of a server computer. The server computer **200** includes three fundamental layers: (1) a hardware layer or level **202**; (2) an operating-system layer or level **204**; and (3) an application-program layer or level **206**. The hardware layer **202** includes one or more processors **208**, system memory **210**, various different types of input-output ("I/O") devices **210** and **212**, and mass-storage devices **214**. Of course, the hardware level also includes many other components, including power supplies, internal communications links and busses, specialized integrated circuits, many different types of processor-controlled or microprocessor-controlled peripheral devices and controllers, and many other components. The operating system **204** interfaces to the hardware level **202** through a low-level operating system and hardware interface **216** generally comprising a set of non-privileged computer instructions **218**, a set of privileged

computer instructions **220**, a set of non-privileged registers and memory addresses **222**, and a set of privileged registers and memory addresses **224**. In general, the operating system exposes non-privileged instructions, non-privileged registers, and non-privileged memory addresses **226** and a system-call interface **228** as an operating-system interface **230** to application programs **232-236** that execute within an execution environment provided to the application programs by the operating system. The operating system, alone, accesses the privileged instructions, privileged registers, and privileged memory addresses. By reserving access to privileged instructions, privileged registers, and privileged memory addresses, the operating system can ensure that application programs and other higher-level computational entities cannot interfere with one another's execution and cannot change the overall state of the computer system in ways that could deleteriously impact system operation. The operating system includes many internal components and modules, including a scheduler **242**, memory management **244**, a file system **246**, device drivers **248**, and many other components and modules. To a certain degree, modern operating systems provide numerous levels of abstraction above the hardware level, including virtual memory, which provides to each application program and other computational entities a separate, large, linear memory-address space that is mapped by the operating system to various electronic memories and mass-storage devices. The scheduler orchestrates interleaved execution of various different application programs and higher-level computational entities, providing to each application program a virtual, stand-alone system devoted entirely to the application program. From the application program's standpoint, the application program executes continuously without concern for the need to share processor devices and other system devices with other application programs and higher-level computational entities. The device drivers abstract details of hardware-component operation, allowing application programs to employ the system-call interface for transmitting and receiving data to and from communications networks, mass-storage devices, and other I/O devices and subsystems. The file system **246** facilitates abstraction of mass-storage-device and memory devices as a high-level, easy-to-access, file-system interface. Thus, the development and evolution of the operating system has resulted in the generation of a type of multi-faceted virtual execution environment for application programs and other higher-level computational entities.

While the execution environments provided by operating systems have proved an enormously successful level of abstraction within computer systems, the operating-system-provided level of abstraction is nonetheless associated with difficulties and challenges for developers and users of application programs and other higher-level computational entities. One difficulty arises from the fact that there are many different operating systems that run within various different types of computer hardware. In many cases, popular application programs and computational systems are developed to run on only a subset of the available operating systems, and can therefore be executed within only a subset of the various different types of computer systems on which the operating systems are designed to run. Often, even when an application program or other computational system is ported to additional operating systems, the application program or other computational system can nonetheless run more efficiently on the operating systems for which the application program or other computational system was originally targeted. Another difficulty arises from the increasingly distributed nature of computer systems. Although distributed operating systems are the subject of considerable research and development efforts, many of the popular operating systems are designed primarily for execution on a single computer system. In many cases, it is difficult to move application programs, in real time, between the different computer systems of a distributed computer system for high-availability, fault-tolerance, and load-balancing purposes. The problems are even greater in heterogeneous distributed computer systems which include different types of hardware and devices running different types of operating systems. Operating systems continue to evolve, as a result of which certain older application programs and other computational entities may be incompatible with more recent versions of operating systems for which they are targeted, creating compatibility issues that are particularly difficult to manage in large distributed systems.

For all of these reasons, a higher level of abstraction, referred to as the "virtual machine," ("VM") has been developed and evolved to further abstract computer hardware in order to address many difficulties and challenges associated with traditional computing systems, including the compatibility issues discussed above. FIGS. **3**A-**3**B show two types of VM and virtual-machine execution environments. FIGS. **3**A-**3**B use the same illustration conventions as used in FIG. **2**. FIG. **3**A shows a first type of virtualization. The server computer **300** in FIG. **3**A includes the same hardware layer **302** as the hardware layer **202** shown in FIG. **2**. However, rather than providing an operating system layer directly above the hardware layer, as in FIG. **2**, the virtualized computing environment shown in FIG. **3**A features a virtualization layer **304** that interfaces through a virtualization-layer/hardware-layer interface **306**, equivalent to interface **216** in FIG. **2**, to the hardware. The virtualization layer **304** provides a hardware-like interface **308** to a number of VMs, such as VM **310**, in a virtual-machine layer **311** executing above the virtualization layer **304**. Each VM includes one or more application programs or other higher-level computational entities packaged together with an operating system, referred to as a "guest operating system," such as application **314** and guest operating system **316** packaged together within VM **310**. Each VM is thus equivalent to the operating-system layer **204** and application-program layer **206** in the general-purpose computer system shown in FIG. **2**. Each guest operating system within a VM interfaces to the virtualization-layer interface **308** rather than to the actual hardware interface **306**. The virtualization layer **304** partitions hardware devices into abstract virtual-hardware layers to which each guest operating system within a VM interfaces. The guest operating systems within the VMs, in general, are unaware of the virtualization layer and operate as if they were directly accessing a true hardware interface. The virtualization layer **304** ensures that each of the VMs currently executing within the virtual environment receive a fair allocation of underlying hardware devices and that all VMs receive sufficient devices to progress in execution. The virtualization-layer interface **308** may differ for different guest operating systems. For example, the virtualization layer is generally able to provide virtual hardware interfaces for a variety of different types of computer hardware. This allows, as one example, a VM that includes a guest operating system designed for a particular computer architecture to run on hardware of a different architecture. The number of VMs need not be equal to the number of physical processors or even a multiple of the number of processors.

The virtualization layer **304** includes a virtual-machine-monitor module **318** that virtualizes physical processors in the hardware layer to create virtual processors on which

each of the VMs executes. For execution efficiency, the virtualization layer attempts to allow VMs to directly execute non-privileged instructions and to directly access non-privileged registers and memory. However, when the guest operating system within a VM accesses virtual privileged instructions, virtual privileged registers, and virtual privileged memory through the virtualization-layer interface **308**, the accesses result in execution of virtualization-layer code to simulate or emulate the privileged devices. The virtualization layer additionally includes a kernel module **320** that manages memory, communications, and data-storage machine devices on behalf of executing VMs ("VM kernel"). The VM kernel, for example, maintains shadow page tables on each VM so that hardware-level virtual-memory facilities can be used to process memory accesses. The VM kernel additionally includes routines that implement virtual communications and data-storage devices as well as device drivers that directly control the operation of underlying hardware communications and data-storage devices. Similarly, the VM kernel virtualizes various other types of I/O devices, including keyboards, optical-disk drives, and other such devices. The virtualization layer **304** essentially schedules execution of VMs much like an operating system schedules execution of application programs, so that the VMs each execute within a complete and fully functional virtual hardware layer.

