US010713265B2

(12) **United States Patent**
Poghosyan et al.

(10) **Patent No.: US 10,713,265 B2**
(45) **Date of Patent: Jul. 14, 2020**

(54) **METHODS AND SYSTEMS TO QUANTIZE AND COMPRESS TIME SERIES DATA**

(71) Applicant: **VMware, Inc.**, Palo Alto, CA (US)

(72) Inventors: **Arnak Poghosyan**, Yerevan (AM); **Ashot Nshan Harutyunyan**, Yerevan (AM); **Naira Movses Grigoryan**, Yerevan (AM)

(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 199 days.

(21) Appl. No.: **15/627,925**

(22) Filed: **Jun. 20, 2017**

(65) **Prior Publication Data**

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(51) **Int. Cl.**

G06F 16/00	(2019.01)
G06F 16/2458	(2019.01)
G06F 12/08	(2016.01)

(52) **U.S. Cl.**
CPC ***G06F 16/2477*** (2019.01); ***G06F 12/08*** (2013.01)

(58) **Field of Classification Search**
CPC G06F 16/00
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

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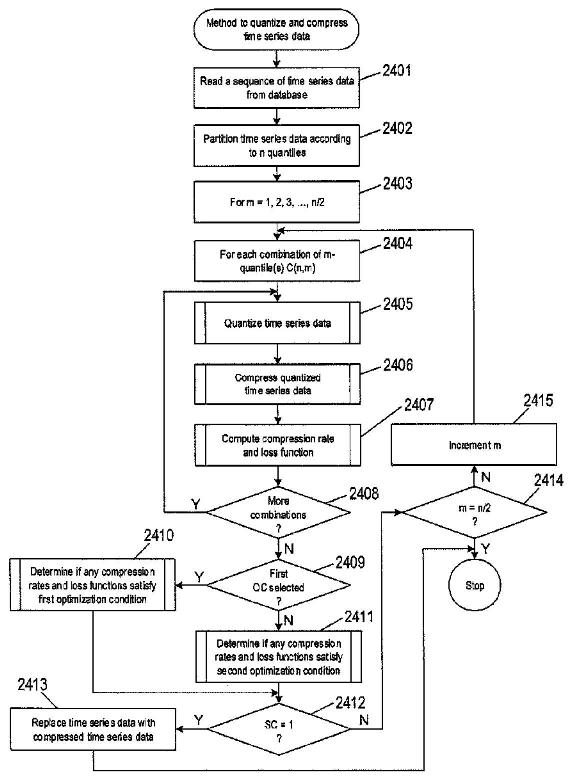
* cited by examiner

Primary Examiner — Khanh B Pham

(57) **ABSTRACT**

Methods and systems quantize and compress time series data generated by a resource of a distributed computing system. The time series data is partitioned according to a set of quantiles. Quantized time series data is generated from the time series data and the quantiles. The quantized time series data is compressed by deleting sequential duplicate quantized data points from the quantized time series data to obtain compress time series data. Quantization and compression are performed for different combinations of quantiles. The user may choose to minimize information loss of information due to quantization while selecting a lower bound for the compression rate. Alternatively, the user may choose to maximize the compression rate while placing an upper limit on the loss of information due to quantization. The compressed time series data that satisfies the user selected optimization conditions may be used to replace the original time series data in the data-storage device.

27 Claims, 36 Drawing Sheets


Method to quantize and compress time series data
Read a sequence of time series data from database
2401
Partition time series data according to n quantiles
2402
For m = 1, 2, 3, ..., n/2
2403
For each combination of m-quantile(s) C(n,m)
2404
Quantize time series data
2405
Compress quantized time series data
2406
Compute compression rate and loss function
2407
Increment m
2415
More combinations ?
2408
Y
N
m = n/2 ?
2414
N
Y
Stop
2410
Determine if any compression rates and loss functions satisfy first optimization condition
First OC selected ?
2409
Y
N
Determine if any compression rates and loss functions satisfy second optimization condition
2411
2413
Replace time series data with compressed time series data
SC = 1 ?
2412
Y
N

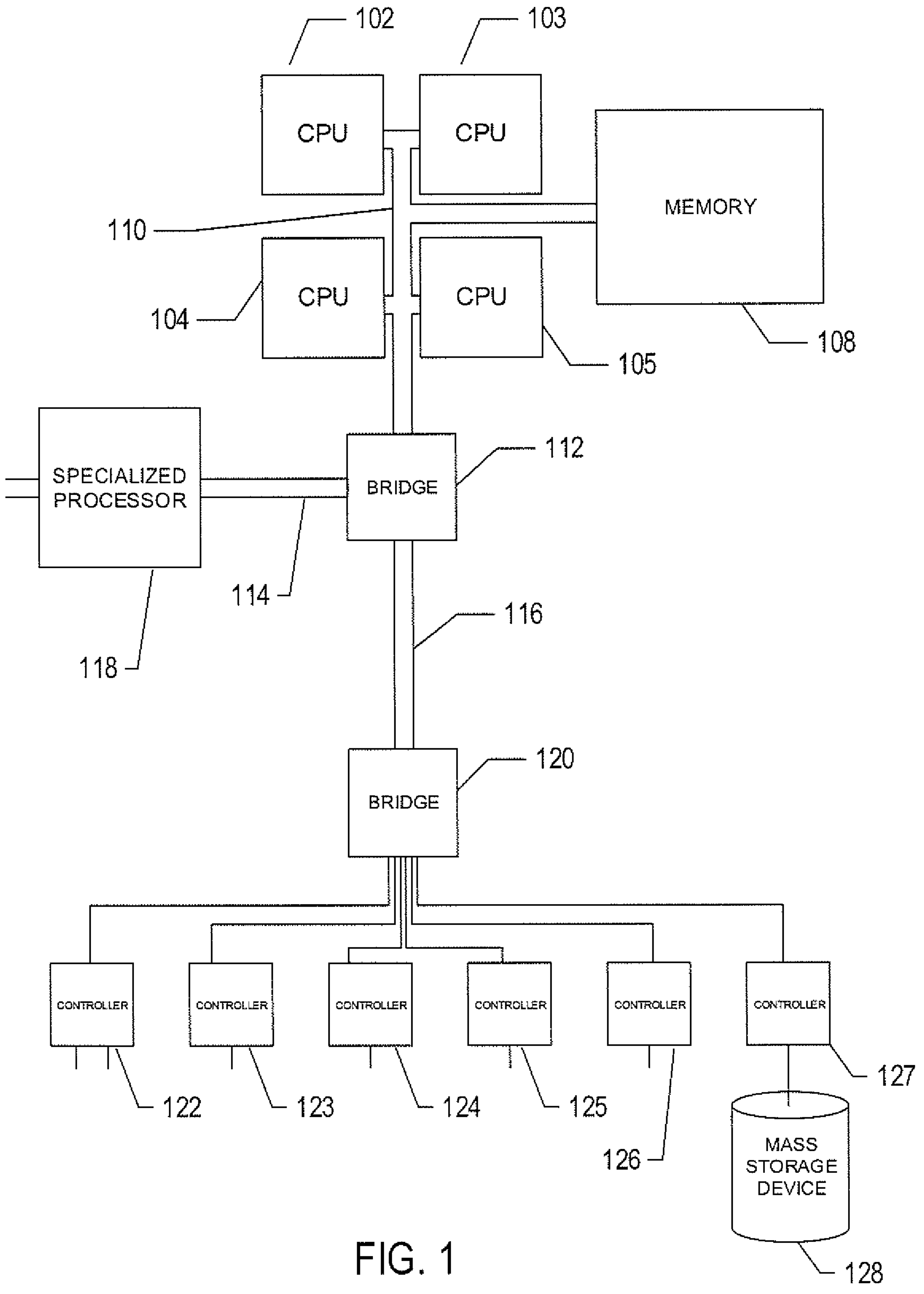

102
103
CPU
CPU
CPU
CPU
MEMORY
110
104
105
108
SPECIALIZED PROCESSOR
BRIDGE
112
114
116
118
BRIDGE
120
CONTROLLER
CONTROLLER
CONTROLLER
CONTROLLER
CONTROLLER
CONTROLLER
122
123
124
125
126
127
MASS STORAGE DEVICE
128

FIG. 1

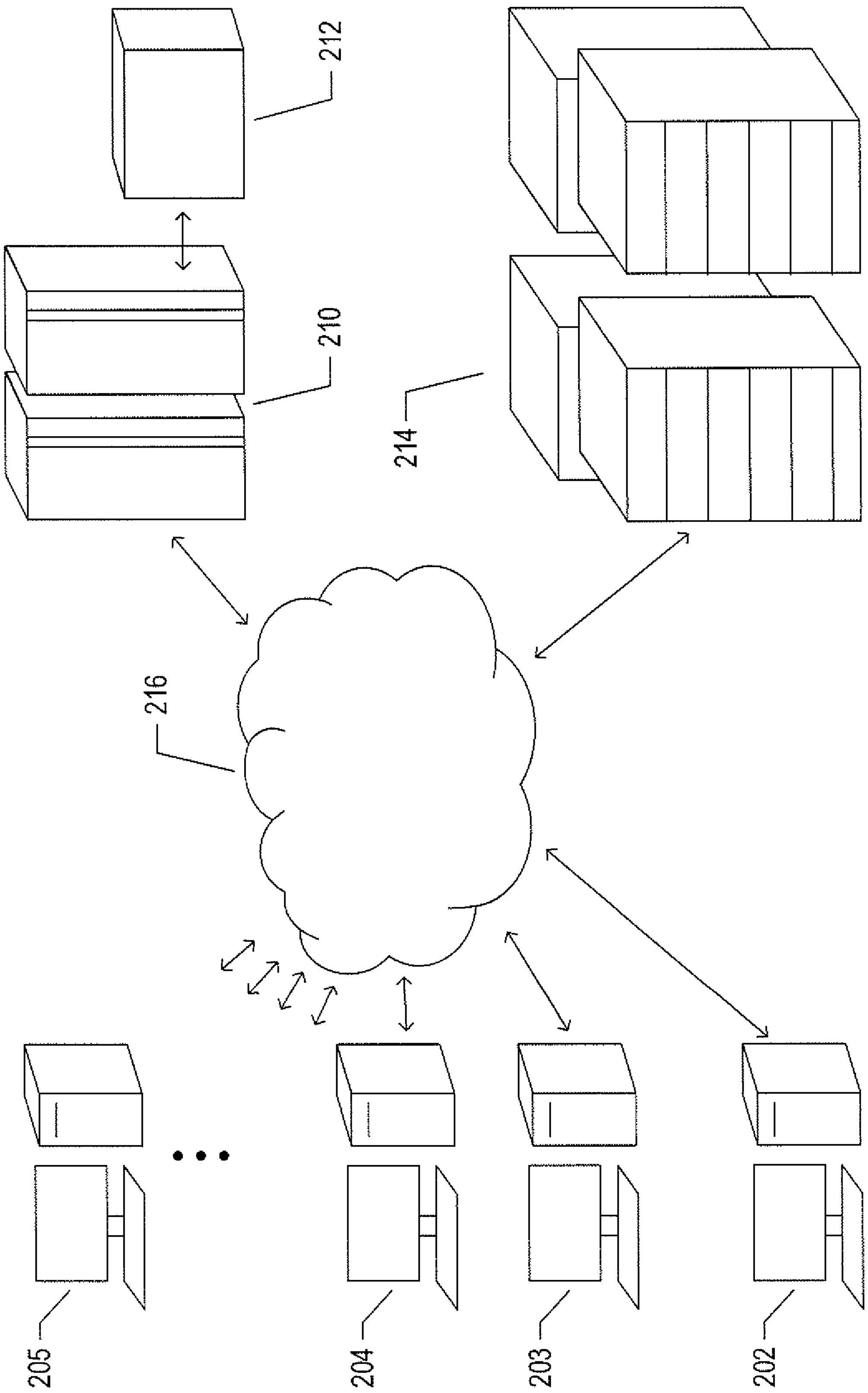


FIG. 2

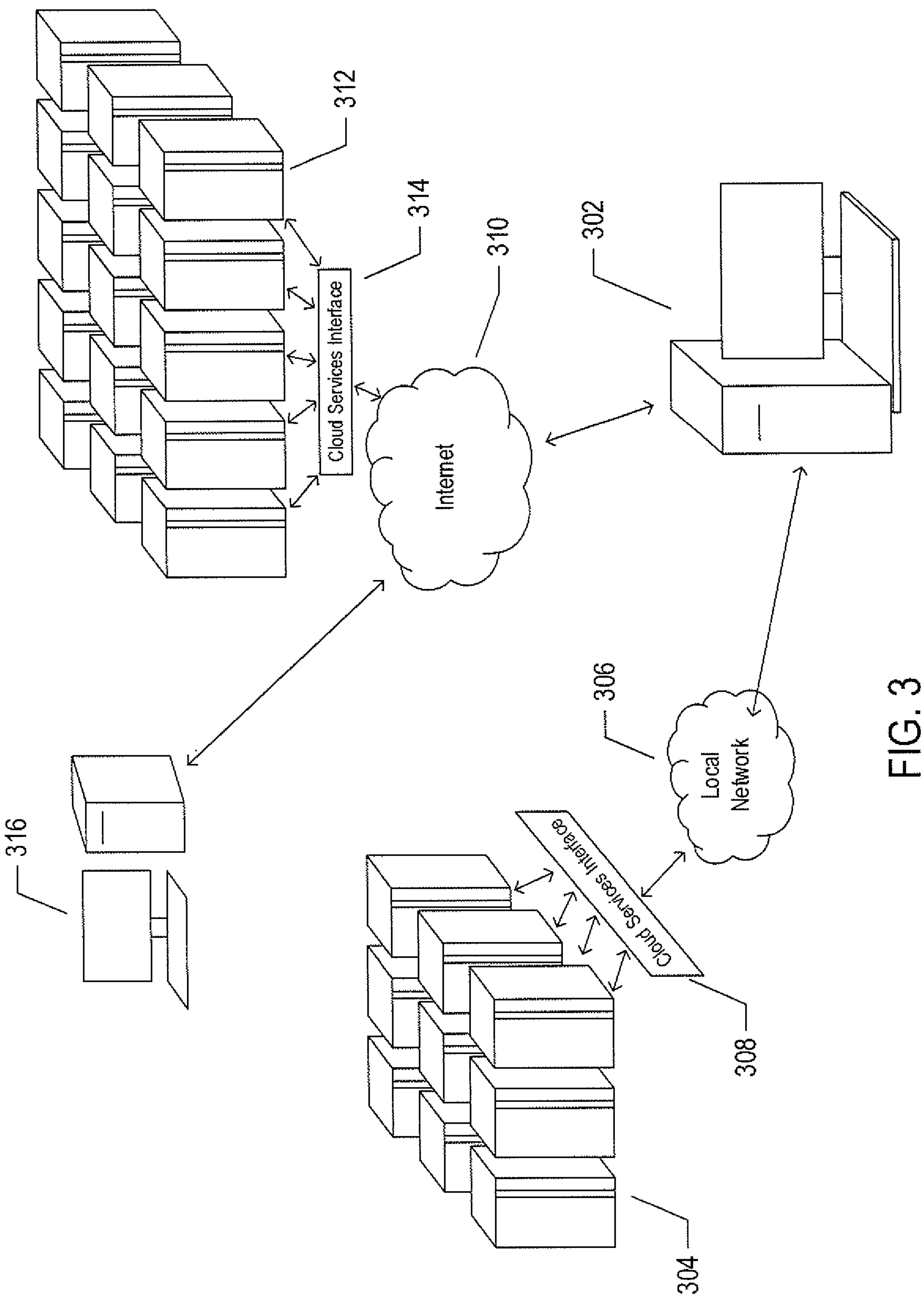

312
314
Cloud Services Interface
310
Internet
302
316
306
Local Network
Cloud Services Interface
308
304

FIG. 3

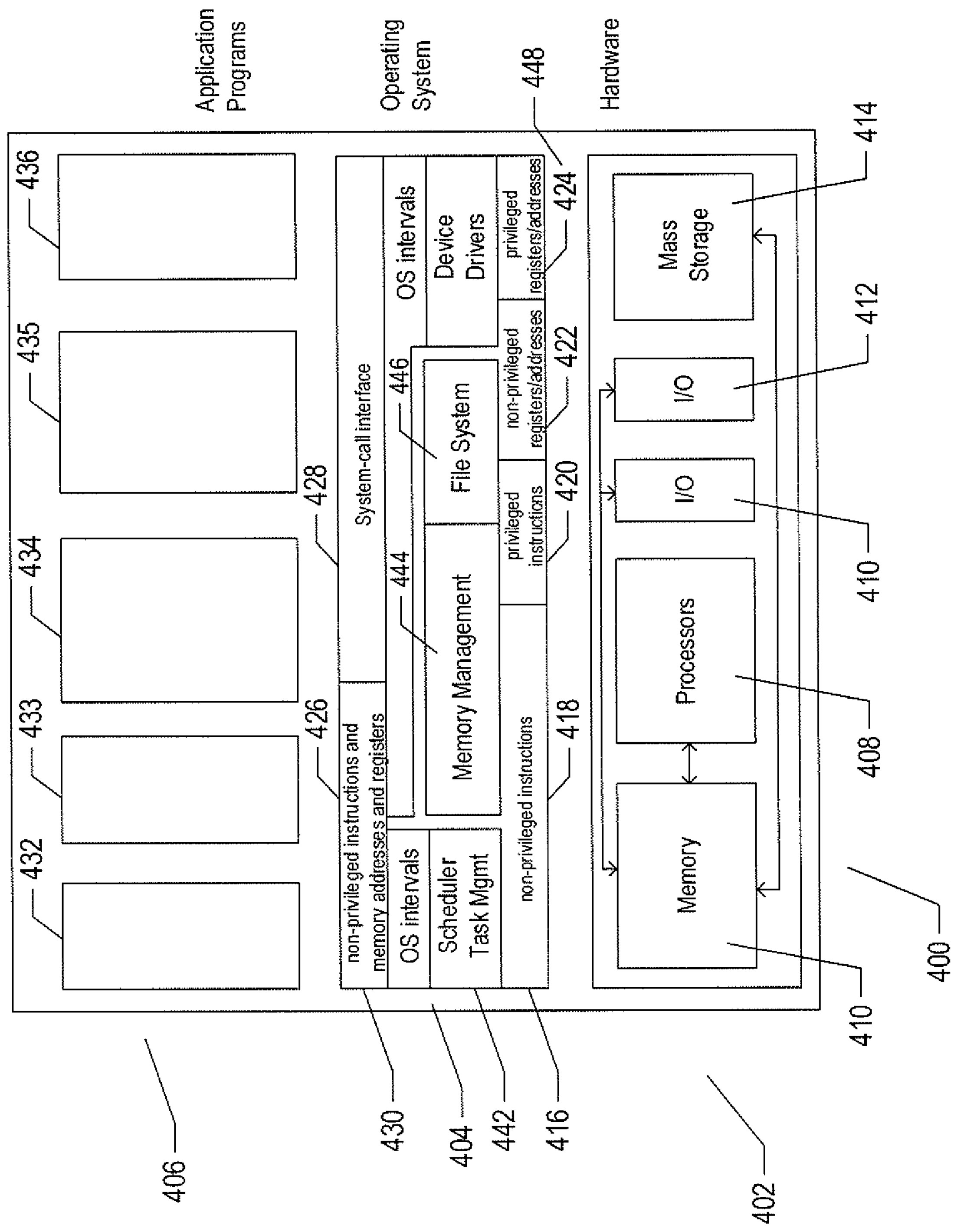
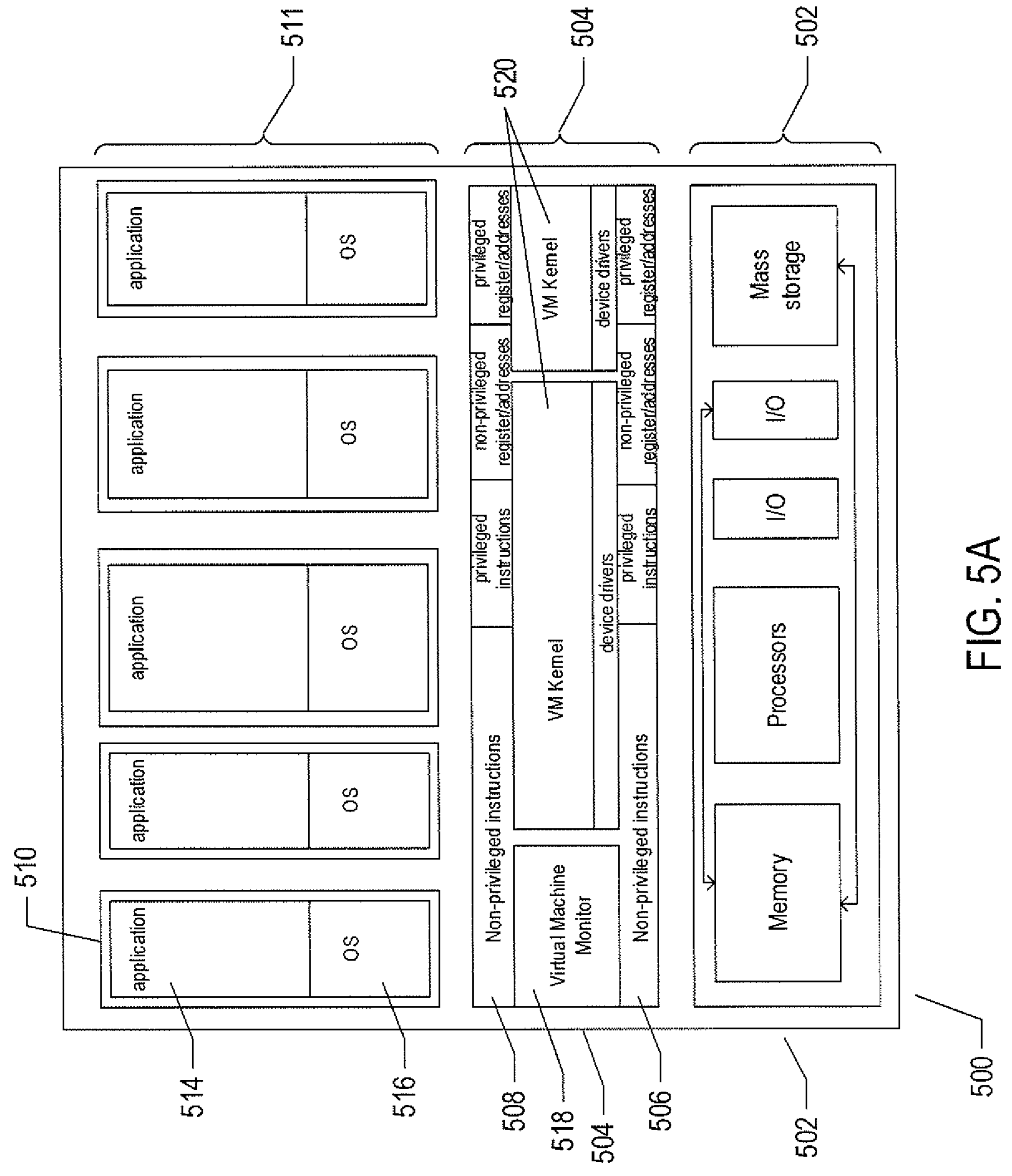