FIG. **3**B shows a second type of virtualization. In FIG. **3**B, the server computer **340** includes the same hardware layer **342** and operating system layer **344** as the hardware layer **202** and the operating system layer **204** shown in FIG. **2**. Several application programs **346** and **348** are shown running in the execution environment provided by the operating system **344**. In addition, a virtualization layer **350** is also provided, in computer **340**, but, unlike the virtualization layer **304** discussed with reference to FIG. **3**A, virtualization layer **350** is layered above the operating system **344**, referred to as the "host OS," and uses the operating system interface to access operating-system-provided functionality as well as the hardware. The virtualization layer **350** comprises primarily a VMM and a hardware-like interface **352**, similar to hardware-like interface **308** in FIG. **3**A. The virtualization-layer/hardware-layer interface **352**, equivalent to interface **216** in FIG. **2**, provides an execution environment for a number of VMs **356**-**358**, each including one or more application programs or other higher-level computational entities packaged together with a guest operating system.

In FIGS. **3**A-**3**B, the layers are somewhat simplified for clarity of illustration. For example, portions of the virtualization layer **350** may reside within the host-operating-system kernel, such as a specialized driver incorporated into the host operating system to facilitate hardware access by the virtualization layer.

FIG. **4** shows an example set of thirty VMs **402**, such as VM **404**, and set of datastore ("DS") **406**, such as DS **408**, above a virtual interface plane **410**. The virtual interface plane **410** represents a separation between a physical resource level that comprises the server computers and mass-data storage arrays and a virtual resource level that comprises the VMs and DSs. The set of VMs **404** may be partitioned to run on different server computers, and the set of DSs **406** may be partitioned on different mass-storage arrays. Because the VMs are not bound physical devices, the VMs may be moved to different server computers in an attempt to maximize efficient use of the cloud-computing infrastructure **100** resources. For example, each of the server computers **104**-**107** may initially run three VMs. However, because the VMs have different workloads and storage requirements, the VMs may be moved to other server computers with available data storage and computational resources. Certain VMs may also be grouped into resource pools. For example, suppose a host is used to run five VMs and a first department of an organization uses three of the VMs and a second department of the same organization uses two of the VMs. Because the second department needs larger amounts of CPU and memory, a systems administrator may create one resource pool that comprises the three VMs used by the first department and a second resource pool that comprises the two VMs used by the second department. The second resource pool may be allocated more CPU and memory to meet the larger demands.

In the following description, the terms is "parent" and "child" are used to describe a tiered relationship between cloud infrastructure resources. The term parent refers to a server computer or host. The term "child" refers to an individual virtual resource, such as a VM, DS, or virtual object that runs in the virtualization layer. The term "children" refers to any two or more of the VMs, DSs, or other virtual objects. The children within the same tier are considered peers. The term child may also be used to refer to a resource pool formed from a number of VMs.

Methods now described evaluate parent to child relations when the performance of the parent has deteriorated. Methods also evaluate peer-to-peer correlations between the children. The parent and each child generates an anomaly score. In certain embodiments, an anomaly score may be calculated as the sum of the number of metrics. In other embodiments, the anomaly score may be calculated as a sum of key performance indicator ("KPI") metrics, excluding the non-KPI metrics. In other embodiments, the anomaly score may be calculated as a weighted sum of the KPI metrics in certain KPI metrics are given more weight than other KPI metrics.

An anomaly-score threshold may be used to evaluate the performance of the parent and generate an alert when the behavior of the parent has deteriorated. An anomaly score of a parent that is below the anomaly-score threshold may be used as an indication that the parent exhibits normal behavior. An anomaly score of a parent that exceeds the anomaly-score threshold generates an alert that indicates a problem or at least a situation that requires attention.

FIG. **5** shows a plot of an anomaly score for a parent. Horizontal axis **502** represents time. Vertical axis **504** represents the anomaly score. Curve **506** represents the anomaly score of the parent over time. Dashed line **508** represents an anomaly score threshold, T_k. The anomaly score of the parent exceeds the threshold T_h at an alert time denoted by t_a, which generates an alert indicating that a problem has occurred with the parent. FIG. **5** also shows separate plots of anomaly scores of the children running on the parent. The children are denoted by Child_1, Child_2, Child_3, and Child_4. Each plot includes a time axis and an anomaly score axis. Curves **510-513** represent the separate anomaly scores of the children recorded over the same period of time as the anomaly score **506** of the parent. However, it is not clear which child alone, or combination of children, is responsible for the violation of the threshold T_h at the alert time t_a.

As shown in the example of FIG. **5**, when an alert is generated as a result of a parent anomaly score exceeding the anomaly-score threshold, the following conditions exist: 1) the parent's anomaly score has a positive slope while increasing toward the threshold; and 2) the children may show either negatively or positively sloped anomaly scores around the alert time t_a. Methods described below determine

which child or children exhibit a change in behavior around the alert time t_a and provide a recommendation list of children to examine for a root cause of the problem.

Although the alert time t_a is an indication of when the anomaly score violated the threshold T_h, the actual start time of the problem at the parent may have occurred prior to the alert time t_a. Based on the alert time t_a and the anomaly scores of the parent that precede the alert time t_a, an estimated problem start time is determined by first determining the maximum slope of parent anomaly scores that precede the alert time t_a. The estimated problem start time is calculated from the maximum slope.

FIGS. **6**A-**6**E show calculation of a maximum slope of parent anomaly scores that precede the alert time t_a. In FIG. **6**A, horizontal axis **602** represents time and vertical axis **604** represents anomaly score values. Dots represent anomaly score data (t_i, y_i), where y_i represents an anomaly score recorded at time t_i. The times t_i are represented by regularly spaced marks along the time axis **602**. FIG. **6**A shows an anomaly score data point **606** that exceeds a threshold T_h represented by dot-dash line **608** at alert time t_a, which triggers an alert Base on the alert time t_a, a time range $[t_a-\Delta, t_a]$ **610** that extends backward in time from the alert time t_a is created, where Δ is the duration of the time range **610**. The duration Δ of the time range **610** may be any duration greater than or equal to about 60 minutes, such as about 75 minutes, about 90 minutes, about 120 minutes, about 240 minutes, about 360 minutes or larger. A list of times in the time range **610**, called the "time list," is generated and represented by:

$$\text{timeList}=\text{data}[t_a-\Delta,t_a] \tag{1}$$

FIG. **6**B shows a maximum time window **612** is created with a duration:

$$_{max}\Delta_t=t_e-t_s \tag{2}$$

where

$t_e=t_a$ is the maximum time of the timeList, and

t_s is the minimum time of the timeList,

For example, in FIG. **6**B, the minimum time t_s is the minimum time at which an anomaly score **614** is recorded in the time range **610**. The maximum time window **612** in the time range **610** has minimum time t_s and maximum time t_e.

The slope and y-intercept of parent anomaly score data are calculated for each of a number of overlapping time windows of the maximum time window. The time window with the maximum slope is identified. The overlapping time windows are called backward and forward time windows.

FIG. **6**C shows a series of backward time windows **616**, **618**, and **620** denoted by $[t_l, t_e]$. Each of the backward time windows has the same upper time limit given by the maximum time t_e and a different lower time limit calculated according to

$$t_l=t_e-(\Delta_t+i\beta) \tag{3a}$$

where

Δ_t is an initial time window duration;

β is a time window adjustment parameter, and

$i=0, 1, 2, \ldots$ is a backward time window index.

The slope, m_i, and y-intercept, b_i, of the set of anomaly score data in each of the backward time windows are calculated separately, for $i=0, 1, 2, \ldots$. For example, m_0 is the slope and b_0 is the y-intercept of the anomaly score data **622** in the time window **616**. Calculation stops when $(\Delta_t+i\beta)>_{max}\Delta_t$. The minimum time t_s is set equal to the lower time limit t_l of the backward time window with the largest slope (i.e., $|m_i|$). For example, if m_i is the largest slope of the backward time windows **616**, **618**, and **620** in FIG. **6**C, the minimum time t_s is set equal to the lower time limit t_l of the backward time window **620**.

FIG. **6**D shows a series of forward time windows **624**, **626**, and **628** denoted by $[t_s, t_u]$, where t_s is the reset minimum time described above with reference to FIG. **6**C. Each of the forward time windows has the same lower time limit t_s and an upper time limit calculated according to

$$t_u = t_s + \Delta_t + j\beta \tag{3b}$$

where j=0, 1, 2, . . . is a time window index.

The slope, m'_j, and y-intercept, b'_j, of the set of anomaly score data in each of the forward time windows are calculated, for j=0, 1, 2, ... For example, m'_0 is the slope and b'_0 is the y-intercept of the set of anomaly score data **624** in the forward time window **626**. Calculation of the slope and y-intercept for each of the forward time windows stops when $t_u > t_a$. The time t_e is set equal to the upper time limit t_u of the forward time window with the largest magnitude slope. For example, if m'_j is the largest slope of the forward time windows **624**, **626**, and **628**, then the time t_e is set equal to the upper time limit t_u of the forward time window **630**.

The slope and y-intercept of a set of anomaly score data in a backward or forward time window is calculated by first rescaling the anomaly score data to a common reference frame followed by applying weighted least squares to calculate the slope and y-intercept of the rescaled anomaly score data. Rescaling to a common reference frame includes mapping the data from the time windows into the same coordinate system and normalizing the data between 0 and 1. Let $(\bar{t}_0, \bar{y}_0)$ be an anomaly score data point in a time window with the smallest time $\bar{t}_0$, and let $(\bar{t}_c, \bar{y}_c)$ be an anomaly score data point in the same time window with the largest time $\bar{t}_c$. Rescaling the anomaly score data points $(\bar{t}_i, \bar{y}_i)$ in the time window to a common reference frame may be accomplished by first defining a scaling factor.

$$\bar{y}_M \equiv \begin{cases} \max(\bar{y}_i) & \bar{y}_c = 0 \\ \bar{y}_c & \bar{y}_c \neq 0 \end{cases} \tag{4a}$$

For each anomaly score $\bar{y}_i$ in the sub-time interval, the anomaly score is rescaled by

$$y_i \equiv \begin{cases} \dfrac{\bar{y}_i}{\bar{y}_M} & \bar{y}_M \neq 0 \\ \bar{y}_c & \bar{y}_M = 0 \end{cases} \tag{4b}$$

The times $\bar{t}_i$ are rescaled according to

$$t_i \equiv C\bar{t}_i \tag{4c}$$

where C is a constant that changes the time units (e.g., C may be used to change the units of time to minutes).

FIG. **6**E shows an example of rescaling anomaly score data **632** in a time window $[\bar{t}_0, \bar{t}_c]$. Horizontal axis **634** represents time. Vertical axis **636** represent anomaly score values. Dot **638** represents the anomaly score data point $(\bar{t}_0, \bar{y}_0)$ with the smallest time $\bar{t}_0$. Dot **640** represents the anomaly score data point $(\bar{t}_c, \bar{y}_c)$ with the largest time $\bar{t}_c$. Rescaling the anomaly score data **632** according Equations (4a)-(4c) gives rescaled anomaly score data **642**. Because $\bar{y}_c$ does not equal zero, the scaling factor is $\bar{y}_M = \bar{y}_c$, the anomaly scores are rescaled according to Equation (4b), and the associated time coordinates are rescaled according to Equation (4c). The rescaled time window is $[t_0, t_c]$.

Using the following boundary conditions:

$$t = t_c \text{ gives } y = y_c$$

$$t = t_q \text{ gives } y = 0 \tag{5a}$$

for the linear equation y(t)=mx+b, weighted least squares gives the slope of a set of N anomaly score data points in a time window as:

$$m = \frac{y_c}{t_c - t_q} \tag{5b}$$

and the y-intercept:

$$b = y_c - mt_c \tag{5c}$$

In order to calculate the slope in Equation (5b), the time t_q in the denominator is calculated as:

$$t_q = \frac{\sum_{n=1}^{N} (A_n t_n - A_n t_c)}{\sum_{n=1}^{N} (B_n t_c - B_n t_n)} \tag{6a}$$

where

$$A_n = w_n^2 (y_c t_n - y_n t_c) \tag{6b}$$

$$B_n = w_n^2 (y_n - y_c) \tag{6c}$$

and the weight is given by

$$w_n = \mu^{\ln(n)}; \mu \geq 2 \tag{6d}$$

After the largest slope m_i of the backward time windows and the largest slope m'_j of the forward time window have been determined, the larger of the two slopes is identified as the maximum slope:

$$m_{max} = \max(m_i, m'_j) \tag{7}$$

The maximum slope m_{max} and the corresponding y-intercept b and backward or forward time window are used to calculate a transition time given by:

$$t_T = \begin{cases} \min(t_i) \text{ such that } y(t_i) < y_i & \text{for } m_{max} > 0 \\ \min(t_i) \text{ such that } y(t_i) > y_i & \text{for } m_{max} < 0 \end{cases} \tag{8}$$

where $y(t_i) = m_{max} t_i + b$ is the weighted least-squares line. The transition is an approximation to the estimated start time. When the maximum slope m_{max} of the anomaly score data is positive, the transition time t_T is the minimum time t_i at which the anomaly score data value y_i is less than $y(t_i)$. When the maximum slope m_{max} of the anomaly score data is negative, the transition time t_T is the minimum time t_i at which the anomaly score data value y_i is greater than $y(t_i)$.

FIG. **7**A shows a plot of anomaly score data close to the reset minimum time t_s of either a backward or forward time window associated with the maximum slope m_{max}. Horizontal axis **702** represents time. Dashed line **704** represents a weighted least-squares fit line to the anomaly score data with slope m_{max} and y-intercept b. Dot **706** represents an anomaly score data point (t_{i-1}, y_{i-1}) in which $y(t_{i-1})$ is greater than y_{i-1}. Dot **708** represents an anomaly score data point (t_i, y_i) in which $y(t_i)$ is less than y_i. According to Equation (8), the transition time t_T is set equal to the time t_i.