Application Programs
Operating System
Hardware
448
414
436
435
434
433
432
428
426
System-call interface
non-privileged instructions and memory addresses and registers
OS intervals
Device Drivers
privileged registers/addresses
424
non-privileged registers/addresses
422
446
File System
privileged instructions
420
444
Memory Management
non-privileged instructions
418
OS intervals
Scheduler Task Mgmt
Mass Storage
I/O
412
I/O
410
Processors
408
Memory
410
400
406
430
404
442
416
402

FIG. 4



511
504
502
520
510
application
OS
Non-privileged instructions
privileged instructions
non-privileged register/addresses
privileged register/addresses
VM Kernel
device drivers
Virtual Machine Monitor
Mass storage
I/O
Processors
Memory
514
516
508
518
506
500

FIG. 5A

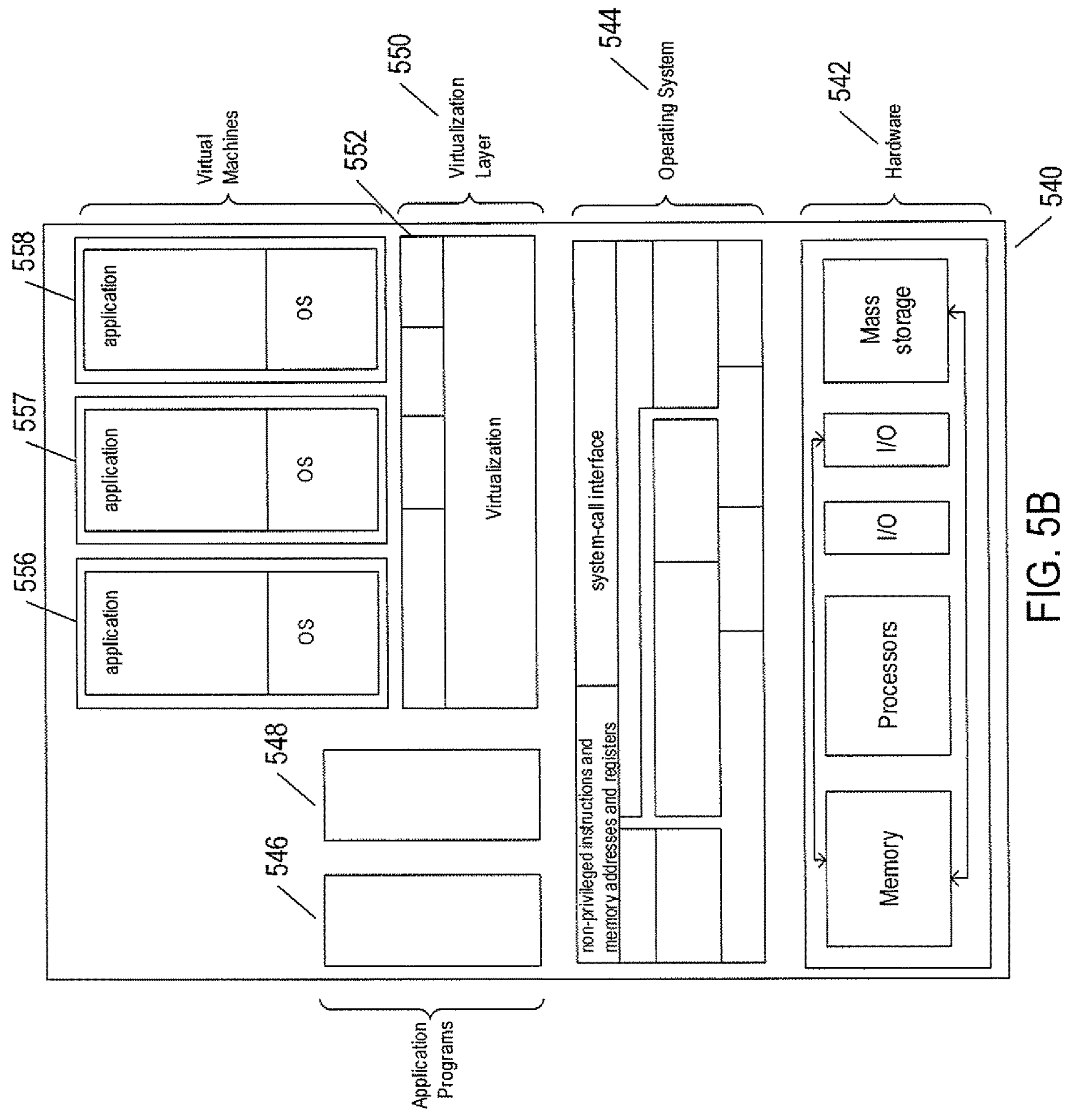

Virtual Machines
Virtualization Layer
Operating System
Hardware
Application Programs
540
542
544
546
548
550
552
556
557
558
application
OS
application
OS
application
OS
Virtualization
system-call interface
non-privileged instructions and memory addresses and registers
Mass storage
I/O
I/O
Processors
Memory

FIG. 5B

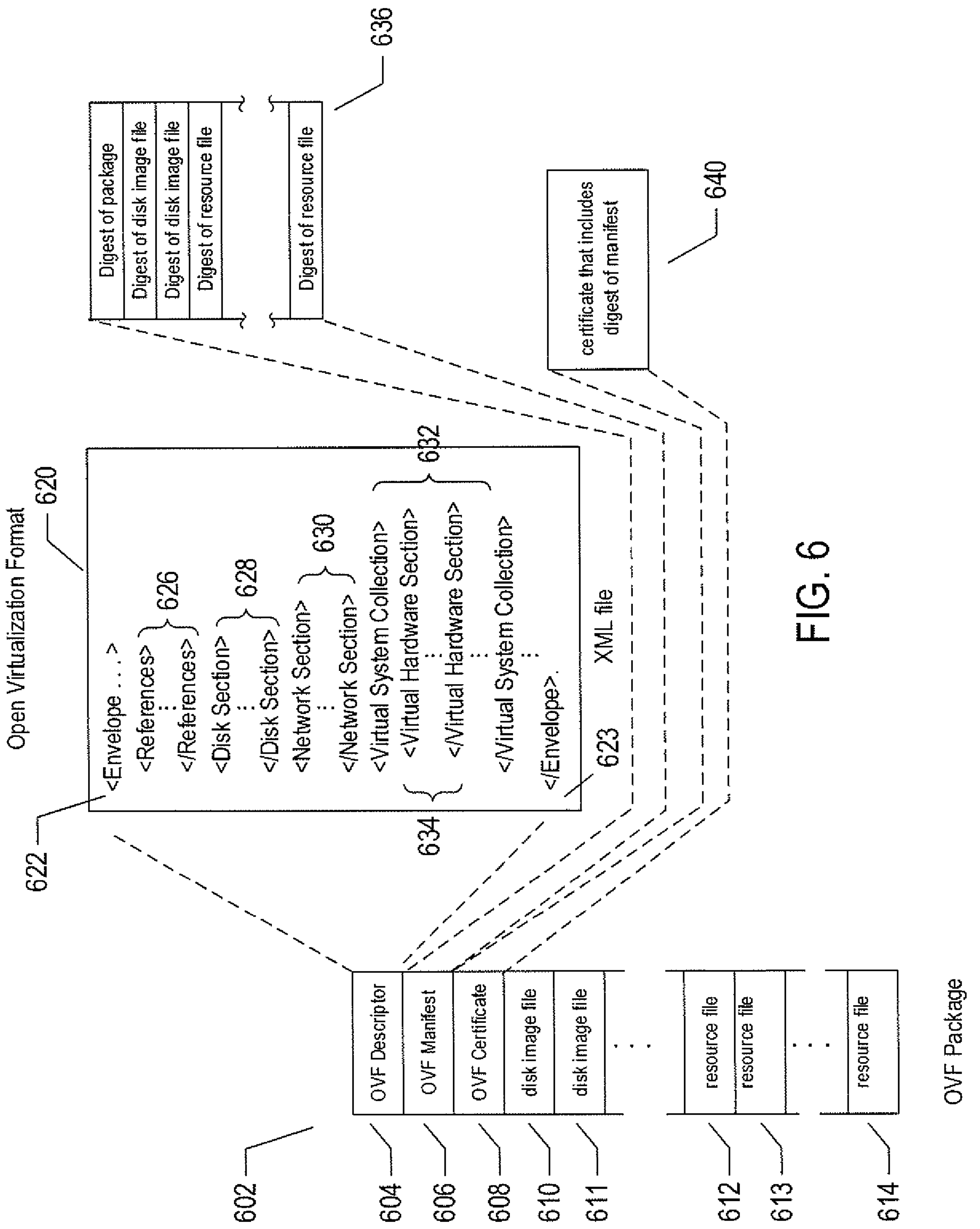

Open Virtualization Format
620
622
<Envelope . . .>
<References>
</References>
626
<Disk Section>
</Disk Section>
628
<Network Section>
</Network Section>
630
<Virtual System Collection>
<Virtual Hardware Section>
</Virtual Hardware Section>
</Virtual System Collection>
632
634
</Envelope>
623
XML file
636
Digest of package
Digest of disk image file
Digest of disk image file
Digest of resource file
Digest of resource file
certificate that includes digest of manifest
640
602
OVF Descriptor
OVF Manifest
OVF Certificate
disk image file
disk image file
resource file
resource file
resource file
OVF Package
604
606
608
610
611
612
613
614

FIG. 6

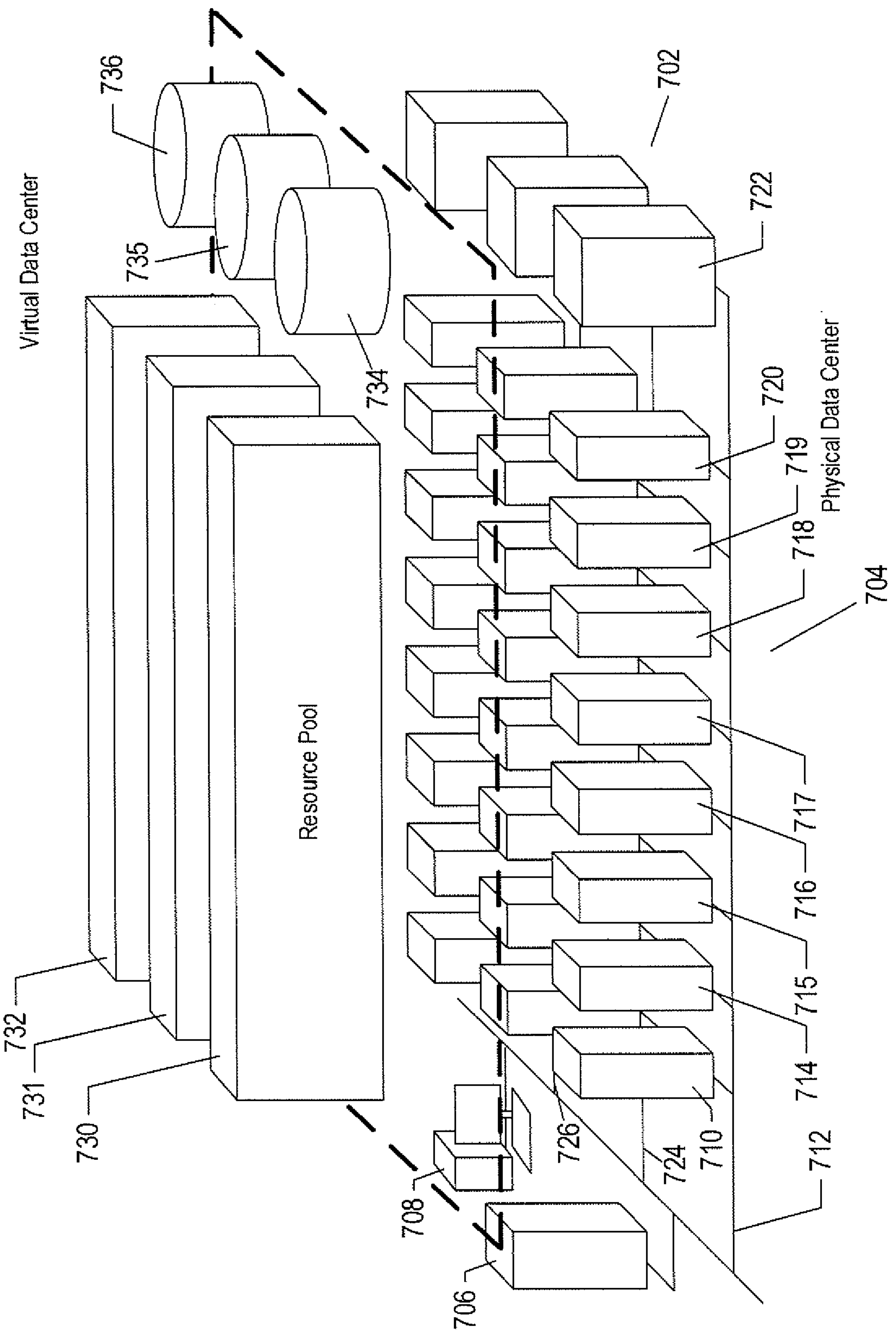

Virtual Data Center
Resource Pool
Physical Data Center
702
704
706
708
710
712
714
715
716
717
718
719
720
722
724
726
730
731
732
734
735
736

FIG. 7

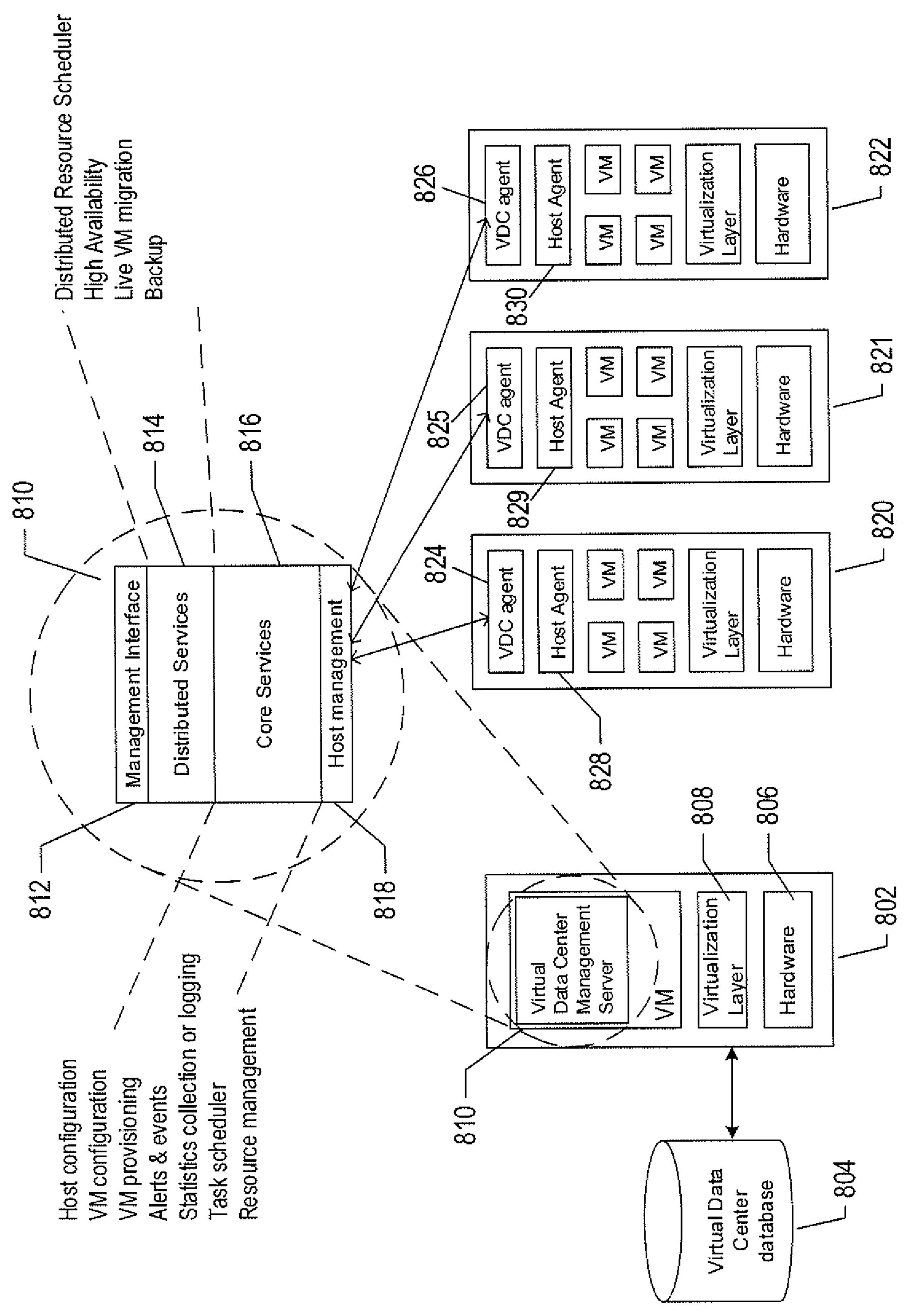

Distributed Resource Scheduler
High Availability
Live VM migration
Backup
810
814
816
Management Interface
Distributed Services
Core Services
Host management
812
818
Host configuration
VM configuration
VM provisioning
Alerts & events
Statistics collection or logging
Task scheduler
Resource management
826
825
824
VDC agent
Host Agent
VM
Virtualization Layer
Hardware
830
829
828
822
821
820
Virtual Data Center Management Server
VM
Virtualization Layer
Hardware
808
806
802
810
Virtual Data Center database
804

FIG. 8

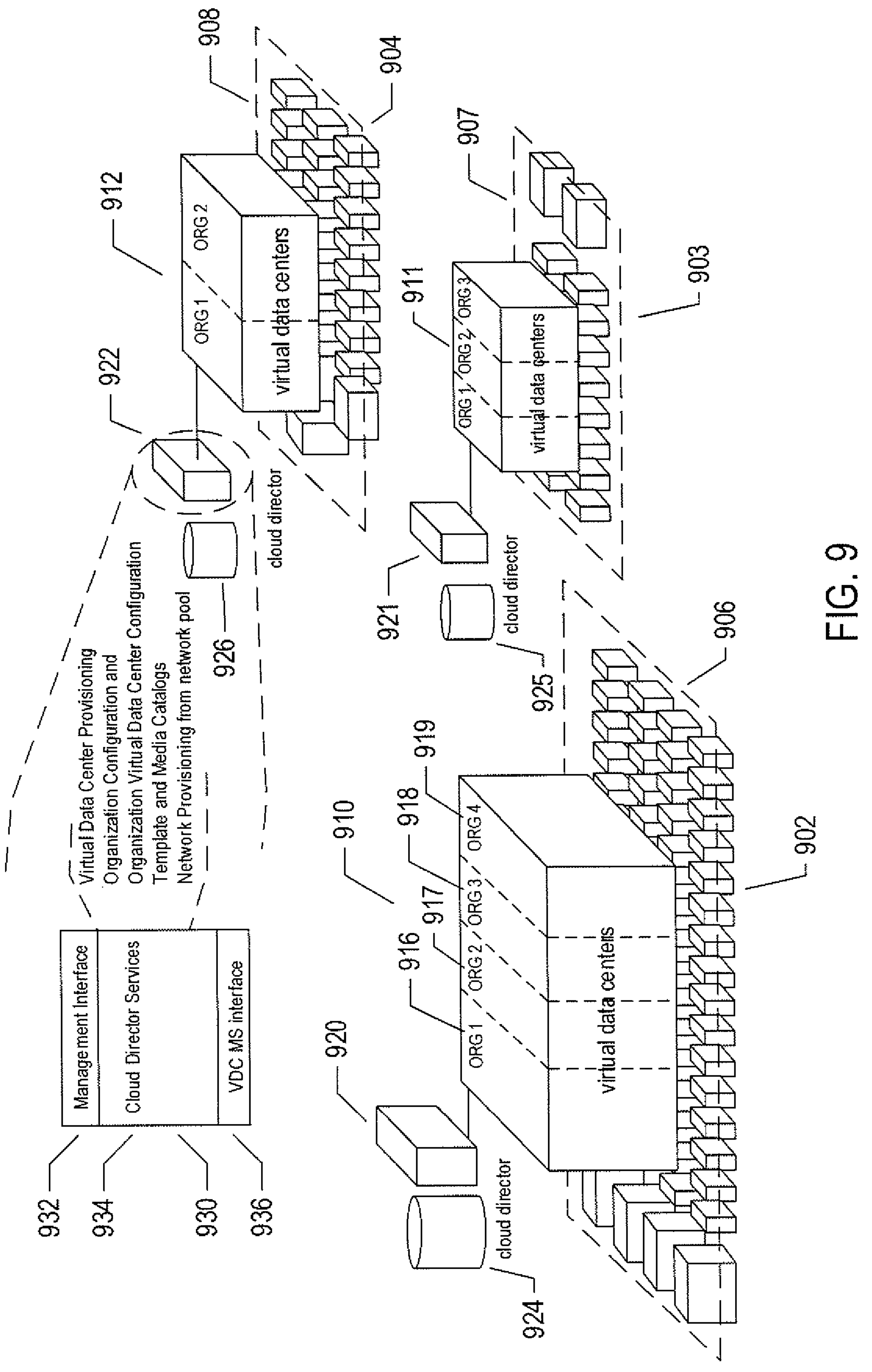

932
934
930
936
Management Interface
Cloud Director Services
VDC MS interface
Virtual Data Center Provisioning
Organization Configuration and
Organization Virtual Data Center Configuration
Template and Media Catalogs
Network Provisioning from network pool
922
926
cloud director
912
ORG 1
ORG 2
virtual data centers
908
904
907
911
ORG 1
ORG 2
ORG 3
virtual data centers
903
921
925
cloud director
906
910
916
917
918
919
ORG 1
ORG 2
ORG 3
ORG 4
virtual data centers
902
920
924
cloud director

FIG. 9

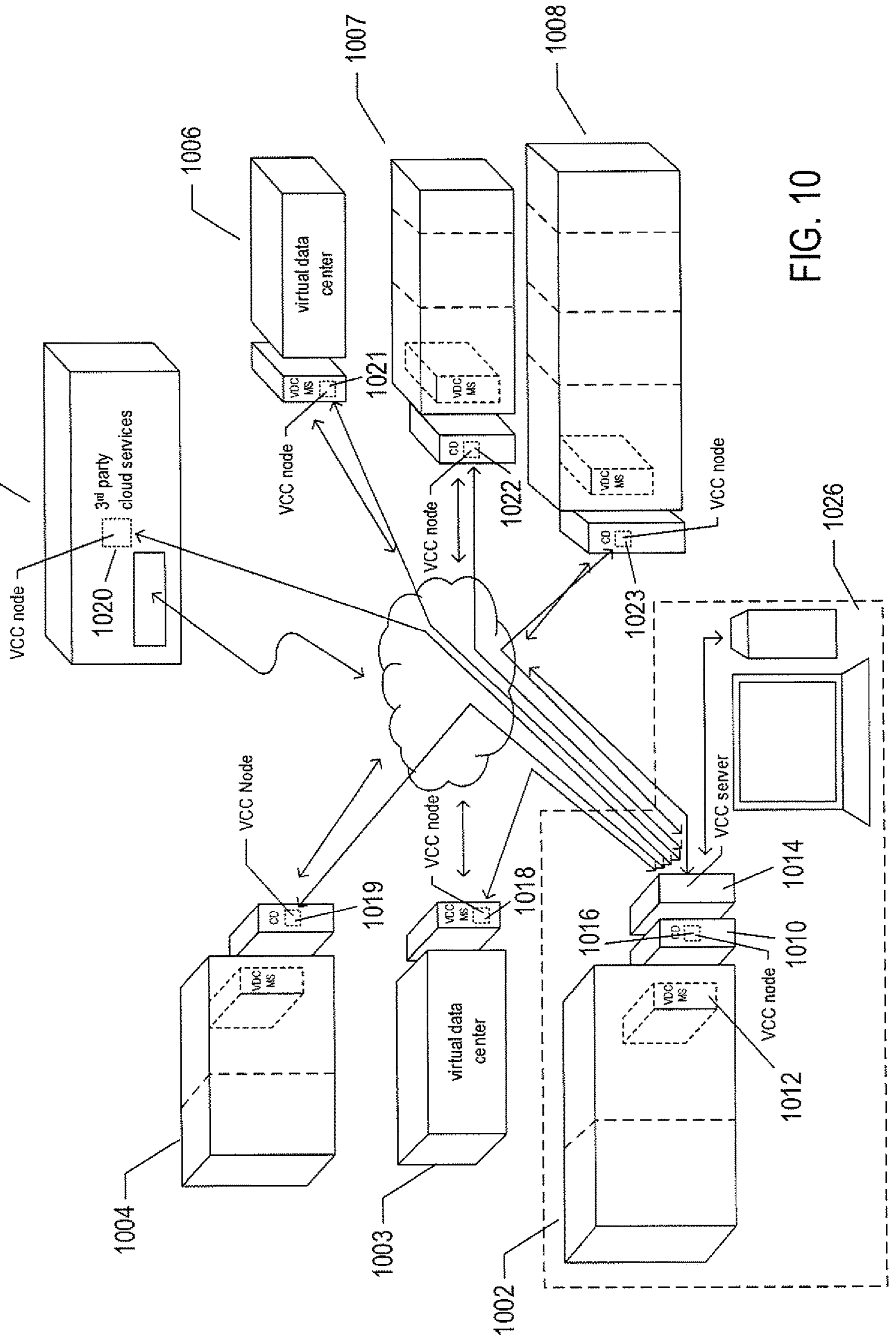

1005
VCC node
1020
3rd party
cloud services
1006
virtual data
center
VDC
MS
1021
VCC node
1007
VDC
MS
CD
1022
VCC node
1008
VDC
MS
CD
1023
VCC node
1026
VCC server
1014
1016
CD
1010
VCC node
VDC
MS
1012
1002
VCC Node
CD
1019
1004
VCC node
VDC
MS
1018
virtual data
center
1003

FIG. 10

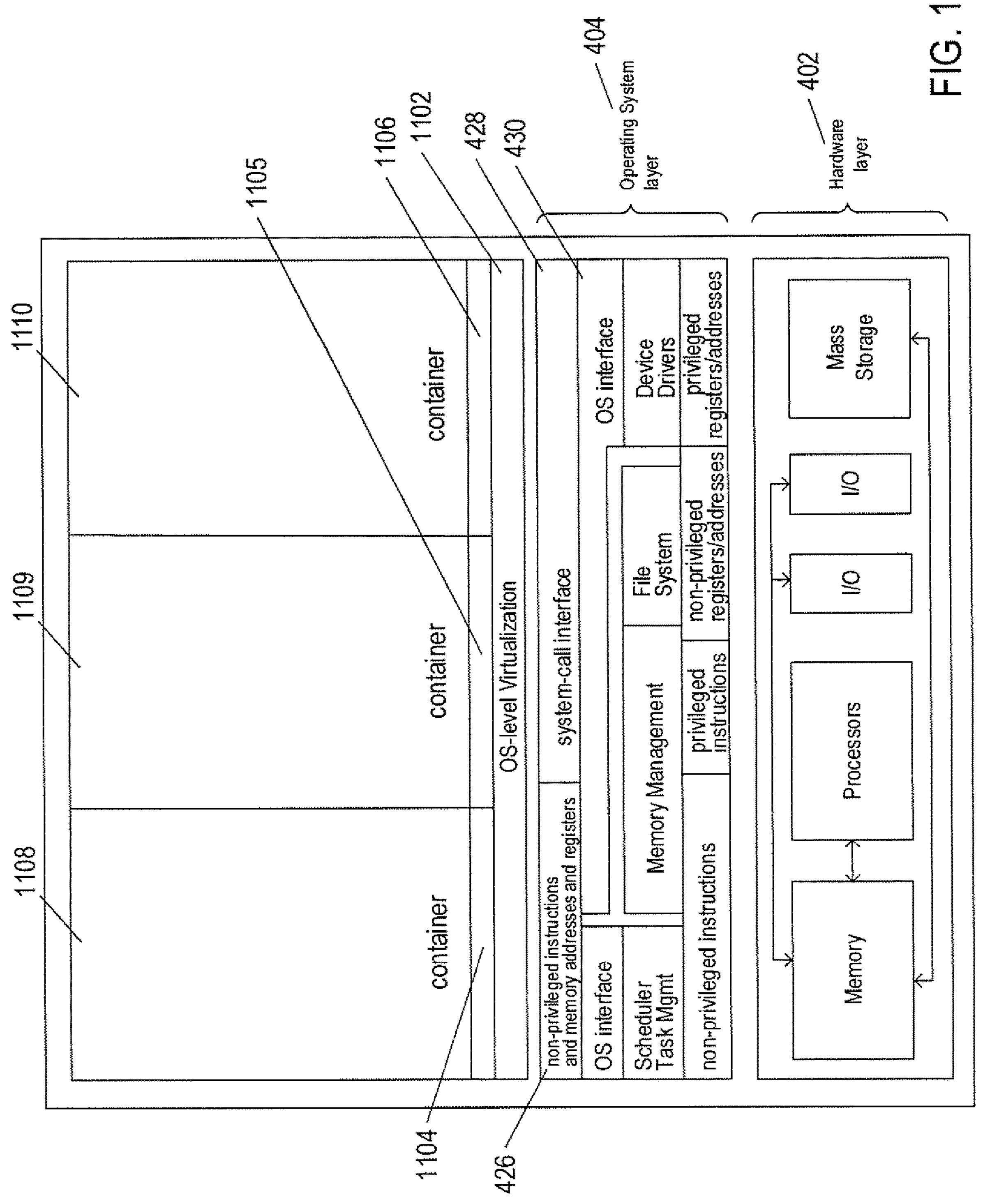

1108
1109
1110
container
container
container
1104
1105
1106
1102
OS-level Virtualization
428
430
426
non-privileged instructions and memory addresses and registers
system-call interface
OS interface
OS interface
Scheduler Task Mgmt
Memory Management
File System
Device Drivers
non-privileged instructions
privileged instructions
non-privileged registers/addresses
privileged registers/addresses
Operating System layer
404
Hardware layer
402
Memory
Processors
I/O
I/O
Mass Storage

FIG. 11

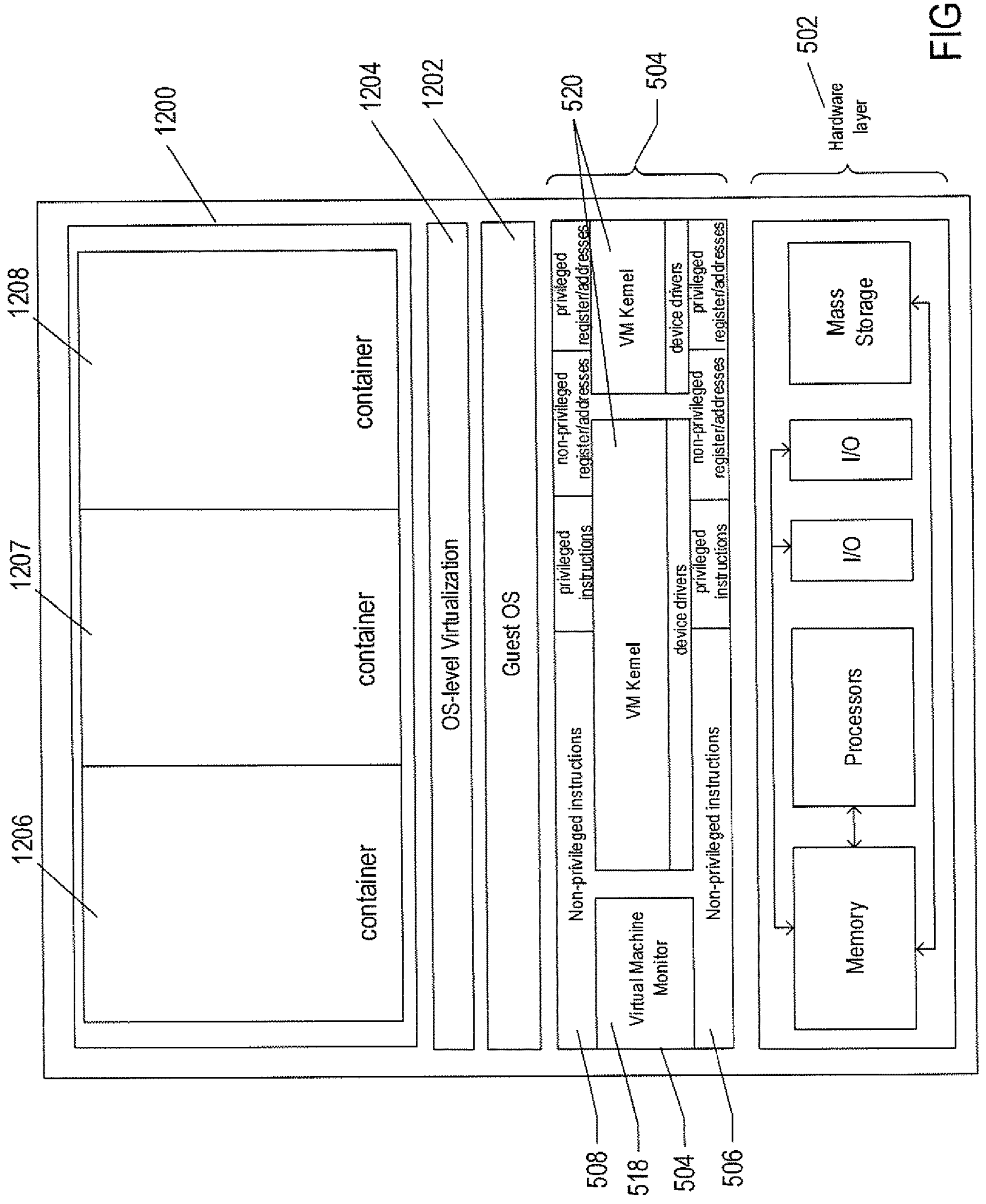

1200
1206
1207
1208
container
container
container
1204
OS-level Virtualization
1202
Guest OS
520
504
privileged register/addresses
non-privileged register/addresses
privileged instructions
Non-privileged instructions
VM Kernel
device drivers
VM Kernel
device drivers
privileged register/addresses
non-privileged register/addresses
privileged instructions
Non-privileged instructions
Virtual Machine Monitor
508
518
504
506
502
Hardware layer
Mass Storage
I/O
I/O
Processors
Memory

FIG. 12

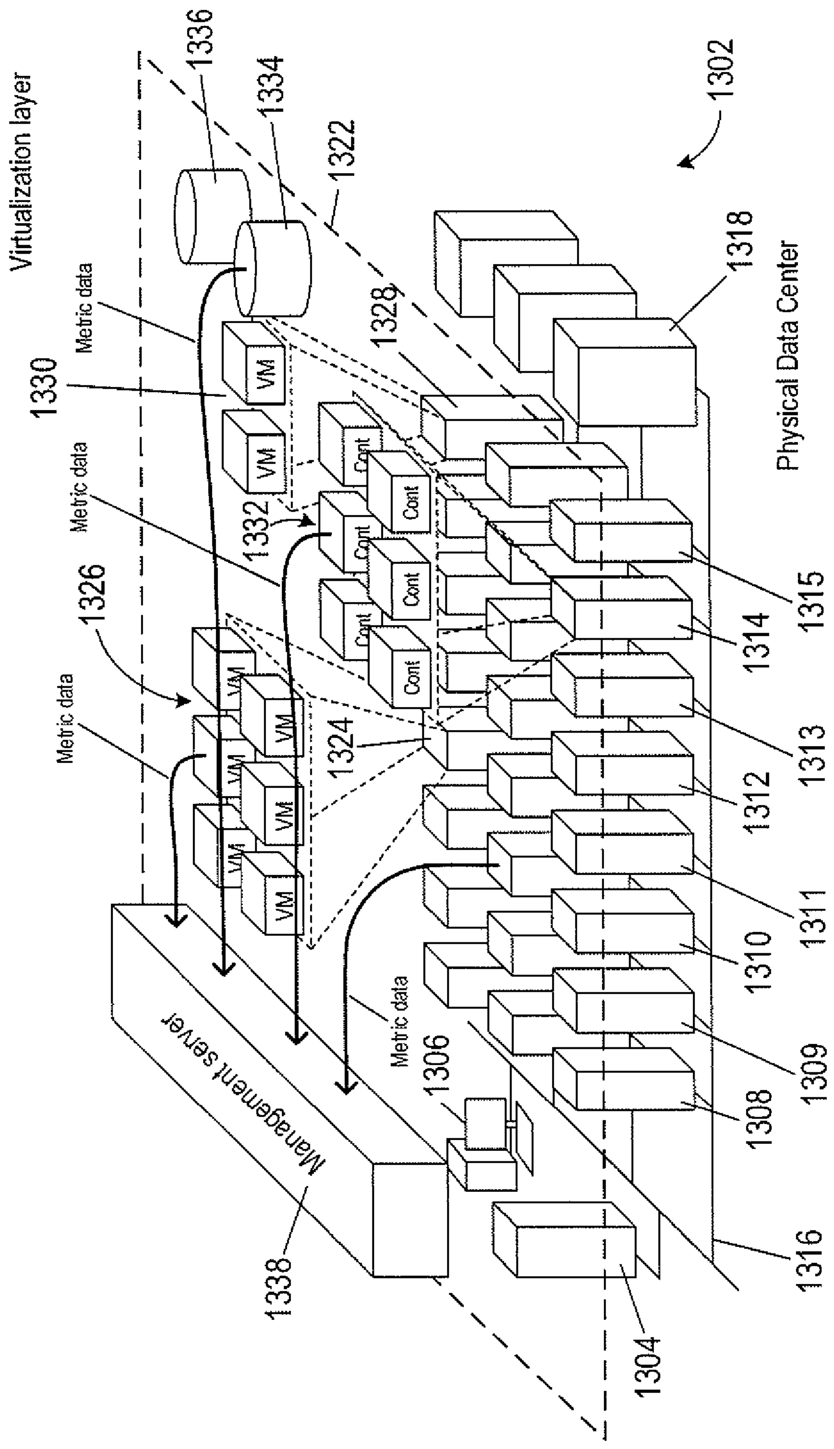

1320
Virtualization layer
1336
1334
1322
1302
1318
Physical Data Center
1328
Metric data
1330
VM
VM
Metric data
Cont
Cont
Cont
Cont
Cont
Cont
1332
1326
Metric data
VM
VM
VM
VM
VM
VM
1324
1315
1314
1313
1312
1311
1310
1309
1308
Metric data
1306
Management server
1338
1304
1316

FIG. 13

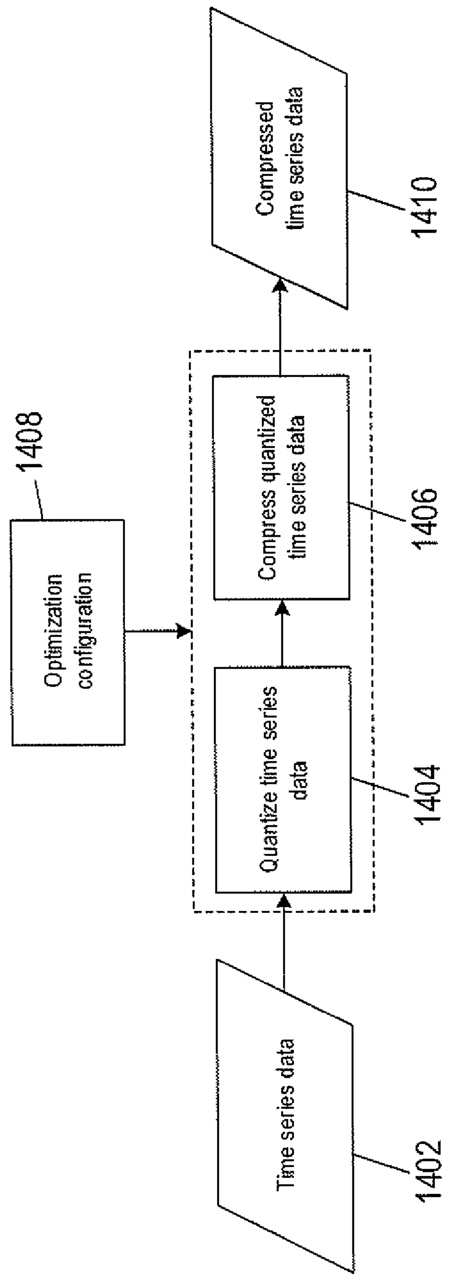

Time series data
1402
Quantize time series data
1404
Compress quantized time series data
1406
Optimization configuration
1408
Compressed time series data
1410