In certain cases, the transition time t_T may not actually correspond to the smallest anomaly data point. In such cases, the transition time t_T may be adjusted to correspond to the anomaly score data point with the largest vertical distance from the weighted least-squares line given by:

$$\Delta_p = \max|y(t_i) - y_i| \text{ for } i \geq T \tag{9}$$

where $\Delta_i = |y(t_i) - y_i|$ is the vertical distance between anomaly score data point (t_i, y_i) and the weighted least-squares value $y(t_i)$.
The estimated problem start time t_k is selected based on the following conditions:

$$k = \begin{cases} T \text{ when } \Delta_P < \delta \\ P \text{ when } \Delta_P \geq \delta \end{cases} \tag{10}$$

The parameter δ is a user selected transition-time threshold. For example, $\delta = 0.15$. In other words, when $\Delta_p < \delta$ the estimated problem start time t_k is set equal to the transition time T_r. Otherwise, when $\Delta_p \geq \delta$ the estimated problem start time t_k is set equal to an adjusted-transition time t_p.

FIG. **7**B show a plot of vertical distances the anomaly score data from the weighted least-squares line **704** shown in FIG. **7**A. The vertical distances for $i \geq T$ are represented by Δ_i. In this example, all of the vertical distances are less then 0.15. Thus, according to Equation (10), the estimated problem start time t_k is set equal to the transition time t_T. FIG. **7**C shows a plot of vertical distances for a different set of anomaly score data from a weighted least-squares line **710**. Dot **712** represents an anomaly score data point (t_i, y_i) in which $y(t_i)$ is less than y_{i-1}. In this example, $\Delta_p = \Delta_{i+2} = |y(t_{i+2}) - y_{i+2}| \geq 0.15$. According to Equation (10), rather than setting the estimated problem start time t_k equal to the transition time t_T, the estimated problem start time t_k is set equal to the adjusted-transition time t_p associated with the largest vertical distance between the anomaly data score points and the weighted least-squares line (i.e., $t_k = t_p$).

Equations (8)-(10) may also be used to calculate the estimated problem start time for negatively sloped anomaly score data. FIG. **8**A shows a plot of anomaly score data close to the reset minimum t_s of either a backward or forward time window with the maximum slope m_{max}. Horizontal axis **802** represents time. Dashed line **804** represents a weighted least-squares fit line to the anomaly score data with slope m_{max} and y-intercept b. Dot **806** represents an anomaly score data point (t_i, y_i) in which $y(t_i)$ is greater than y_i for a minimum time t_i. According to Equation (8), the transition time t_T is set equal to the time t_i. FIG. **8**B show plots of vertical distances calculated for the anomaly score data shown in FIG. **8**A. In FIG. **8**B, the vertical distances Δ_i for $i \geq T$ are indicated. In this example, all of the vertical distances are less then 0.15. Thus, according to Equation (10), the estimated problem start time t_k is set equal to the transition time t_T. FIG. **8**C shows a plot of vertical distances calculated for a different set of anomaly score data from a weighted least-squares line **810**. Dot **812** represents an anomaly score data point (t_i, y_i) in which $y(t_i)$ is less than y_i. In this example, $\Delta_p = \Delta_{i+2} = |y(t_{i+2}) - y_{i+2}| \geq \delta$. According to Equation (10), the estimated problem start time t_k is set equal to the adjusted-transition time t_p.

The estimated problem start time t_k of the parent is used to create a target time window that, in turn, may be used to calculate maximum slopes and estimate problem start time for the children running on the parent. FIG. **9** show plots of the anomaly scores for the parent and four children

described above with reference to FIG. **5**. An estimated problem start time t_k of the parent is identified on time axis **502**. A target time window that includes the estimated problem start time is given by:

$$[t_x, t_y] = [t_k - t_{h1}, t_k + t_{h2}] \tag{11}$$

A large target time window time range is used to capture estimated problem start time for the children. The time t_{h1} is typically much larger than the time t_{22} in order to try and determine if the estimated problem start time for problems associated with the children that start much earlier than the estimated problem start time t_k for the parent. For example, the time t_{h1} may be about 3 hours and the time t_{h2} may be about 0.5 hours in order to create a target time window with a three and half hour time range that captures estimated problem start times for the children.

Using the target time window given by Equation (11), a maximum slope and estimated problem start time i are calculated for each set of anomaly score data of the children that lie within the target time window as described above. The anomaly scores that lie within the target time window for each child are used to calculate an associated maximum slope, denoted by m_{ci}, and estimated child start time, denoted by t_{ci}, where the subscript i is the child index.

FIG. **9** shows the target time window **902** along the time axis of each of the children. For Child$_1$, the anomaly score data **904** that lies within the target time window **902** is used to calculate a maximum slope, m_{c1}, as described above with reference to FIGS. **6**A-**6**E and Equations (1)-(7). The maximum slope and associated y-intercept are then used to calculate an estimated problem start time t_{c1}, as described above with reference to FIGS. **7** and **8** and Equations (8)-(10).

Based on the maximum slope for the parent, m_{max}, and the maximum slopes associated with children, m_{ei}, recommendation lists of the children are created according to the following rules. A set of children with estimated problem start times that are less than the parent start time is created:

$$B = \{\text{Child}_i; \text{ for all } i : t_{ci} < t_k\} \tag{12}$$

The children in the set B are then sorted into data buckets as follows:

$$R_1 = \left\{B: \left(\frac{m_{ci}}{m_{max}} \geq 1.0\right) \text{ or } m_{ci} \geq 0.0083\right\} \tag{13a}$$

$$R_2 = \left\{B: \left(\frac{m_{ci}}{m_{max}} \leq -1.0\right) \text{ or } m_{ci} \leq 0.0083\right\} \tag{13b}$$

$$R_3 = \left\{B: 0.80 < \frac{m_{ci}}{m_{max}} < 1.0\right\} \text{ and} \tag{13c}$$

$$R_4 = \left\{B: 0.80 \geq \frac{m_{ci}}{m_{max}} > -1.0\right\} \tag{13d}$$

In certain embodiments, the children in each data bucket may be sorted from smallest to largest.

The separate data buckets indicate which children are the strongest contributors to the anomalous behavior exhibited by the parent. For example, children in the data buckets R_1 and R_2 are larger contributors to the anomalous behavior at the parent than are children in the data buckets R_3 and R_4. The children within each data bucket may also be ranked from largest to smallest based on estimated problem start times and/or based on the ratio of slopes m_{ci}/m_{max} The larger the magnitude of the ratio of slopes, $|m_{ci}/m_{max}|$, the higher the probability that the ith child is a root cause of the anomalous behavior at the parent. The data buckets may then be displayed, such on a computer monitor, so that a systems administrator may examine the children identified in each data bucket, each child's estimated problem start times, and each child ratio of slopes in order to determine which child is or children are, most likely responsible for the anomalous behavior at the parent. Thresholds may also be used to identify which children are most likely responsible for the anomalous behavior at the parent. For example, when the ratio $|m_{ci}/m_{max}|$ is greater than a threshold T_R, where the threshold is used as an indication that the ith child is most likely a contributor to, or responsible for, the anomalous behavior at the parent.