FIG. 14

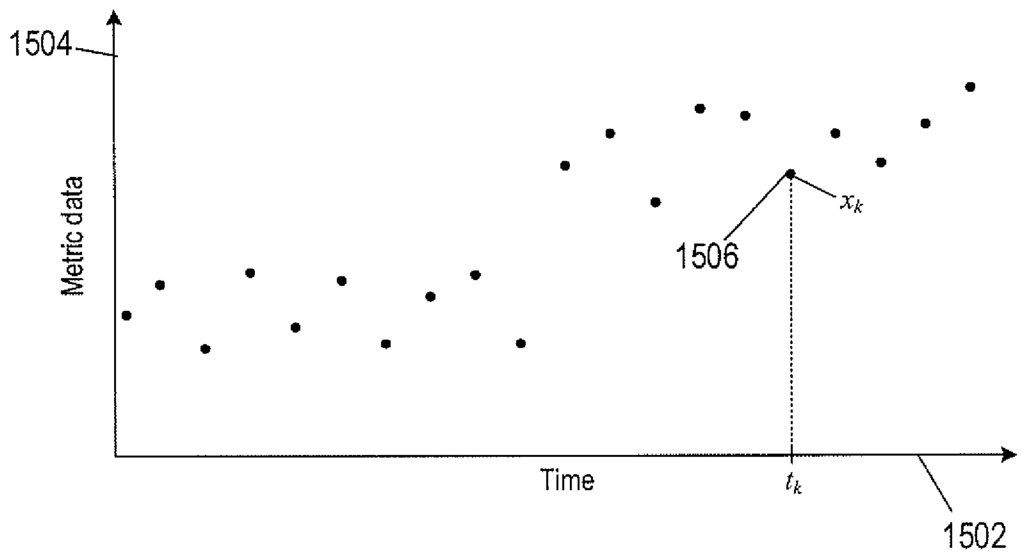

1504
Metric data
1506
x_k
Time
t_k
1502

FIG. 15

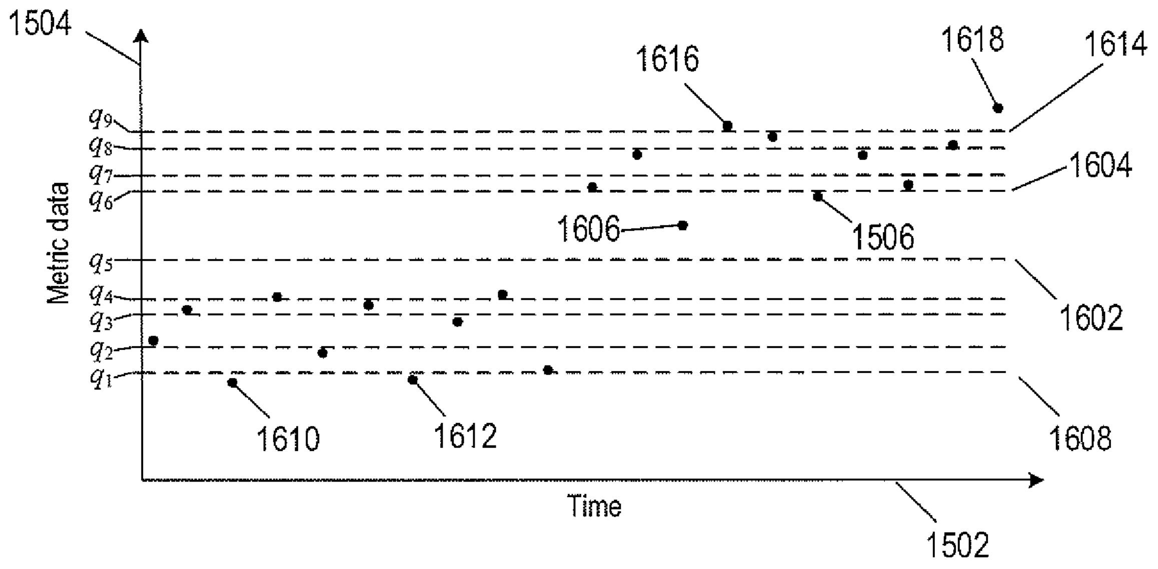

1504
1616
1618
1614
q_9
q_8
q_7
q_6
q_5
q_4
q_3
q_2
q_1
Metric data
1604
1606
1506
1602
1610
1612
1608
Time
1502

FIG. 16

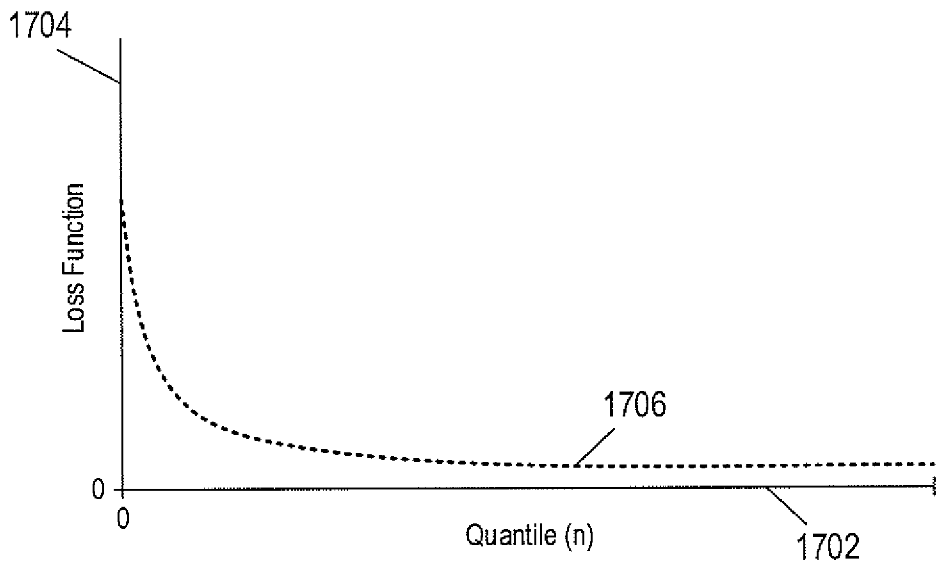

1704
Loss Function
1706
0
0
Quantile (n)
1702

FIG. 17

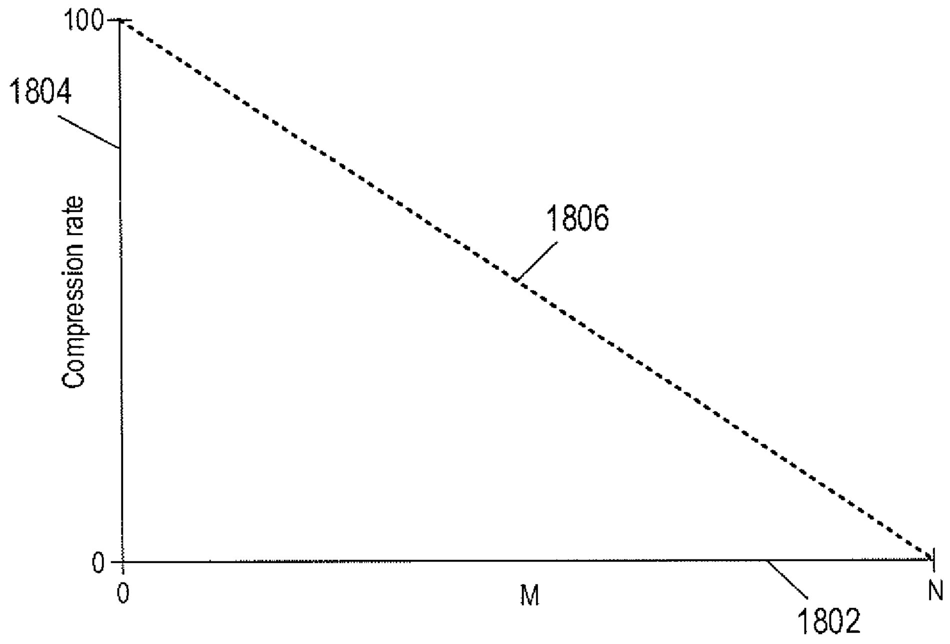

100
1804
Compression rate
1806
0
0
M
N
1802

FIG. 18

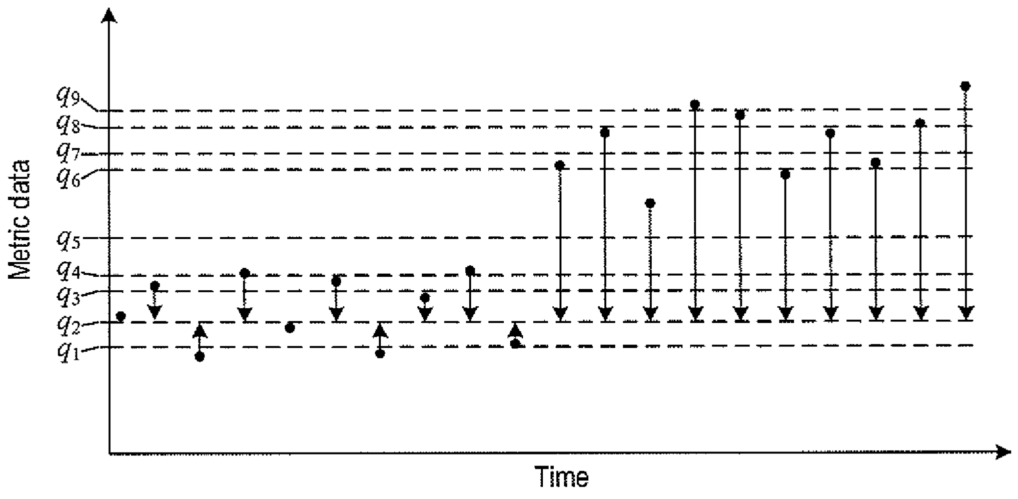


FIG. 19A

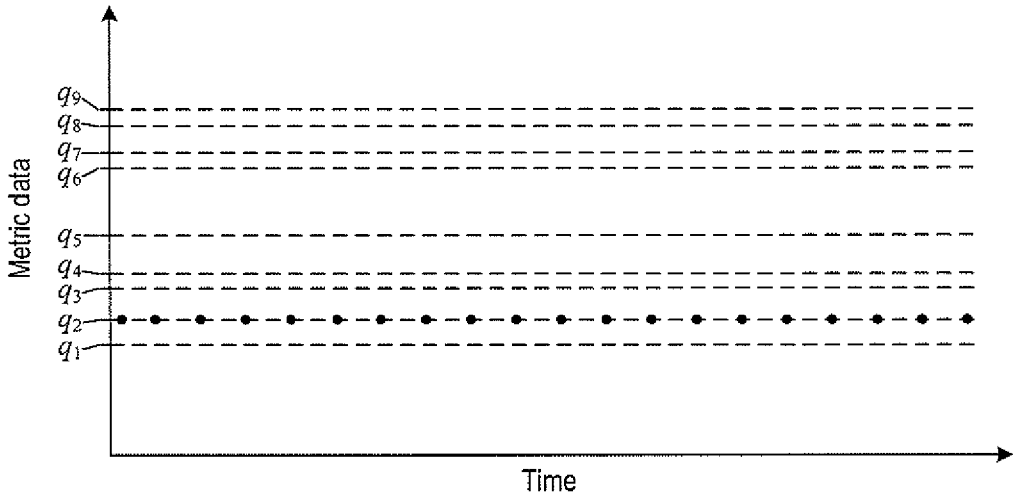


FIG. 19B

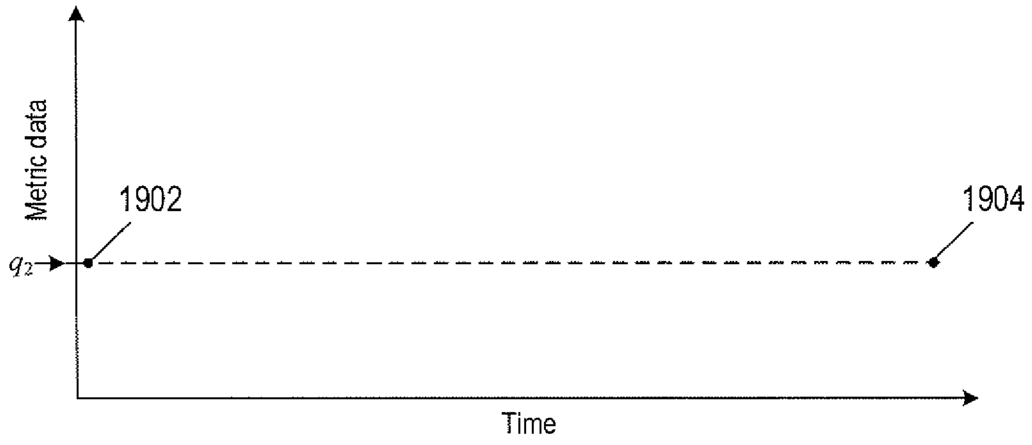


FIG. 19C

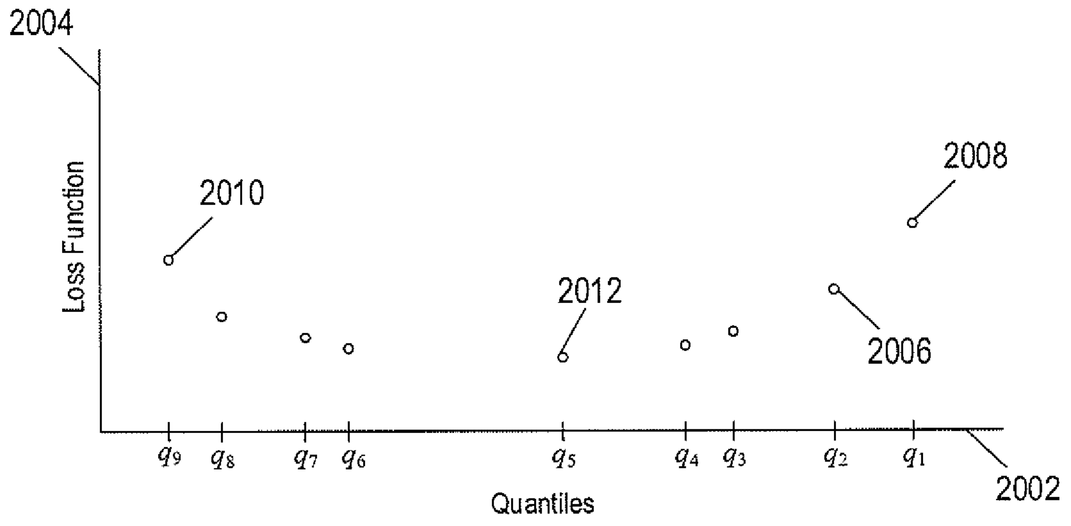

2004
Loss Function
2010
2012
2008
2006
q_9
q_8
q_7
q_6
q_5
q_4
q_3
q_2
q_1
Quantiles
2002

FIG. 20

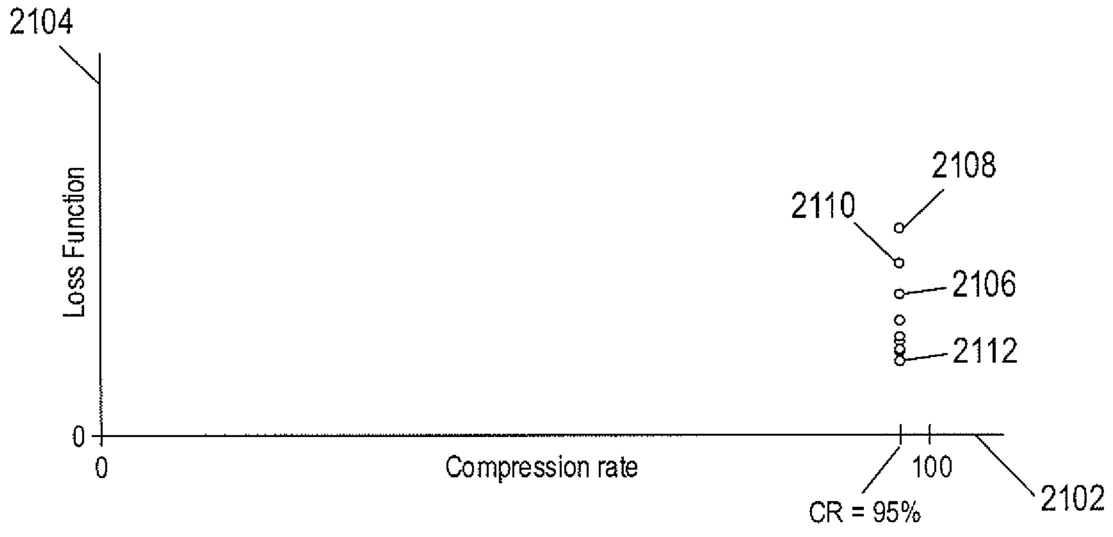

2104
Loss Function
2108
2110
2106
2112
0
0
Compression rate
100
CR = 95%
2102

FIG. 21

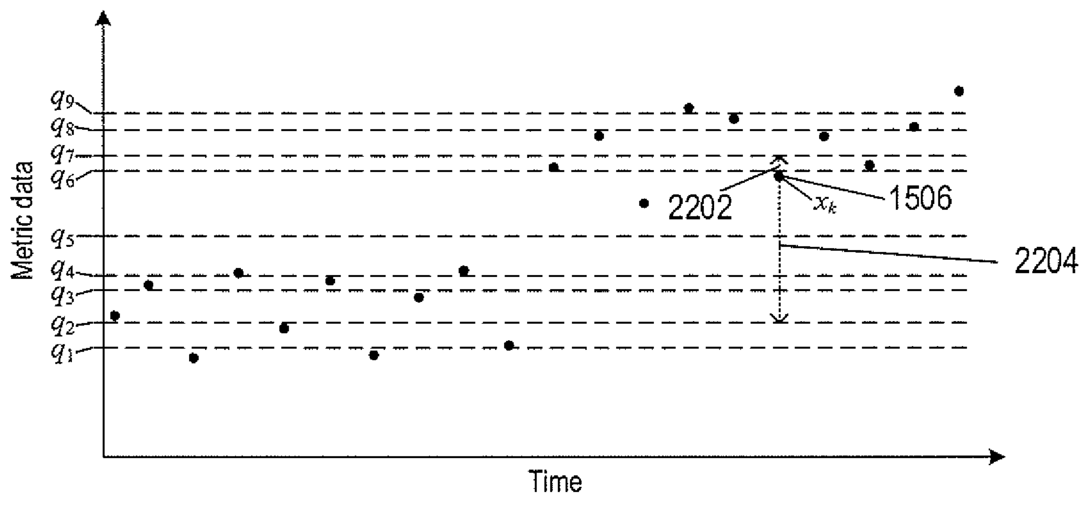


FIG. 22A

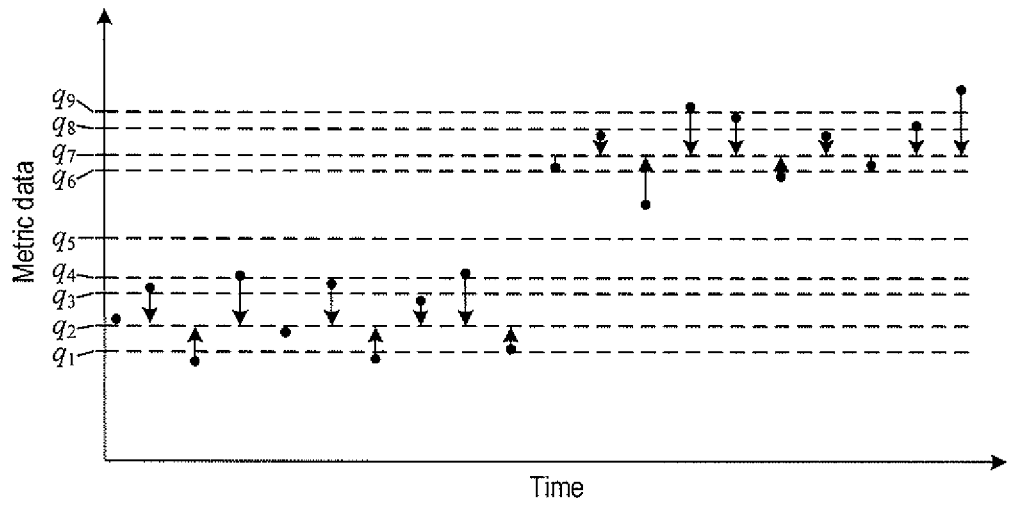


FIG. 22B

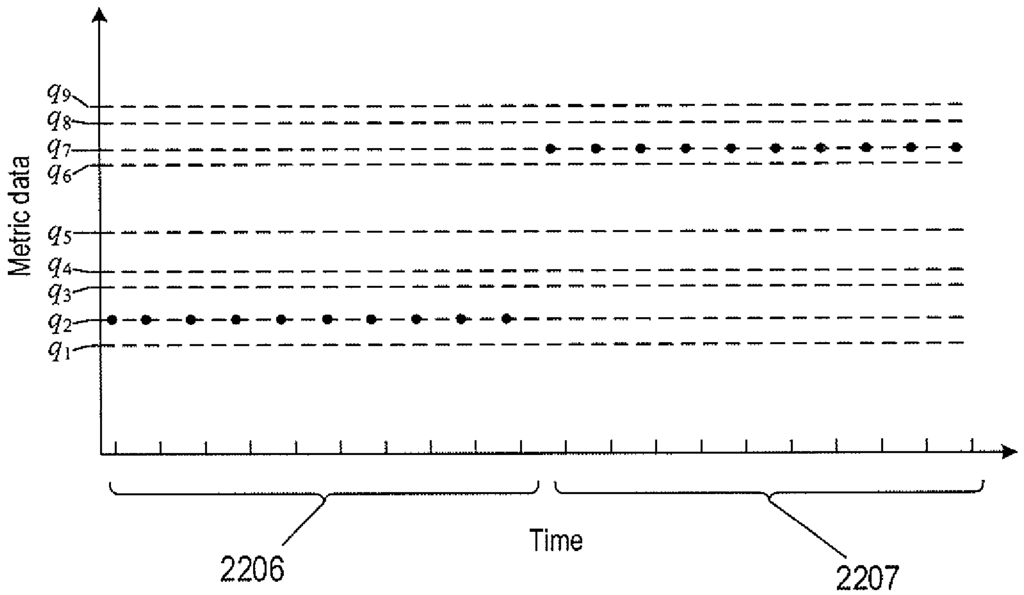


FIG. 22C

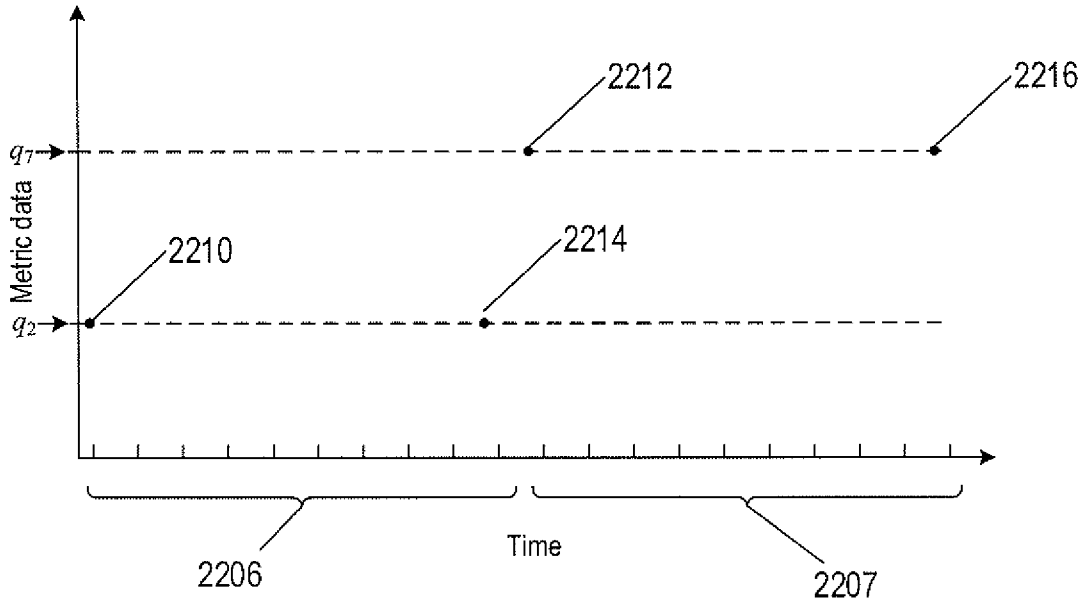


FIG. 22D

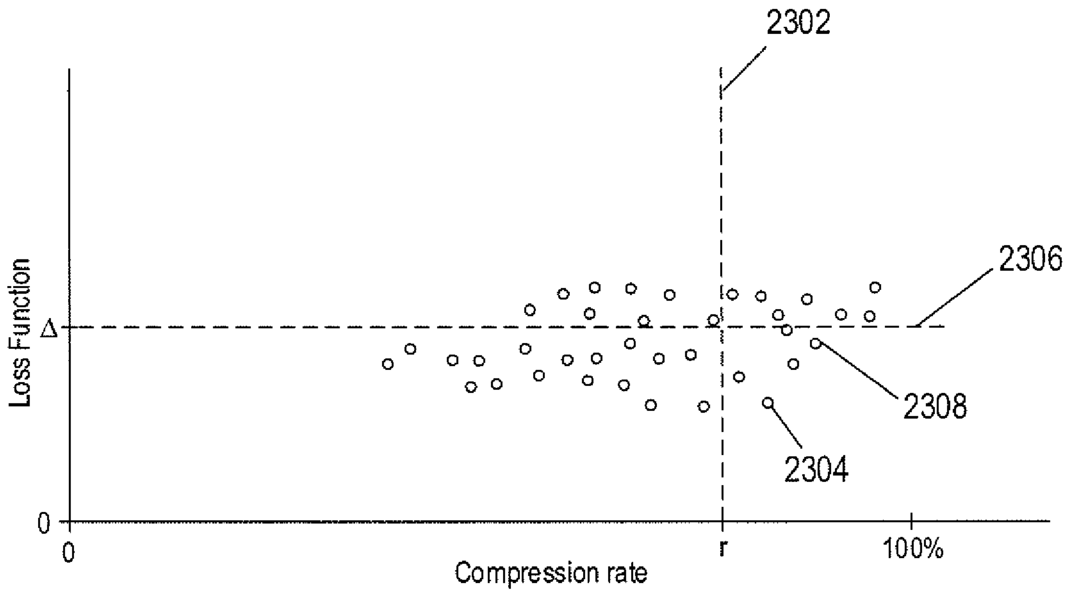
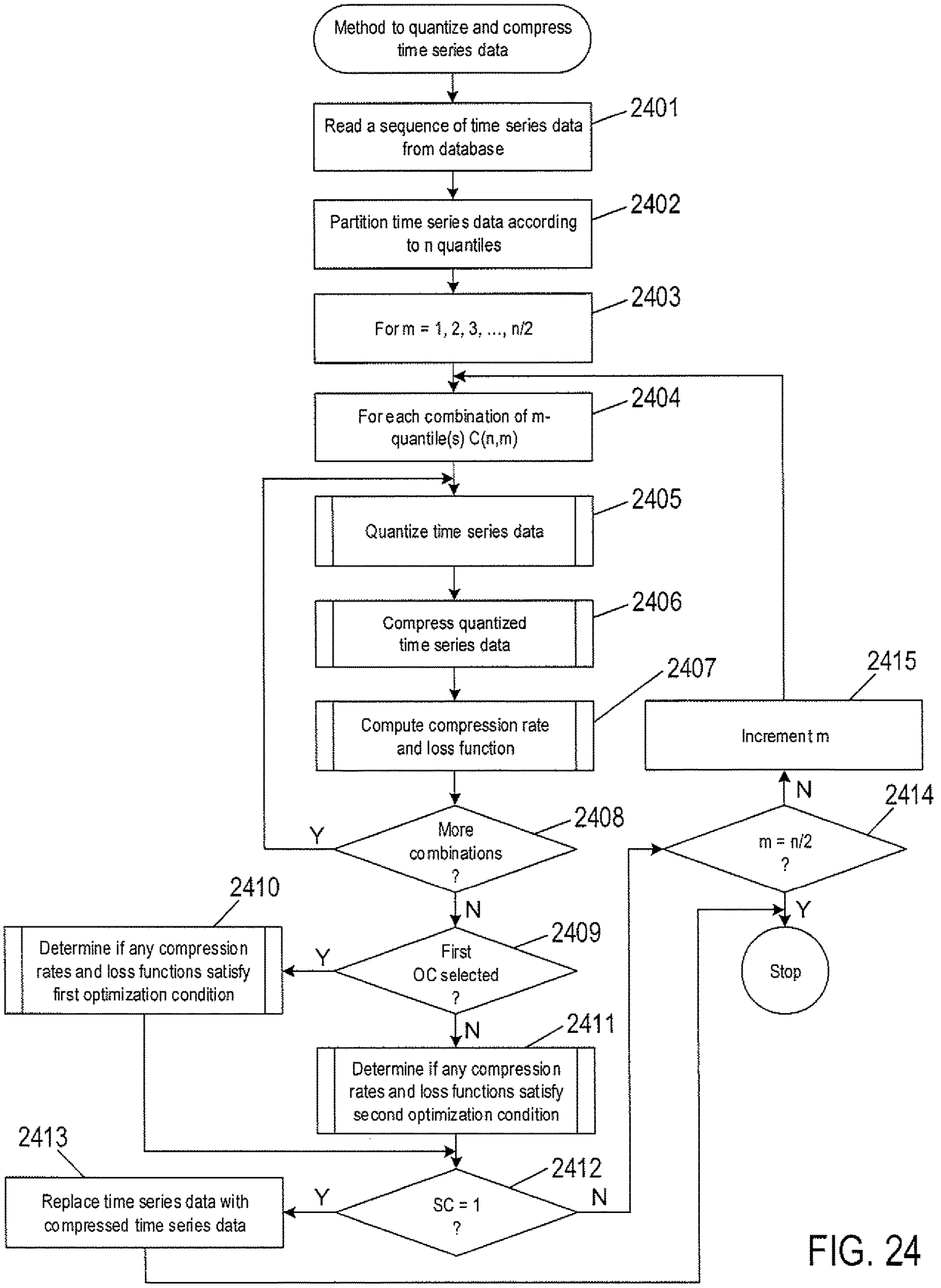

2302
2306
2308
2304
Loss Function
Δ
0
0
r
100%
Compression rate

FIG. 23



Method to quantize and compress time series data
Read a sequence of time series data from database
2401
Partition time series data according to n quantiles
2402
For m = 1, 2, 3, ..., n/2
2403
For each combination of m-quantile(s) C(n,m)
2404
Quantize time series data
2405
Compress quantized time series data
2406
Compute compression rate and loss function
2407
More combinations ?
2408
Y
N
First OC selected ?
2409
Y
N
Determine if any compression rates and loss functions satisfy first optimization condition
2410
Determine if any compression rates and loss functions satisfy second optimization condition
2411
SC = 1 ?
2412
Y
N
Replace time series data with compressed time series data
2413
m = n/2 ?
2414
N
Y
Increment m
2415
Stop

FIG. 24

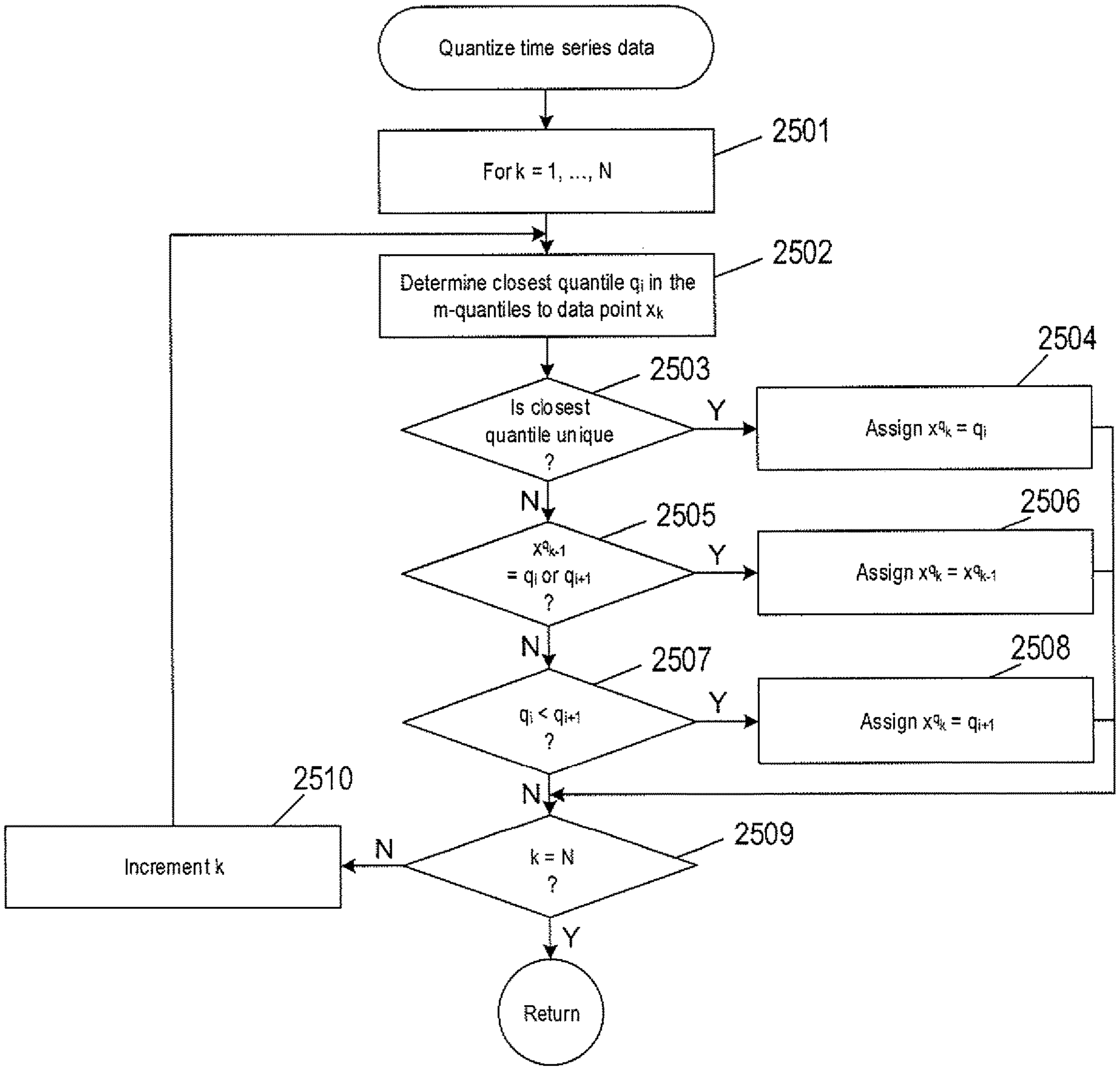

Quantize time series data
For k = 1, ..., N
2501
Determine closest quantile q_i in the m-quantiles to data point x_k
2502
Is closest quantile unique ?
2503
Y
Assign $x^q_k = q_i$
2504
N
$x^q_{k-1} = q_i$ or q_{i+1} ?
2505
Y
Assign $x^q_k = x^q_{k-1}$
2506
N
$q_i < q_{i+1}$?
2507
Y
Assign $x^q_k = q_{i+1}$
2508
N
k = N ?
2509
N
Increment k
2510
Y
Return

FIG. 25

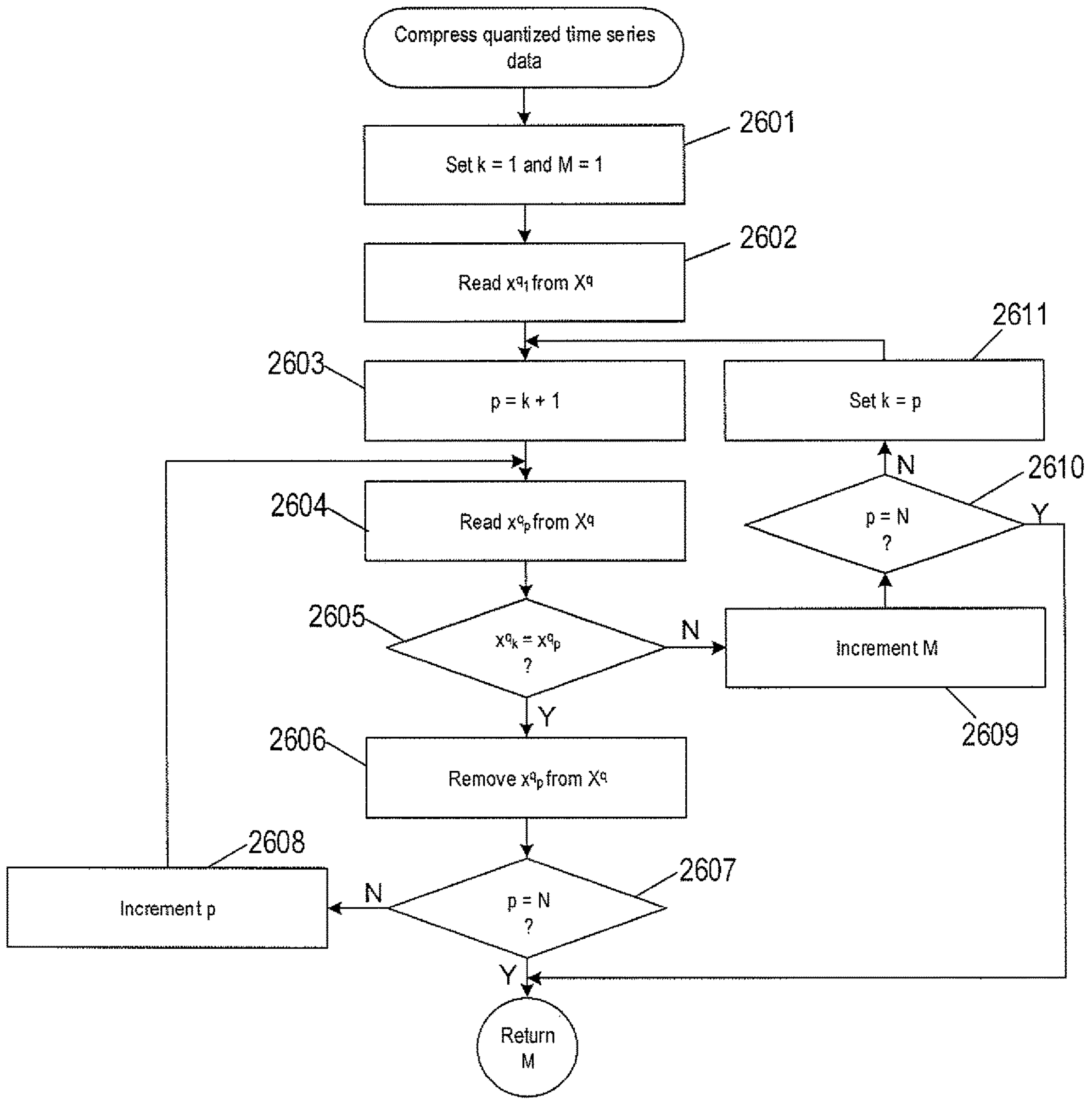

Compress quantized time series data
Set k = 1 and M = 1
2601
Read x^q_1 from X^q
2602
2611
2603
p = k + 1
Set k = p
2610
N
p = N ?
Y
2604
Read x^q_p from X^q
2605
$x^q_k = x^q_p$?
N
Increment M
2609
Y
2606
Remove x^q_p from X^q
2608
2607
N
Increment p
p = N ?
Y
Return M

FIG. 26

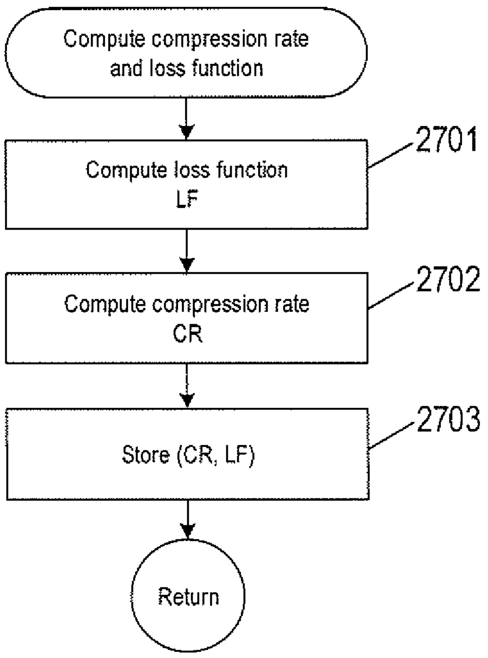

Compute compression rate and loss function
Compute loss function LF
2701
Compute compression rate CR
2702
Store (CR, LF)
2703
Return