For each pair of children of the parent, a correlation coefficient may be calculated from anomaly score data with times between the estimate problem start time of the parent t_k and the alert time t_a as follows:

$$\rho = \frac{1}{M}\sum_{m=1}^{M}\left(\frac{X_m-\mu_X}{\sigma_X}\right)\left(\frac{Y_m-\mu_Y}{\sigma_Y}\right) \tag{14}$$

where

X_m and Y_m are anomaly scores of a first child and a second child in the time interval $[t_k, t_a]$;

μ_x and μ_y are the mean values of the anomaly scores of the first child and the second child in the time interval $[t_k, t_a]$; and

σ_x and σ_y are the standard deviations of the anomaly scores of the first child and the second child in the time interval $[t_k, t_a]$.

FIG. **10** shows a control-flow diagram of a method to diagnose anomalies in a cloud infrastructure. In block **1001**, parent anomaly score data is received as described above with reference to FIG. **5**. The parent may be a server computer or a host that runs in the cloud infrastructure. In decision block **1002**, when an anomaly-score threshold is violated, an alert time t_a is recorded and control flows to block **1003**. In block **1003**, a routine "calculate maximum slope of parent anomalies within a time range" is called. The time range extends backward in time from the alert time as described above with reference to FIG. **6**A. In block **1004**, a routine "calculate estimated problem start time" is called to calculate an estimated problem start time within the time range based on the slope. In block **1005**, a routine "calculate maximum slopes of child anomalies and estimated problems start times" is called to calculate the maximum slopes of child anomalies and estimated problem start times of the children associated with the parent based on the estimated problem start time of the parent. The children may be VMs, DSs, and resource pools. In block **1006**, a routine "generate recommendations list of children" is called to generate recommendation lists of the children based on the maximum slope of the parent and the maximum slopes of the children. In block **1007**, for each pair of children of the parent, a correlation coefficient is calculated from anomaly score data of the children recorded between the estimate problem start time of the parent and the alert time t_a, as described above with reference to Equation (14).

FIG. **11** shows a control-flow diagram of a method "calculate maximum slope of parent anomalies within a time range" called in block **1003** of FIG. **10**. In block **1101**, the alert time t_a is received. In block **1102**, the time range is $[t_a-\Delta, t_a]$ is created. In block **1103**, a time list is formed from the anomaly scores recorded in the time range, as described

above with reference to Equation (1) and FIG. **6**B. In block **1103**, a minimum time t_s is initialized as the minimum time of the times in the time list and a maximum time t_e is set equal to the alert time t_a, as described above with reference to Equation (2). In block **1104**, a maximum time window is formed as the difference between the minimum time t_s and the maximum time t_e of the time list, as described above with reference to Equation (2). In decision block **1105**, when the duration of the maximum time window, ${}_{max}\Delta_t$, is less than a user selected parameter α, control flows to block **1106**, otherwise, control flows to block **1107**. For example, in certain embodiments, the parameter α may be set to about 75 minutes. In block **1106**, the maximum slope and y-intercept for parent anomaly score data in $[t_s, t_e]$ is calculated as described above with reference to Equations (4)-(6). In block **1107**, a routine "calculate t_s, $m_{max,s}$, b_s for backward time windows" is called to calculate maximum slope and y-intercept of the parent anomaly score data in a series of overlapping backward time windows of the maximum time window, as described above with reference to FIG. **6**C. In block **1108**, a routine "calculate t_e, $m_{max,e}$, b_e for forward time windows" is called to calculate maximum slope and y-intercept of the parent anomaly score data in a series of overlapping forward time windows of the maximum time window, as described above with reference to FIG. **6**D. In block **1109**, the maximum slope and y-intercept of the parent anomaly score data is set equal to the larger of the maximum slopes and y-intercept of the backward and forward time windows determined in blocks **1107** and **1108**, as described above with reference to Equation (7).

FIG. **12** shows a control-flow diagram of the routine "calculate t_s, $m_{max,s}$, b_s for backward time windows" called in block **1107** of FIG. **11**. In block **1201**, the parameters Δ_t and β are initialized. For example, the initial time window duration Δ_t may be set of about 60 minutes and the time window adjustment parameter β may be set to about 15 minutes. A maximum slope $m_{max,s}$ and corresponding y-intercept b_s of the backward time window and the index i are initialized to zero. In block **1202**, a slope m and y-intercept b are calculated according to Equations (4)-(6) for parent anomaly data in the backward time window $[t_l, t_e]$, where the lower time limit t_l of the backward time window is calculated as described above with reference to Equation (3a). In decision block **1203**, if the slope m calculated in block **1202** is greater than the slope $m_{max,s}$, control flows block **1204**, otherwise, control flows to decision block **1205**. In block **1204**, the maximum slope $m_{max,s}$, of the backward time interval is set equal to m and the y-intercept b_s is set equal to the y-intercept b. In decision block **1205**, as long as the parameter $(\Delta_t+i\beta)$ is less than the duration of the maximum time window, ${}_{max}\Delta$, control flows to block **1206** in which the index i is incremented. In block **1207**, the minimum time t_s is set equal to the lower time limit t_l of the backward time window with the largest slope.

FIG. **13** shows a control-flow diagram of the routine "calculate t_e, $m_{max,e}$, b_e for forward time windows" called in block **1108** of FIG. **11**. In block **1301**, a maximum slope $m_{max,e}$ and corresponding y-intercept b_e of the forward time window are initially set equal to the maximum slope $m_{max,s}$ and corresponding y-intercept b_s of the backward time windows and the index j is initialized to zero. The parameters Δ_t and β remain unchanged. In block **1302**, a slope m and y-intercept b are calculated according to Equations (4)-(6) for parent anomaly data in the forward time window $[t_s, t_u]$, where the minimum time t_s set in block **1207** of FIG. **12** is used and the upper time limit t_u of the forward time window is calculated as described above with reference to

Equation (3b). In decision block **1303**, if the slope m calculated in block **1302** is greater than the slope $m_{max,e}$, control flows to block **1304**, otherwise, control flows to decision block **1305**. In block **1304**, the maximum slope $m_{max,e}$ of the forward time windows is set equal to m and the y-intercept b_e is set equal to the y-intercept b. In decision block **1305**, as long as the upper time limit t_u is less than the alert time t_a control flows to block **1306** in which the index j is incremented. In block **1307**, the maximum time t_e is set equal to the upper time limit t_u of the forward time window with the largest slope.