FIG. 27

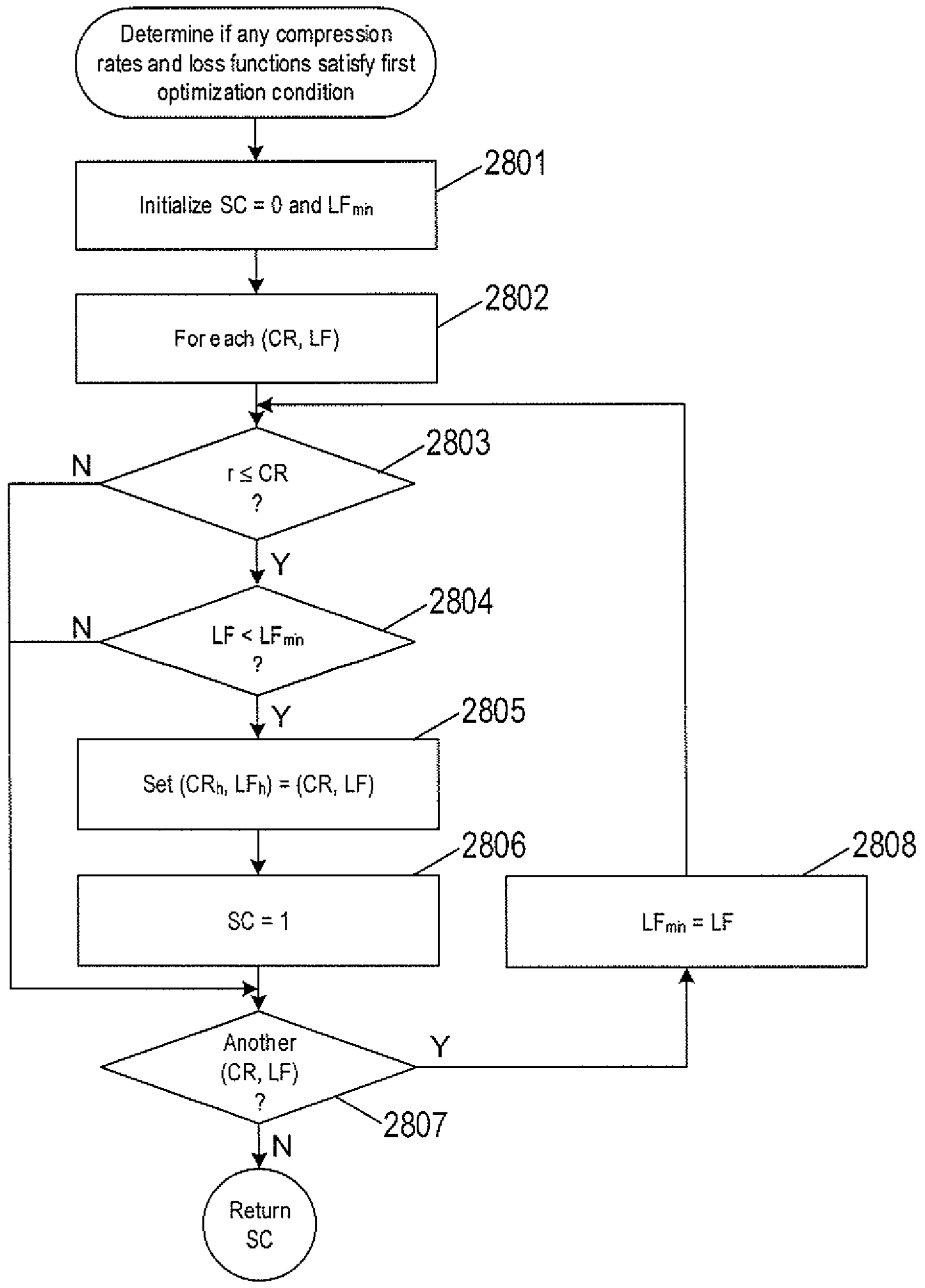

Determine if any compression rates and loss functions satisfy first optimization condition
Initialize SC = 0 and LF_{min}
2801
For each (CR, LF)
2802
$r \leq CR$?
2803
N
Y
$LF < LF_{min}$?
2804
N
Y
Set (CR_h, LF_h) = (CR, LF)
2805
SC = 1
2806
LF_{min} = LF
2808
Another (CR, LF) ?
2807
Y
N
Return SC

FIG. 28

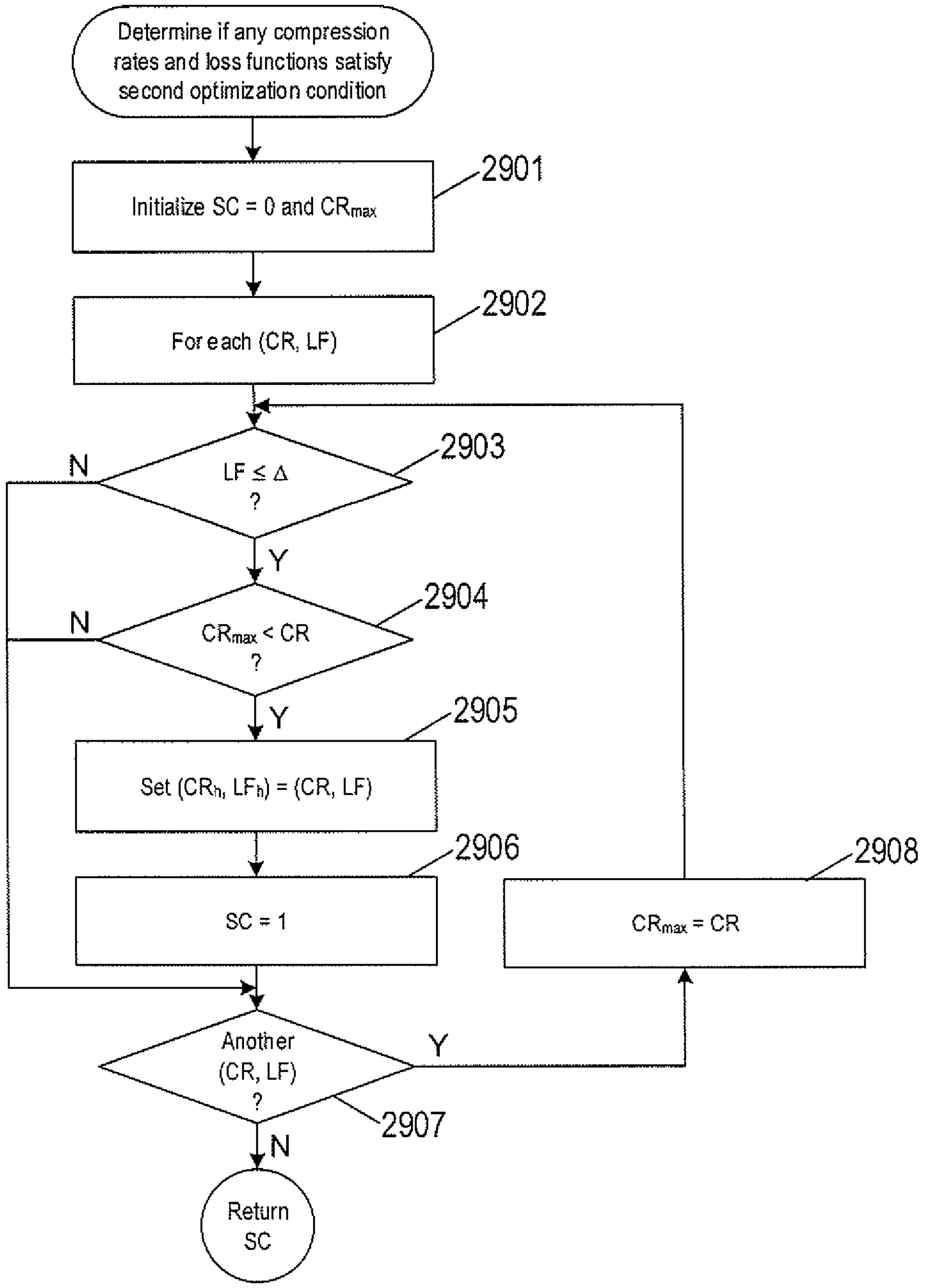

Determine if any compression rates and loss functions satisfy second optimization condition
Initialize SC = 0 and CR_{max}
2901
For each (CR, LF)
2902
$LF \leq \Delta$?
2903
N
Y
$CR_{max} < CR$?
2904
N
Y
Set $(CR_h, LF_h) = (CR, LF)$
2905
SC = 1
2906
$CR_{max} = CR$
2908
Another (CR, LF) ?
2907
Y
N
Return SC