FIG. **14** shows a control-flow diagram of the routine "calculate estimated problem start time" called in block **1004** of FIG. **10**. In block **1401**, the reset minimum time t_s, a slope m and y-intercept b for the weighted least-squares linear equation $y(t_i)=mt_i+b$ are received. A for-loop beginning with block **1402** repeats the operations represented by blocks **1403-1406** for anomaly score times t_i greater than the minimum time t_s. In block **1403**, the anomaly score value is calculated using the weight least-squares linear equation. In decision block **1404**, when the slope m>0 and $y(t_i)<y_i$ control flows to block **1407**, otherwise control flows to decision block **1405**. In decision block **1405**, when the slope m<0 and $y(t_i)>y_i$ control flows to block **1407**, otherwise control flows to decision block **1406** and the next anomaly score time t_i is considered. In block **1407**, a transition time t_T is set equal to the time t_i and the largest vertical distance Δ_p between the weighted least-squares line and the anomaly score data is initialized to zero. A for-loop beginning with block **1408**, repeats the operations represented by blocks **1409-1412** to determine the largest vertical distance between times greater than the transition time t_T and the weighted least-squares line for R number of anomaly score times. In block **1409**, the anomaly score value is calculated using the weight least-squares linear equation. In decision block **1410**, when the distance $|y(t_i)-y_i|$ is greater than Δ_p control flows to block **1411** in which $\Delta_p=|y(t_i)-y_i|$. In decision block **1412**, when the index r equals R, control flows to decision block **1414**, otherwise control flows to block **1413** and the index r is incremented. In decision block **1414**, when the largest vertical distance $\Delta_p<\delta$, control flows to block **1416** and the estimated problem start time t_k is set equal to the transition time t_T, as described with reference to FIGS. **7**B and **8**B. Otherwise, control flows to block **1415** and estimated problem start time t_k is set equal to the adjusted-transition time t_p associated with the largest vertical distance as described above with reference to FIGS. **7**C and **8**C.

FIG. **15** shows a control-flow diagram of the routine "calculate maximum slopes of child anomalies and estimated problem start times" called in block **1005** of FIG. **10**. In block **1501**, a target time windows is created based on the estimated problem start time t_k as described above with reference to Equation (11). A for-loop beginning with block **1502** repeats the operations represented by blocks **1503** and **1504** for each of the children, where J is the number of children. In block **1503**, a routine "calculate maximum slope of anomalies over the target time window" is called. In block **1504**, the routine "calculate estimate problem start time" described above with reference to FIGS. **14**A-**14**B is called to calculate the estimated problem start time for the jth child.

FIG. **16** shows a control-flow diagram of the routine "calculate maximum slope of anomalies over the target time window" called in block **1503** of FIG. **15**. In block **1601**, the parameter ${}_{max}\Delta_t$ is set equal to the length of the target time window. In block **1602**, the routine "calculate t_x, $m_{max,x}$, b_x for backward time windows" is called to calculate maximum slope and y-intercept of the jth child anomaly score data in a series of overlapping backward time windows as described above with reference to FIG. **12**. In block **1108**, the routine "calculate t_y, $m_{max,y}$, b_y for forward time windows" is called to calculate maximum slope and y-intercept of the jth child anomaly score data in a series of overlapping forward time windows, as described above with reference to FIG. **13**. In block **1604**, the maximum slope m_{cj} of the jth child is calculated.

FIG. **17** shows a control-flow diagram of the routine "generate recommendations list of children" called in block **1006**. A for-loop beginning with block **1701** repeats the operations represented by blocks **1702-1712** for each child. In block **1702**, when the estimated problem start time t_{cj} of the jth child is less than the estimated problem start time t_k of the parent, control flows to decision blocks **1703**. Decision blocks **1703**, **1705**, **1707**, and **1709** separate the children into the data buckets R_1, R_2, R_3, and R_4, as described above with reference to Equations (13a)-(13d), respectively. In blocks **1704**, **1706**, **1708**, and **1710**, the children separated in decision blocks **1703**, **1705**, **1707**, and **1709** are added to data buckets R_1, R_2, R_3, and R_4, respectively. In block **1711**, when j is less than J, the operations of blocks **1702-1710** are repeated. Otherwise, control flows to block **1713** in which a for-loop repeats the operation of sorting children in each of the data buckets R_1, R_2, R_3, and R_4 from the smallest to largest estimated problem start times.

FIG. **18** shows a general architectural diagram for various types of computers used to execute the methods described above. The computer system contains one or multiple central processing units ("CPUs") **1802-1805**, one or more electronic memories **1808** interconnected with the CPUs by a CPU/memory-subsystem bus **1810** or multiple busses, a first bridge **1812** that interconnects the CPU/memory-subsystem bus **1810** with additional busses **1814** and **1816**, or other types of high-speed interconnection media, including multiple, high-speed serial interconnects. These busses or serial interconnections, in turn, connect the CPUs and memory with specialized processors, such as a graphics processor **1818**, and with one or more additional bridges **1820**, which are interconnected with high-speed serial links or with multiple controllers **1822-1827**, such as controller **1827**, that provide access to various different types of mass-storage devices **1828**, electronic displays, input devices, and other such components, subcomponents, and computational devices. It should be noted that computer-readable data-storage devices include optical and electromagnetic disks, electronic memories, and other physical data-storage devices. Those familiar with modern science and technology appreciate that electromagnetic radiation and propagating signals do not store data for subsequent retrieval, and can transiently "store" only a byte or less of information per mile, far less information than needed to encode even the simplest of routines.

FIGS. **19**A-**19**L show experimental results. FIG. **19**A shows a diagram of a parent ESX host **1901** and children **1902** (VM's, datastore, resource pool). FIG. **19**B shows a total anomaly score of the host with an alert generated at 12:09 PM **1903**. Executing the above described method at 12:20 PM **1904** identifies the problem start time and a recommendation list of children in FIGS. **19**C-**19**F, with R representing object's rank (not normalized). FIG. **19**C shows that the first child VM (ControllerListener) experienced the highest rate of anomalies increase during the problem evolution after 12:00 PM. Table I in FIG. **19**F shows that for the same problematic time window, the children metrics are correlated using to correlation coefficient of Equation (14) to observe how the impact is propagated over the peers. Table

1 reveals that the most highly correlated children are in a resource pool formed from the first three entries, as shown in FIG. **19**G. Table II in FIG. **191** shows the historic correlations of total metrics of the children. Table II reveals that VC-10-monitor gives a high correlation with the parent resource pool "Hovo," compared to the run-time results displayed in Table I. As a result, from a historical perspective, the anomaly status of the resource pool "Hovo" is mostly associated with one child, which is the VC-10-monitor.

In these experiments, positive correlations dominate in correlation matrices. In other words, in an IT environment, the problem causes other problems, or at least does not eliminate existing ones. Similar peer-to-peer correlation may be performed for hosts within the same cluster. The host was followed and observed for about 6 hours after the alert (which was still active). The host's "Badge|Anomaly" metric was increased, as shown in FIG. **19**J, which indicates the host experienced an additional performance problem. FIG. **19**J shows the status changed to critical at about 06:00 PM. The methods described above were then executed for the total anomaly score and the Badge|Anomaly again, which identified only one recommended child as contributing to those metrics in both cases. The problem interval detected by the method was Oct. 30, 2015 14:02:23 PM-Oct. 30, 2015 17:32:23 PM for both anomaly metrics. VC-10-Monitor represented in FIG. **19**K had rank scores of R=37.97 and R=4.05, respectively. Based on the four recommended children for the alert, only the VC-10-Monitor continued to contributing to the problem. Moreover, the VC-10-Monitor was responsible for the problem of Badge|Anomaly that indicated out-of-normal performance of a significant portion of child metrics. FIG. **19**L shows the highest rank object ControllerListener stabilized.

Of course, there are many different types of computer-system architectures that differ from one another in the number of different memories, including different types of hierarchical cache memories, the number of processors and the connectivity of the processors with other system components, the number of internal communications busses and serial links, and in many other ways. However, computer systems generally execute stored programs by fetching instructions from memory and executing the instructions in one or more processors. Computer systems include general-purpose computer systems, such as personal computers ("PCs"), various types of servers and workstations, and higher-end mainframe computers, but may also include a plethora of various types of special-purpose computing devices, including data-storage systems, communications routers, network nodes, tablet computers, and mobile telephones.

It is appreciated that the various implementations described herein are intended to enable any person skilled in the art to make or use the present disclosure. Various modifications to these implementations will be readily apparent to those skilled in the art, and the generic principles defined herein may be applied to other implementations without departing from the spirit or scope of the disclosure. For example, any of a variety of different implementations can be obtained by varying any of many different design and development parameters, including programming language, underlying operating system, modular organization, control structures, data structures, and other such design and development parameters. Thus, the present disclosure is not intended to be limited to the implementations described herein but is to be accorded the widest scope consistent with the principles and novel features disclosed herein.

The invention claimed is:

1. In a process to diagnose anomalies in a cloud infrastructure in which computers and virtual resources of the cloud infrastructure generate metric data stored in one or more data-storage devices, the specific improvement comprising:

calculating anomaly score data of a computer running one or more virtual resource in the cloud infrastructure based on the metric data generated by the computer;

calculating a maximum slope of anomaly score data of the computer within a time range that extends backward in time from an alert time that indicates when an anomaly score of the computer exceeds a threshold;

calculating an estimated problem start time based on the maximum slope, the estimated problem start time identifies an approximate time when anomalous behavior with the computer began;

calculating a maximum slope of anomaly score data and estimated problems start times for each of the one or more virtual resources running on the computer based on the estimated problem start time of the computer;

generating a recommendation list of virtual resources that likely cause anomalous behavior at the computer based on ratios of the maximum slope of anomaly score data associated with each of the one or more virtual resources and the maximum slope of anomaly score data associate with the computer; and

moving one or more virtual resources identified as the likely cause of anomalous behavior at the computer to different computers in the cloud infrastructure, thereby increasing efficient use of the computer.

2. The process of claim **1**, wherein calculating the maximum slope of computer anomaly score data within the time range further comprises:

calculating a maximum slope and y-intercept of the computer anomaly score data in a series of overlapping backward time windows within the time range;

calculating a maximum slope and y-intercept of the computer anomaly score data in a series of overlapping forward time windows within the time range; and

setting the maximum slope and y-intercept of the computer anomaly score data equal to the larger of the maximum slopes and y-intercepts of the backward and forward time windows.

3. The process of claim **2**, calculating the maximum slope and y-intercept of the computer anomaly score data in the series of backward time windows further comprises:

rescaling the anomaly score data in a backward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in the backward time window;

decreasing a lower time limit of the backward time window to generate a backward time window with a longer duration;

repeating rescaling, calculating, and decreasing until the duration of the backward time window exceeds a minimum time limit of the time range; and

identifying a maximum slope of the slopes calculated for the series of backward time windows.

4. The process of claim **2**, calculating the maximum slope and y-intercept of the computer anomaly score data in the series of forward time windows further comprises:

rescaling the anomaly score data in a forward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in the forward time window;

increasing an upper time limit of the forward time window to generate a forward time window with a longer duration;

repeating rescaling, calculating, and decreasing until the duration of the forward time window exceeds a maximum time limit of the time range; and

identifying a maximum slope of the slopes calculated for the series of forward time windows.

5. The process of claim **1**, wherein calculating the estimated problem start time based on the maximum slope further comprises determining a transition time.

6. The process of claim **5**, determining the transition time further comprises:

settting the estimated problem start time equal to the transition time when vertical distances between anomaly score data and a least squares line fit to the anomaly score data is less than a transition-time threshold; and

setting the estimated problem start time equal to an adjusted-transition time when vertical distances between anomaly score data and a least squares line fit to the anomaly score data is greater than a transition-time threshold.

7. The process of claim **1**, where calculating a maximum slope of anomaly scores and estimated problems start times for each of one or more virtual resources further comprises:

calculating a target time window from the estimated problem start time of the computer;

for each of the one or more virtual resources,

resealing the anomaly score data in a backward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in the backward time window;

decreasing a lower time limit of the backward time window to generate a backward time window with a longer duration;

repeating resealing, calculating, and decreasing until the duration of the backward time window exceeds a minimum time limit of the target time window; and

identifying a maximum slope of the slopes calculated for the series of backward time windows.

8. The process of claim **7** further comprises:

rescaling the anomaly score data in a forward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in a forward time window;

increasing an upper time limit of the forward time window to generate a forward time window with a longer duration;

repeating rescaling, calculating, and decreasing until the duration of the forward time window exceeds a maximum time limit of the time range; and

identifying a maximum slope of the slopes calculated for the series of forward time windows.

9. The process of claim **1**, wherein generating the recommendation lists of virtual resources based on the maximum slope of anomaly scores associated with each of the one or more virtual resources further comprises:

sorting the one or more virtual resources into data buckets based on a ratio of the maximum slope of anomaly scores associated with each virtual resource and the maximum slope of anomaly scores associated with the computer; and

within each data bucket, ordering the virtual resources from smallest to largest estimated problem start time.

10. A system to diagnose anomalies in a cloud infrastructure, the system comprising:

one or more processors;

one or more data-storage devices; and

machine-readable instructions stored in the one or more data-storage devices that when executed using the one or more processors controls the system to carry out operations comprising:

calculating anomaly score data of a computer running one or more virtual resource in the cloud infrastructure based on the metric data generated by the computer;

calculating a maximum slope of anomaly score data within a time range that extends backward in time from an alert time that indicates when an anomaly score of a computer exceeds a threshold;

calculating an estimated problem start time based on the maximum slope, the estimated problem start time identifies an approximate time when anomalous behavior with the computer began;

calculating a maximum slope of anomaly score data and estimated problems start times for each of the one or more virtual resources running on the computer based on the estimated problem start time of the computer;

generating a recommendation list of virtual resources that likely cause anomalous behavior at the computer based on ratios of the maximum slope of anomaly score data associated with each of the one or more virtual resources and the maximum slope of anomaly score data associate with the computer and;

moving one or more virtual resources identified as the likely cause of anomalous behavior at the computer to different computers in the cloud infrastructure, thereby increasing efficient use of the computer.

11. The system of claim **10**, wherein calculating the maximum slope of computer anomaly score data within the time range further comprises:

calculating a maximum slope and y-intercept of the computer anomaly score data in a series of overlapping backward time windows within the time range;

calculating a maximum slope and y-intercept of the computer anomaly score data in a series of overlapping forward time windows within the time range; and

setting the maximum slope and y-intercept of the computer anomaly score data equal to the larger of the maximum slopes and y-intercepts of the backward and forward time windows.