FIG. 29

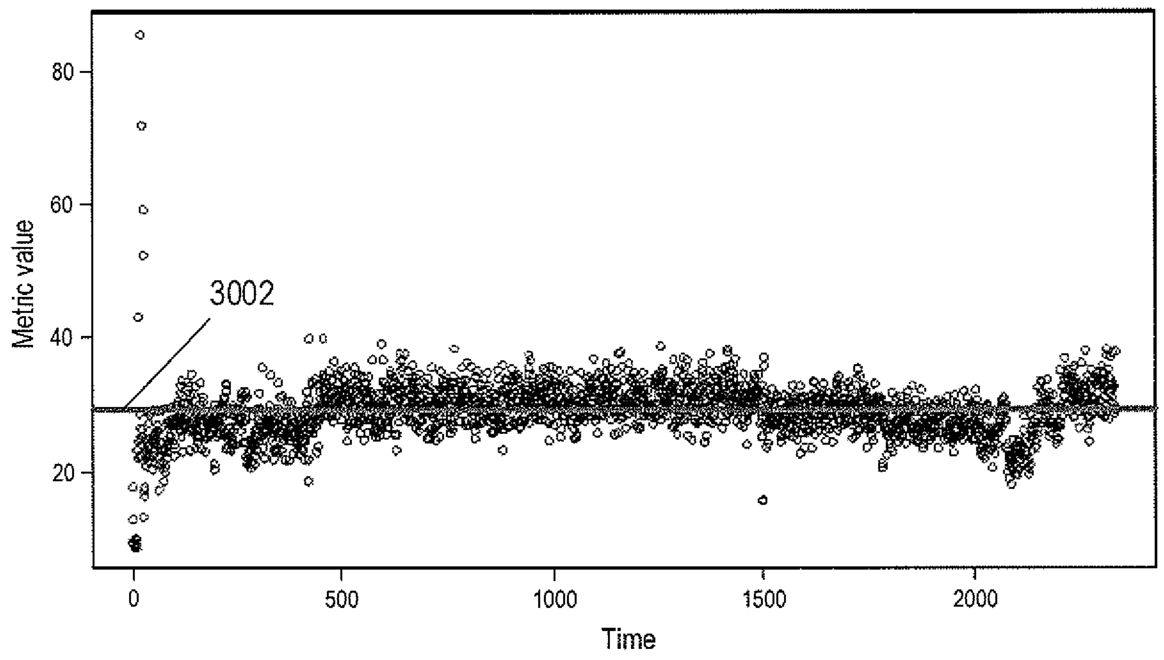


FIG. 30A

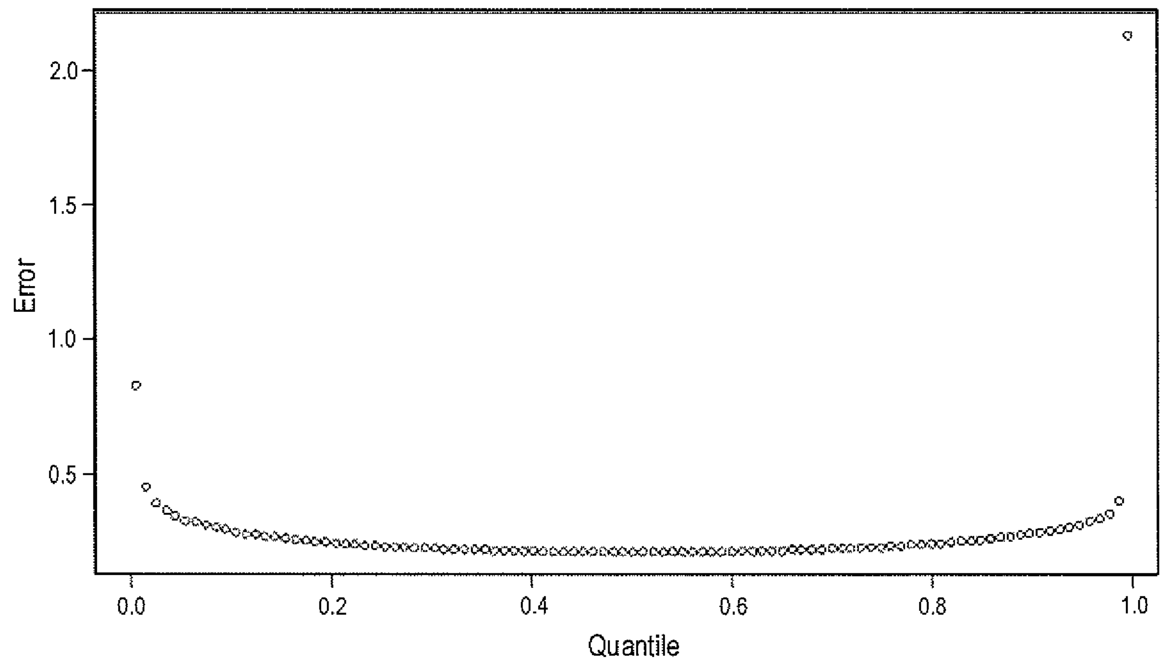


FIG. 30B

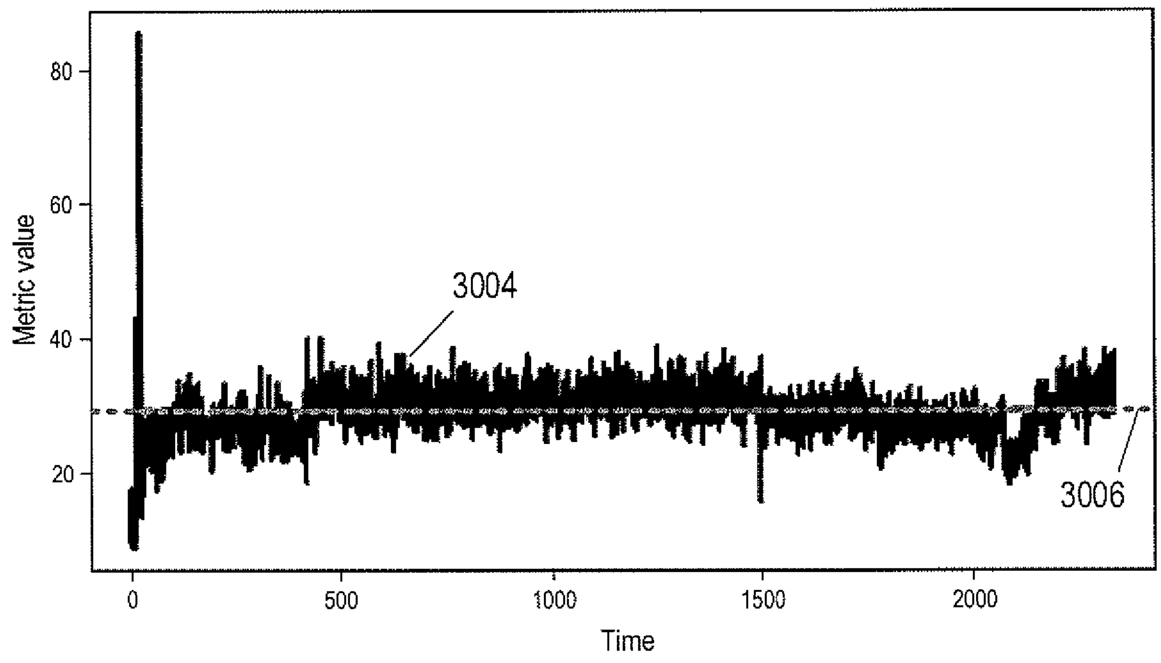


FIG. 30C

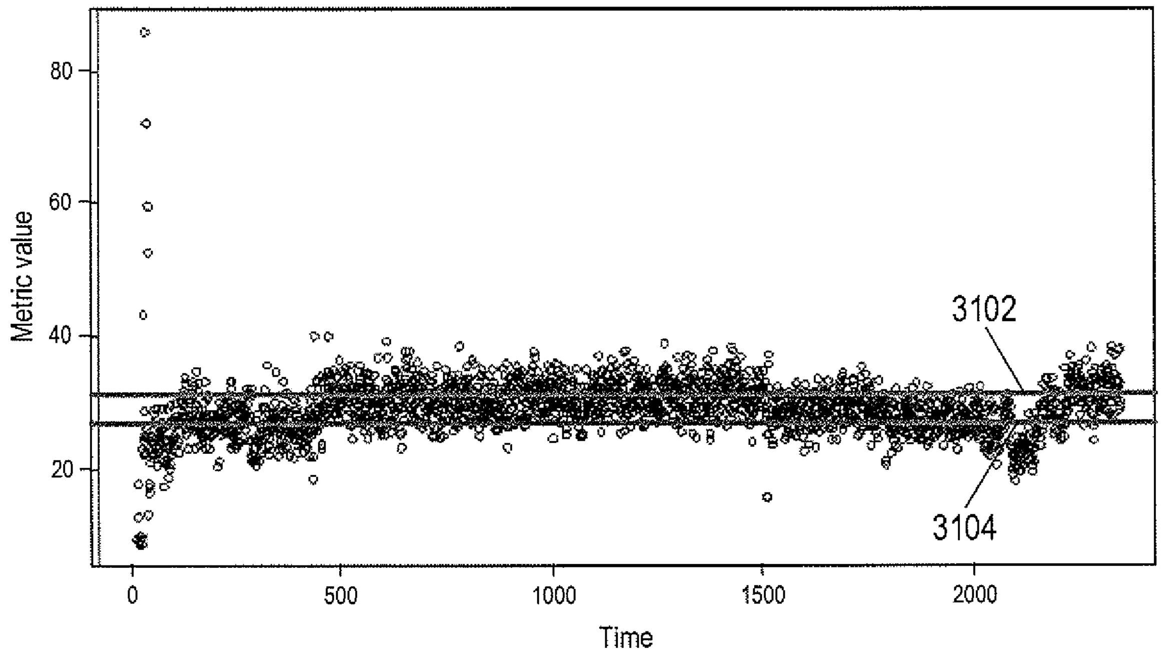


FIG. 31A

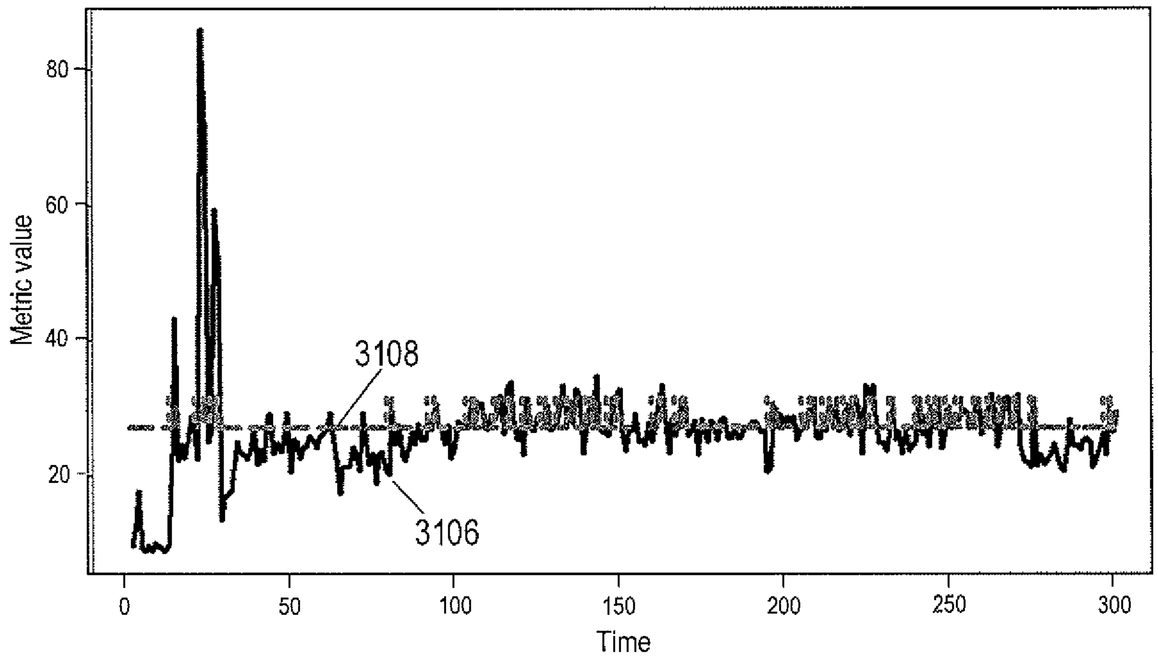


FIG. 31B

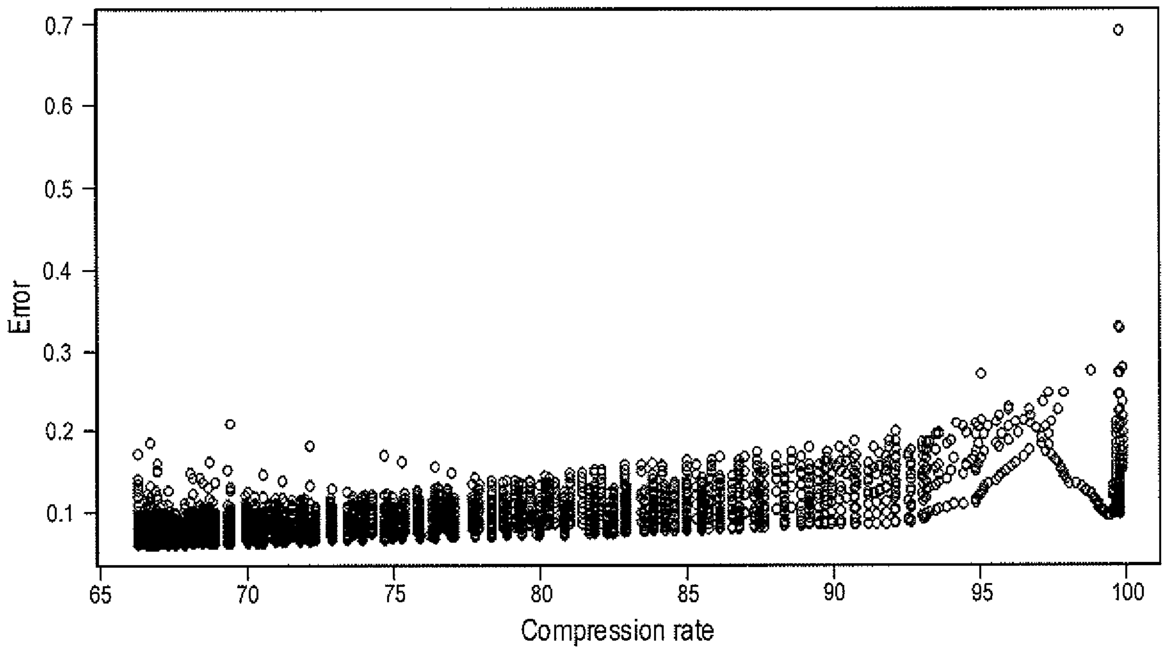


FIG. 31C

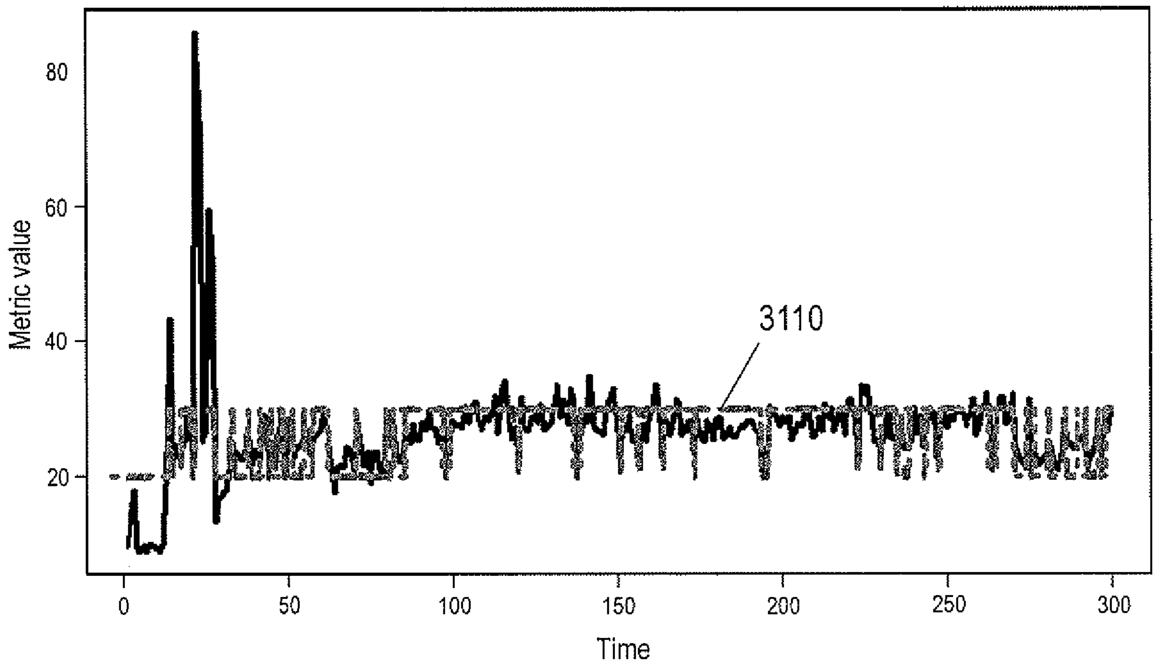


FIG. 31D

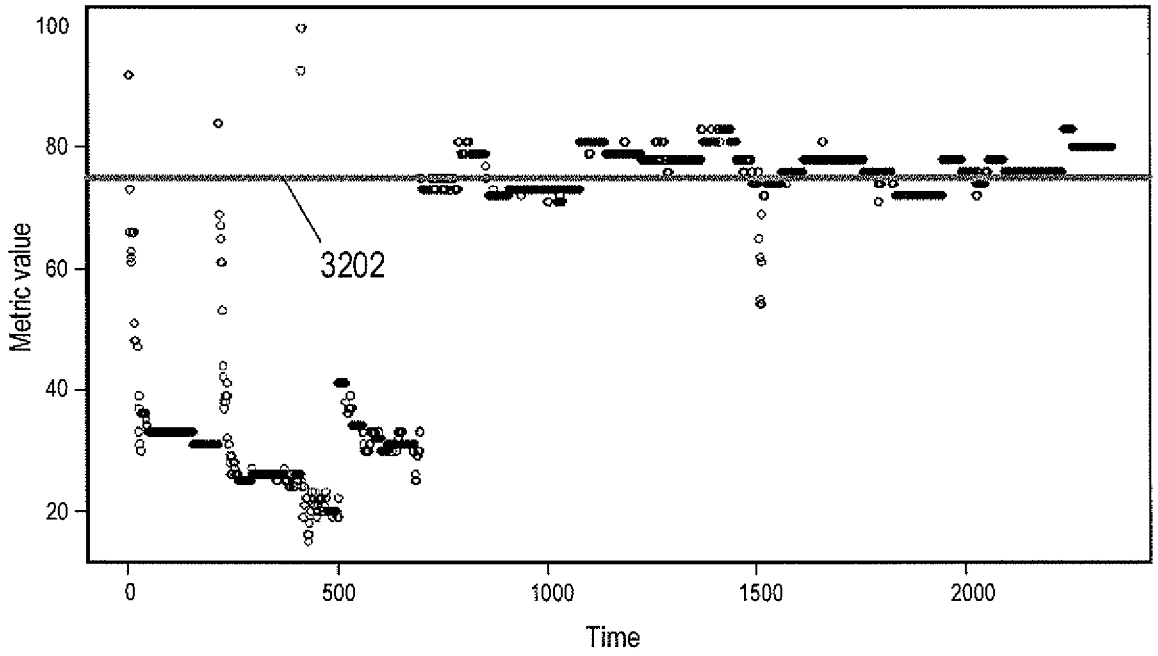


FIG. 32A

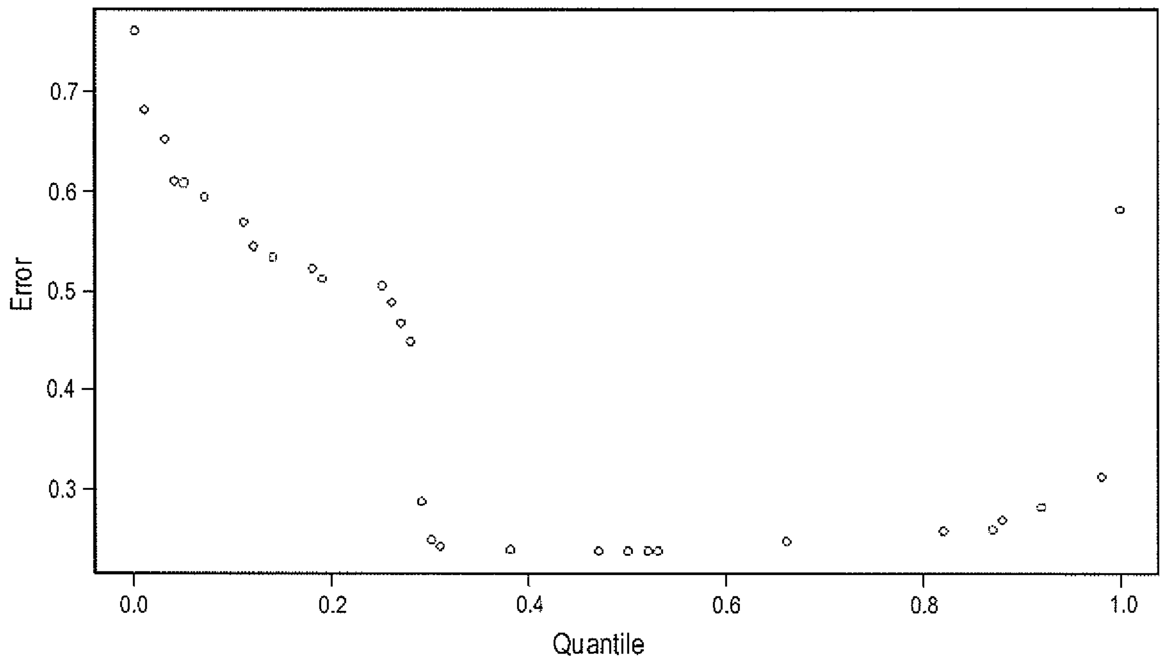


FIG. 32B

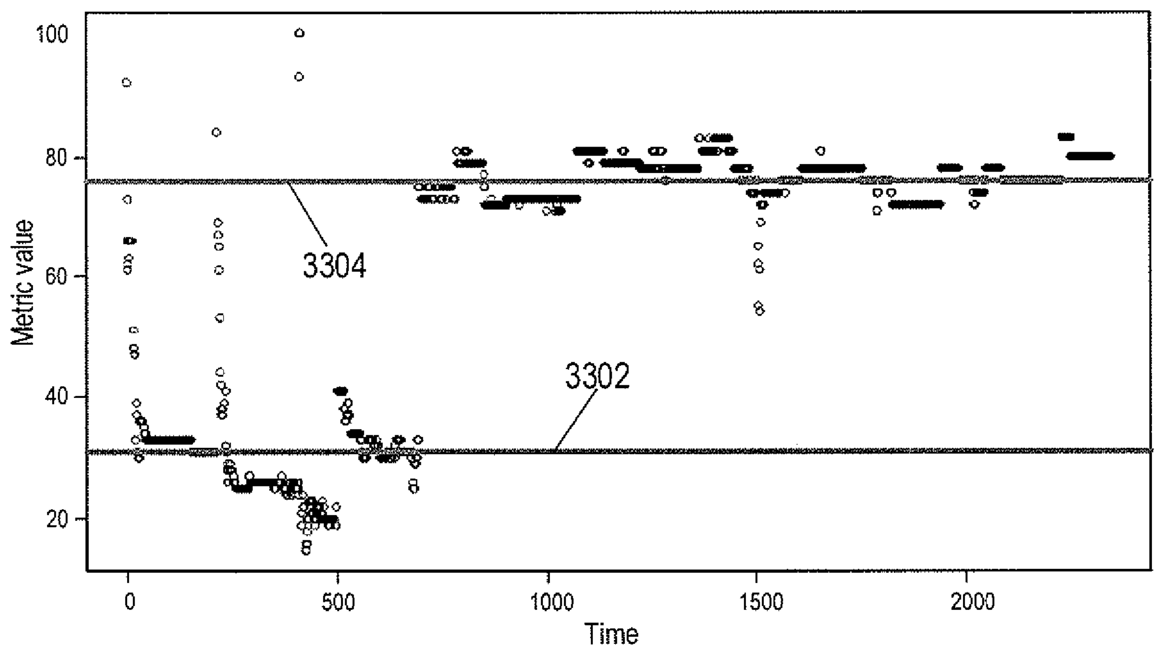


FIG. 33A

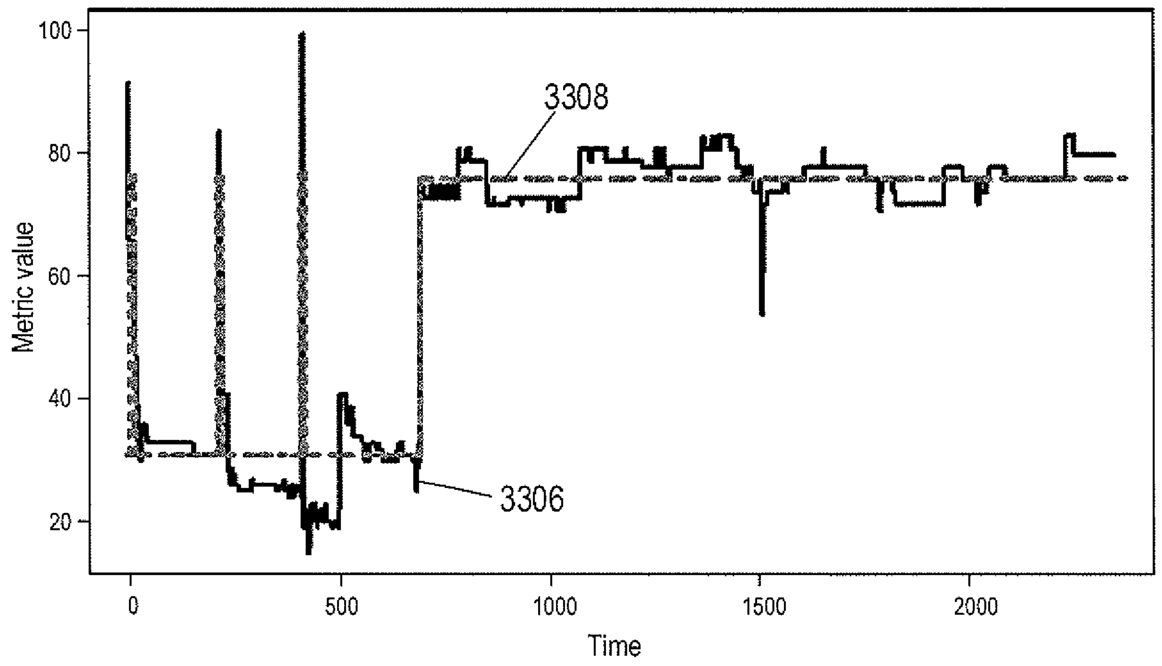


FIG. 33B

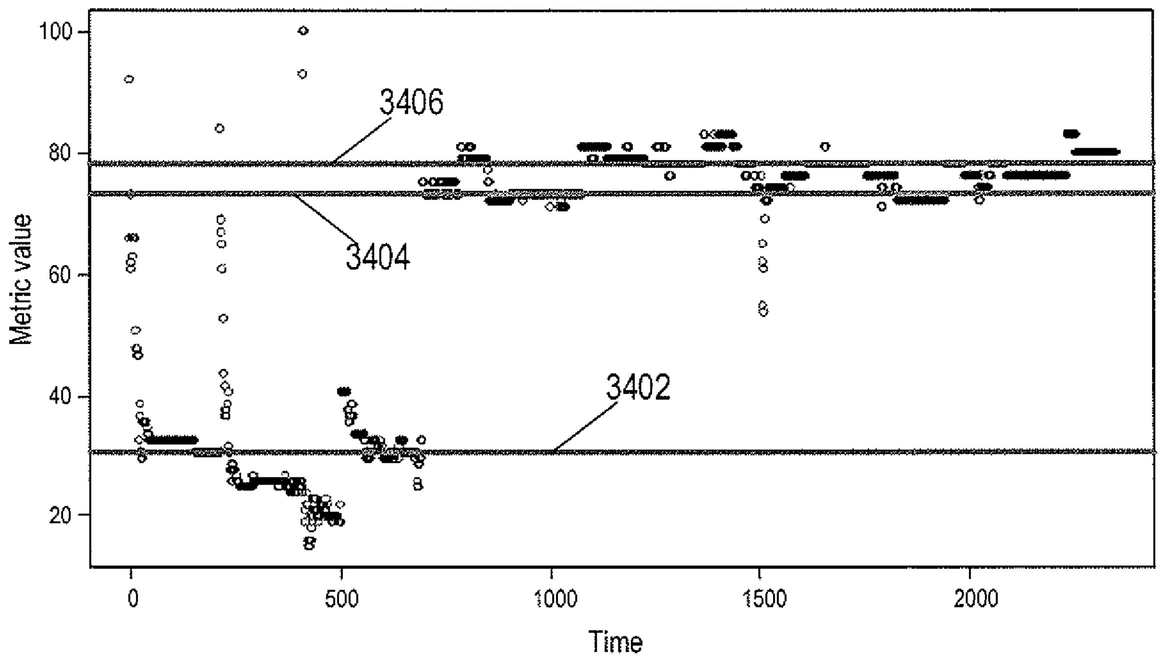


FIG. 34A

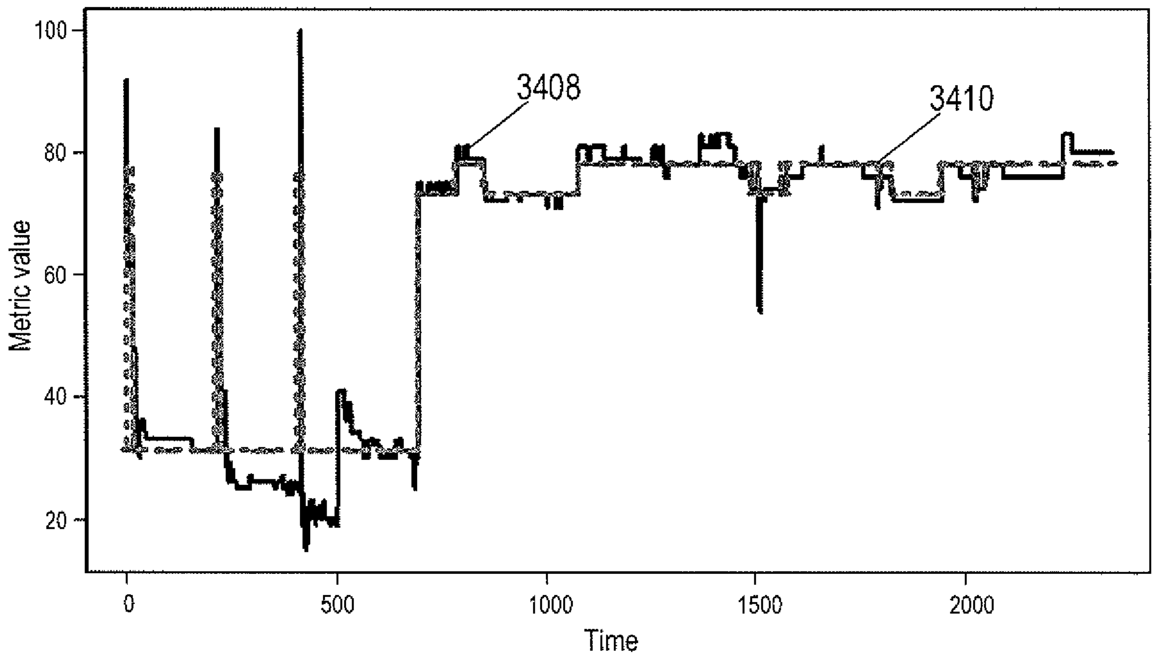


FIG. 34B

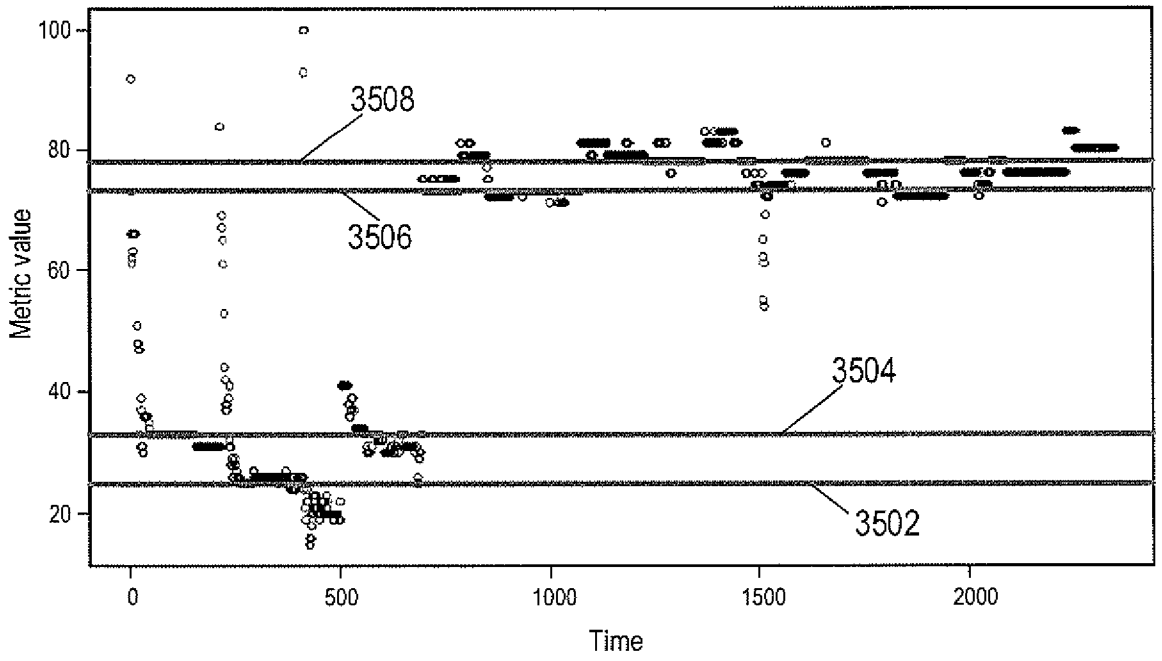


FIG. 35A

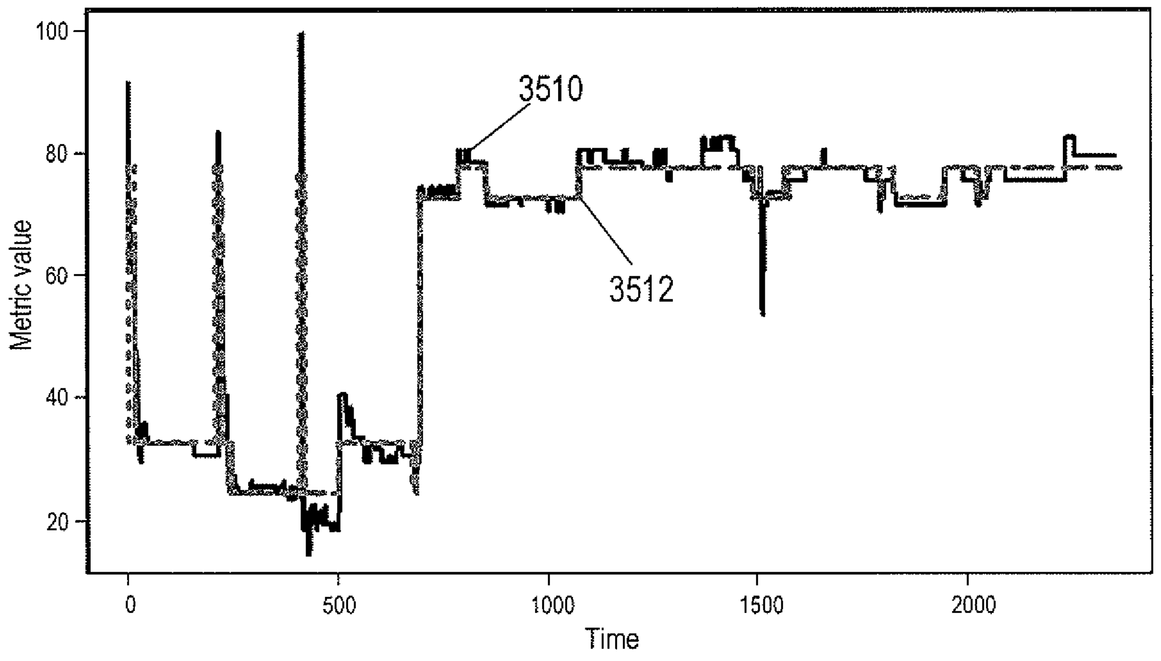


FIG. 35B

METHODS AND SYSTEMS TO QUANTIZE AND COMPRESS TIME SERIES DATA

TECHNICAL FIELD

The present disclosure is directed to quantizing and compressing time series data.

BACKGROUND

Electronic computing has evolved from primitive, vacuum-tube-based computer systems, initially developed during the 1940s, to modern electronic computing systems in which large numbers of multi-processor computer systems, such as server computers, work stations, and other individual computing systems are networked together with large-capacity data-storage devices and other electronic devices to produce geographically distributed computing systems with hundreds of thousands, millions, or more components that provide enormous computational bandwidths and data-storage capacities. These large, distributed computing systems are made possible by advances in computer networking, distributed operating systems and applications, data-storage appliances, computer hardware, and software technologies.

In order to proactively manage a distributed computing system, system administrators are interested in detecting anomalous behavior and identifying problems in the operation of the disturbed computing system. Management tools have been developed to collect time series data from various virtual and physical resources of the distributed computing system and processes the time series data to detect anomalously behaving resources and identify problems in the distributed computing system. However, each set of time series data is extremely large and recording many different sets of time series data over time significantly increases the demand for data storage, which increases data storage costs. Large sets of time series data also slow the performance of the management tool by pushing the limits of memory, CPU usage, and input/output resources of the management tool. As a result, detection of anomalies and identification of problems are delayed. System administrators seek methods and systems to more efficiently and effectively store and process large sets of time series data.

SUMMARY

The disclosure is directed to automated methods and systems to quantize and compress time series data generated by objects of a distributed computing system. Examples of resources include virtual and physical resources, such as virtual and physical CPU, memory, data storage, and network traffic. The types of time series data include CPU usage, memory, data storage, and network traffic of a virtual or a physical resource. The time series data may be stored in a data-storage device, such as a mass-storage array, of a physical data center. The time series data is partitioned according to a set of quantiles. Quantized time series data is generated from the time series data and the quantiles, which may create a loss of information contained in the originally recorded time series data. The quantized time series data is compressed by deleting portions of the sequential duplicate quantized data points from the quantized time series data to obtain compress time series data. Quantization and compression are performed for different combinations of quantiles and subjected to a user selected limitation on loss of information or limitation on a compression rate. The user may choose to minimize information loss resulting from quantization while selecting a lower bound for the compression rate. Alternatively, the user may choose to maximize the compression rate while placing an upper limit on the loss of information due to quantization. The compressed time series data that satisfies the user selected optimization conditions may be used to replace the original time series data in the data-storage device. The compressed time series data occupies far less storage space than the original time series data, freeing storage space in the data-storage device. The smaller data set of compressed time series data also enables faster and more timely analysis by a management server.

DESCRIPTION OF THE DRAWINGS

FIG. **1** shows a general architectural diagram for various types of computers.

FIG. **2** shows an Internet-connected distributed computer system.

FIG. **3** shows cloud computing.

FIG. **4** shows generalized hardware and software components of a general-purpose computer system.

FIGS. **5**A-**5**B show two types of virtual machine ("VM") and VM execution environments.

FIG. **6** shows an example of an open virtualization format package.

FIG. **7** shows virtual data centers provided as an abstraction of underlying physical-data-center hardware components.

FIG. **8** shows virtual-machine components of a virtual-data-center management server and physical servers of a physical data center.

FIG. **9** shows a cloud-director level of abstraction.

FIG. **10** shows virtual-cloud-connector nodes.

FIG. **11** shows an example server computer used to host three containers.

FIG. **12** shows an approach to implementing the containers on a VM.

FIG. **13** shows example sources of time series data in a physical data center.

FIG. **14** shows a flow diagram of a method to optimize and compress the time series data stored in a data-storage device.

FIG. **15** shows a plot of example time series data.

FIG. **16** shows a plot of an example sequence of time series data partitioned into ten groups of data points with nine example quantiles.

FIG. **17** shows a plot of loss function values versus quantiles.

FIG. **18** shows a plot of the compression rate as a function M.

FIGS. **19**A-**19**C show an example of quantizing and compressing the time series data shown in FIG. **15** to a single quantile.

FIG. **20** shows a plot of example loss function values versus quantiles.

FIG. **21** shows a plot of loss function values versus compression rate.

FIGS. **22**A-**22**D show an example of quantizing and compressing the time series data shown in FIG. **15** to two quantiles.

FIG. **23** shows a plot of example loss function values versus compression rates for 36 combinations of different pairs of quantiles.

FIG. **24** shows a control-flow diagram of a method to quantize and compress time series data.

DETAILED DESCRIPTION

This disclosure presents computational methods and systems to quantize and compress time series data. In a first subsection, computer hardware, complex computational systems, and virtualization are described. Containers and containers supported by virtualization layers are described in a second subsection. Methods to quantize and compress time series data are described below in a third subsection.

Computer Hardware, Complex Computational Systems, and Virtualization

The term "abstraction" is not, in any way, intended to mean or suggest an abstract idea or concept. Computational abstractions are tangible, physical interfaces that are implemented, ultimately, using physical computer hardware, data-storage devices, and communications systems. Instead, the term "abstraction" refers, in the current discussion, to a logical level of functionality encapsulated within one or more concrete, tangible, physically-implemented computer systems with defined interfaces through which electronically-encoded data is exchanged, process execution launched, and electronic services are provided. Interfaces may include graphical and textual data displayed on physical display devices as well as computer programs and routines that control physical computer processors to carry out various tasks and operations and that are invoked through electronically implemented application programming interfaces ("APIs") and other electronically implemented interfaces. There is a tendency among those unfamiliar with modern technology and science to misinterpret the terms "abstract" and "abstraction," when used to describe certain aspects of modern computing. For example, one frequently encounters assertions that, because a computational system is described in terms of abstractions, functional layers, and interfaces, the computational system is somehow different from a physical machine or device. Such allegations are unfounded. One only needs to disconnect a computer system or group of computer systems from their respective power supplies to appreciate the physical, machine nature of complex computer technologies. One also frequently encounters statements that characterize a computational technology as being "only software," and thus not a machine or device. Software is essentially a sequence of encoded symbols, such as a printout of a computer program or digitally encoded computer instructions sequentially stored in a file on an optical disk or within an electromechanical mass-storage device. Software alone can do nothing. It is only when encoded computer instructions are loaded into an electronic memory within a computer system and executed on a physical processor that so-called "software implemented" functionality is provided. The digitally encoded computer instructions are an essential and physical control component of processor-controlled machines and devices, no less essential and physical than a cam-shaft control system in an internal-combustion engine. Multi-cloud aggregations, cloud-computing services, virtual-machine containers and virtual machines, communications interfaces, and many of the other topics discussed below are tangible, physical components of physical, electro-optical-mechanical computer systems.

FIG. **1** shows a general architectural diagram for various types of computers. Computers that receive, process, and store event messages may be described by the general architectural diagram shown in FIG. **1**, for example. The computer system contains one or multiple central processing units ("CPUs") **102**-**105**, one or more electronic memories **108** interconnected with the CPUs by a CPU/memory-subsystem bus **110** or multiple busses, a first bridge **112** that interconnects the CPU/memory-subsystem bus **110** with additional busses **114** and **116**, 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 **118**, and with one or more additional bridges **120**, which are interconnected with high-speed serial links or with multiple controllers **122**-**127**, such as controller **127**, that provide access to various different types of mass-storage devices **128**, 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.

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.

FIG. **2** shows an Internet-connected distributed computer system. As communications and networking technologies have evolved in capability and accessibility, and as the computational bandwidths, data-storage capacities, and other capabilities and capacities of various types of computer systems have steadily and rapidly increased, much of modern computing now generally involves large distributed systems and computers interconnected by local networks, wide-area networks, wireless communications, and the Internet. FIG. **2** shows a typical distributed system in which a large number of PCs **202-205**, a high-end distributed mainframe system **210** with a large data-storage system **212**, and a large computer center **214** with large numbers of rack-mounted servers or blade servers all interconnected through various communications and networking systems that together comprise the Internet **216**. Such distributed computing systems provide diverse arrays of functionalities. For example, a PC user may access hundreds of millions of different web sites provided by hundreds of thousands of different web servers throughout the world and may access high-computational-bandwidth computing services from remote computer facilities for running complex computational tasks.

Until recently, computational services were generally provided by computer systems and data centers purchased, configured, managed, and maintained by service-provider organizations. For example, an e-commerce retailer generally purchased, configured, managed, and maintained a data center including numerous web servers, back-end computer systems, and data-storage systems for serving web pages to remote customers, receiving orders through the web-page interface, processing the orders, tracking completed orders, and other myriad different tasks associated with an e-commerce enterprise.