12. The system of claim **11**, calculating the maximum slope and y-intercept of the computer anomaly score data in the series of backward time windows further comprises:

rescaling the anomaly score data in a backward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in the backward time window;

decreasing a lower time limit of the backward time window to generate a backward time window with a longer duration;

repeating rescaling, calculating, and decreasing until the duration of the backward time window exceeds a minimum time limit of the time range; and identifying a maximum slope of the slopes calculated for the series of backward time windows.

13. The system of claim **11**, calculating the maximum slope and y-intercept of the computer anomaly score data in the series of forward time windows further comprises:

rescaling the anomaly score data in a forward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in the forward time window;

increasing an upper time limit of the forward time window to generate a forward time window with a longer duration;

repeating rescaling, calculating, and decreasing until the duration of the forward time window exceeds a maximum time limit of the time range; and

identifying a maximum slope of the slopes calculated for the series of forward time windows.

14. The system of claim **10**, wherein calculating the estimated problem start time based on the maximum slope further comprises determining a transition time.

15. The system of claim **14**, determining the transition time further comprises:

settting the estimated problem start time equal to the transition time when vertical distances between anomaly score data and a least squares line fit to the anomaly score data is less than a transition-time threshold; and

setting the estimated problem start time equal to an adjusted-transition time when vertical distances between anomaly score data and a least squares line fit to the anomaly score data is greater than a transition-time threshold.

16. The system of claim **10**, where calculating a maximum slope of anomaly scores and estimated problems start times for each of one or more virtual resources further comprises:

calculating a target time window from the estimated problem start time of the computer;

for each of the one or more virtual resources,

resealing the anomaly score data in a backward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in the backward time window;

decreasing a lower time limit of the backward time window to generate a backward time window with a longer duration;

repeating resealing, calculating, and decreasing until the duration of the backward time window exceeds a minimum time limit of the target time window; and

identifying a maximum slope of the slopes calculated for the series of backward time windows.

17. The system of claim **16** further comprises:

resealing the anomaly score data in a forward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in a forward time window;

increasing an upper time limit of the forward time window to generate a forward time window with a longer duration;

repeating resealing, calculating, and decreasing until the duration of the forward time window exceeds a maximum time limit of the time range; and

identifying a maximum slope of the slopes calculated for the series of forward time windows.

18. The system of claim **10**, wherein generating the recommendation lists of virtual resources based on the maximum slope of anomaly scores associated with each of the one or more virtual resources further comprises:

sorting the one or more virtual resources into data buckets based on a ratio of the maximum slope of anomaly scores associated with each virtual resource and the maximum slope of anomaly scores associated with the computer; and

within each data bucket, rank ordering the virtual resources from smallest to largest estimated problem start time.

19. A non-transitory computer-readable medium encoded with machine-readable instructions that implement a method carried out by one or more processors of a computer system to perform the operations of comprising:

calculating anomaly score data of a computer running one or more virtual resource in the cloud infrastructure based on the metric data generated by the computer;

calculating a maximum slope of anomaly score data within a time range that extends backward in time from an alert time that indicates when an anomaly score of a computer exceeds a threshold;

calculating an estimated problem start time based on the maximum slope, the estimated problem start time identifies an approximate time when anomalous behavior with the computer began;

calculating a maximum slope of anomaly score data and estimated problems start times for each of the one or more virtual resources running on the computer based on the estimated problem start time of the computer;

generating a recommendation list of virtual resources that likely cause anomalous behavior at the computer based on ratios of the maximum slope of anomaly score data associated with each of the one or more virtual resources and the maximum slope of anomaly score data associate with the computer; and

moving one or more virtual resources identified as the likely cause of anomalous behavior at the computer to different computers in the cloud infrastructure, thereby increasing efficient use of the computer.

20. The medium of claim **19**, wherein calculating the maximum slope of computer anomaly score data within the time range further comprises:

calculating a maximum slope and y-intercept of the computer anomaly score data in a series of overlapping backward time windows within the time range;

calculating a maximum slope and y-intercept of the computer anomaly score data in a series of overlapping forward time windows within the time range; and

setting the maximum slope and y-intercept of the computer anomaly score data equal to the larger of the maximum slopes and y-intercepts of the backward and forward time windows.

21. The medium of claim **20**, calculating the maximum slope and y-intercept of the computer anomaly score data in the series of backward time windows further comprises:

resealing the anomaly score data in a backward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in the backward time window;

decreasing a lower time limit of the backward time window to generate a backward time window with a longer duration;

repeating resealing, calculating, and decreasing until the duration of the backward time window exceeds a minimum time limit of the time range; and

identifying a maximum slope of the slopes calculated for the series of backward time windows.

22. The medium of claim **20**, calculating the maximum slope and y-intercept of the computer anomaly score data in the series of forward time windows further comprises:

resealing the anomaly score data in a forward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in the forward time window;

increasing an upper time limit of the forward time window to generate a forward time window with a longer duration;

repeating resealing, calculating, and decreasing until the duration of the forward time window exceeds a maximum time limit of the time range; and

identifying a maximum slope of the slopes calculated for the series of forward time windows.

23. The medium of claim **19**, wherein calculating the estimated problem start time based on the maximum slope further comprises determining a transition time.

24. The medium of claim **23**, determining the transition time further comprises:

settting the estimated problem start time equal to the transition time when vertical distances between anomaly score data and a least squares line fit to the anomaly score data is less than a transition-time threshold; and

setting the estimated problem start time equal to an adjusted-transition time when vertical distances between anomaly score data and a least squares line fit to the anomaly score data is greater than a transition-time threshold.

25. The medium of claim **19**, where calculating a maximum slope of anomaly scores and estimated problems start times for each of one or more virtual resources further comprises:

calculating a target time window from the estimated problem start time of the computer;

for each of the one or more virtual resources,

resealing the anomaly score data in a backward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in the backward time window;

decreasing a lower time limit of the backward time window to generate a backward time window with a longer duration;

repeating resealing, calculating, and decreasing until the duration of the backward time window exceeds a minimum time limit of the target time window; and

identifying a maximum slope of the slopes calculated for the series of backward time windows.

26. The medium of claim **25** further comprises:

resealing the anomaly score data in a forward time window to a common reference frame;

calculating a slope and a y-intercept for a weighted least-squares fit of a line to the anomaly score data in a forward time window;

increasing an upper time limit of the forward time window to generate a forward time window with a longer duration;

repeating resealing, calculating, and decreasing until the duration of the forward time window exceeds a maximum time limit of the time range; and

identifying a maximum slope of the slopes calculated for the series of forward time windows.

27. The medium of claim **19**, wherein generating the recommendation lists of virtual resources based on the maximum slope of anomaly scores associated with each of the one or more virtual resources further comprises:

sorting the one or more children into data buckets based on a ratio of the maximum slope of anomaly scores associated with each virtual resource and the maximum slope of anomaly scores associated with the computer; and

within each data bucket, rank ordering the virtual resources from smallest to largest estimated problem start time.

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