FIG. **3** shows cloud computing. In the recently developed cloud-computing paradigm, computing cycles and data-storage facilities are provided to organizations and individuals by cloud-computing providers. In addition, larger organizations may elect to establish private cloud-computing facilities in addition to, or instead of, subscribing to computing services provided by public cloud-computing service providers. In FIG. **3**, a system administrator for an organization, using a PC **302**, accesses the organization's private cloud **304** through a local network **306** and private-cloud interface **308** and also accesses, through the Internet **310**, a public cloud **312** through a public-cloud services interface **314**. The administrator can, in either the case of the private cloud **304** or public cloud **312**, configure virtual computer systems and even entire virtual data centers and launch execution of application programs on the virtual computer systems and virtual data centers in order to carry out any of many different types of computational tasks. As one example, a small organization may configure and run a virtual data center within a public cloud that executes web servers to provide an e-commerce interface through the public cloud to remote customers of the organization, such as a user viewing the organization's e-commerce web pages on a remote user system **316**.

Cloud-computing facilities are intended to 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. **4** shows generalized hardware and software components of a general-purpose computer system, such as a general-purpose computer system having an architecture similar to that shown in FIG. **1**. The computer system **400** is often considered to include three fundamental layers: (1) a hardware layer or level **402**; (2) an operating-system layer or level **404**; and (3) an application-program layer or level **406**. The hardware layer **402** includes one or more processors **408**, system memory **410**, various different types of input-output ("I/O") devices **410** and **412**, and mass-storage devices **414**. 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 **404** interfaces to the hardware level **402** through a low-level operating system and hardware interface **416** generally comprising a set of non-privileged computer instructions **418**, a set of privileged computer instructions **420**, a set of non-privileged registers and memory addresses **422**, and a set of privileged registers and memory addresses **424**. In general, the operating system exposes non-privileged instructions, non-privileged registers, and non-privileged memory addresses **426** and a system-call interface **428** as an operating-system interface **430** to application programs **432-436** 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 **442**, memory management **444**, a file system **446**, device drivers **448**, 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 **436** 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 to be 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. **5**A-B show two types of VM and virtual-machine execution environments. FIGS. **5**A-B use the same illustration conventions as used in FIG. **4**. FIG. **5**A shows a first type of virtualization. The computer system **500** in FIG. **5**A includes the same hardware layer **502** as the hardware layer **402** shown in FIG. **4**. However, rather than providing an operating system layer directly above the hardware layer, as in FIG. **4**, the virtualized computing environment shown in FIG. **5**A features a virtualization layer **504** that interfaces through a virtualization-layer/hardware-layer interface **506**, equivalent to interface **416** in FIG. **4**, to the hardware. The virtualization layer **504** provides a hardware-like interface **508** to a number of VMs, such as VM **510**, in a virtual-machine layer **511** executing above the virtualization layer **504**. 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 **514** and guest operating system **516** packaged together within VM **510**. Each VM is thus equivalent to the operating-system layer **404** and application-program layer **406** in the general-purpose computer system shown in FIG. **4**. Each guest operating system within a VM interfaces to the virtualization-layer interface **508** rather than to the actual hardware interface **506**. The virtualization layer **504** 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 **504** 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 **508** 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 **504** includes a virtual-machine-monitor module **518** ("VMM") 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 **508**, the accesses result in execution of virtualization-layer code to simulate or emulate the privileged devices. The virtualization layer additionally includes a kernel module **520** 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 **504** 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. **5**B shows a second type of virtualization. In FIG. **5**B, the computer system **540** includes the same hardware layer **542** and operating system layer **544** as the hardware layer **402** and the operating system layer **404** shown in FIG. **4**. Several application programs **546** and **548** are shown running in the execution environment provided by the operating system **544**. In addition, a virtualization layer **550** is also provided, in computer **540**, but, unlike the virtualization layer **504** discussed with reference to FIG. **5**A, virtualization layer **550** is layered above the operating system **544**, 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 **550** comprises primarily a VMM and a hardware-like interface **552**, similar to hardware-like interface **508** in FIG. **5**A. The virtualization-layer/hardware-layer interface **552**, equivalent to interface **416** in FIG. **4**, provides an execution environment for a number of VMs **556-558**, each including one or more application programs or other higher-level computational entities packaged together with a guest operating system.

In FIGS. **5**A-**5**B, the layers are somewhat simplified for clarity of illustration. For example, portions of the virtualization layer **550** 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.

It should be noted that virtual hardware layers, virtualization layers, and guest operating systems are all physical entities that are implemented by computer instructions stored in physical data-storage devices, including electronic memories, mass-storage devices, optical disks, magnetic disks, and other such devices. The term "virtual" does not, in any way, imply that virtual hardware layers, virtualization layers, and guest operating systems are abstract or intangible. Virtual hardware layers, virtualization layers, and guest operating systems execute on physical processors of physical computer systems and control operation of the physical computer systems, including operations that alter the physical states of physical devices, including electronic memories and mass-storage devices. They are as physical and tangible as any other component of a computer since, such as power supplies, controllers, processors, busses, and data-storage devices.

A VM or virtual application, described below, is encapsulated within a data package for transmission, distribution, and loading into a virtual-execution environment. One public standard for virtual-machine encapsulation is referred to as the "open virtualization format" ("OVF"). The OVF standard specifies a format for digitally encoding a VM within one or more data files. FIG. **6** shows an OVF package. An OVF package **602** includes an OVF descriptor **604**, an OVF manifest **606**, an OVF certificate **608**, one or more disk-image files **610-611**, and one or more device files **612-614**. The OVF package can be encoded and stored as a single file or as a set of files. The OVF descriptor **604** is an XML document **620** that includes a hierarchical set of elements, each demarcated by a beginning tag and an ending tag. The outermost, or highest-level, element is the envelope element, demarcated by tags **622** and **623**. The next-level element includes a reference element **626** that includes references to all files that are part of the OVF package, a disk section **628** that contains meta information about all of the virtual disks included in the OVF package, a network section **630** that includes meta information about all of the logical networks included in the OVF package, and a collection of virtual-machine configurations **632** which further includes hardware descriptions of each VM **634**. There are many additional hierarchical levels and elements within a typical OVF descriptor. The OVF descriptor is thus a self-describing, XML file that describes the contents of an OVF package. The OVF manifest **606** is a list of cryptographic-hash-function-generated digests **636** of the entire OVF package and of the various components of the OVF package. The OVF certificate **608** is an authentication certificate **640** that includes a digest of the manifest and that is cryptographically signed. Disk image files, such as disk image file **610**, are digital encodings of the contents of virtual disks and device files **612** are digitally encoded content, such as operating-system images. A VM or a collection of VMs encapsulated together within a virtual application can thus be digitally encoded as one or more files within an OVF package that can be transmitted, distributed, and loaded using well-known tools for transmitting, distributing, and loading files. A virtual appliance is a software service that is delivered as a complete software stack installed within one or more VMs that is encoded within an OVF package.

The advent of VMs and virtual environments has alleviated many of the difficulties and challenges associated with traditional general-purpose computing. Machine and operating-system dependencies can be significantly reduced or entirely eliminated by packaging applications and operating systems together as VMs and virtual appliances that execute within virtual environments provided by virtualization layers running on many different types of computer hardware. A next level of abstraction, referred to as virtual data centers or virtual infrastructure, provide a data-center interface to virtual data centers computationally constructed within physical data centers.

FIG. **7** shows virtual data centers provided as an abstraction of underlying physical-data-center hardware components. In FIG. **7**, a physical data center **702** is shown below a virtual-interface plane **704**. The physical data center consists of a virtual-data-center management server **706** and any of various different computers, such as PCs **708**, on which a virtual-data-center management interface may be displayed to system administrators and other users. The physical data center additionally includes generally large numbers of server computers, such as server computer **710**, that are coupled together by local area networks, such as local area network **712** that directly interconnects server computer **710** and **714-720** and a mass-storage array **722**. The physical data center shown in FIG. **7** includes three local area networks **712**, **724**, and **726** that each directly interconnects a bank of eight servers and a mass-storage array. The individual server computers, such as server computer **710**, each includes a virtualization layer and runs multiple VMs. Different physical data centers may include many different types of computers, networks, data-storage systems and devices connected according to many different types of connection topologies. The virtual-interface plane **704**, a logical abstraction layer shown by a plane in FIG. **7**, abstracts the physical data center to a virtual data center comprising one or more device pools, such as device pools **730-732**, one or more virtual data stores, such as virtual data stores **734-736**, and one or more virtual networks. In certain implementations, the device pools abstract banks of physical servers directly interconnected by a local area network.

The virtual-data-center management interface allows provisioning and launching of VMs with respect to device pools, virtual data stores, and virtual networks, so that virtual-data-center administrators need not be concerned with the identities of physical-data-center components used to execute particular VMs. Furthermore, the virtual-data-center management server **706** includes functionality to migrate running VMs from one physical server to another in order to optimally or near optimally manage device allocation, provide fault tolerance, and high availability by migrating VMs to most effectively utilize underlying physical hardware devices, to replace VMs disabled by physical hardware problems and failures, and to ensure that multiple VMs supporting a high-availability virtual appliance are executing on multiple physical computer systems so that the services provided by the virtual appliance are continuously accessible, even when one of the multiple virtual appliances becomes compute bound, data-access bound, suspends execution, or fails. Thus, the virtual data center layer of abstraction provides a virtual-data-center abstraction of physical data centers to simplify provisioning, launching, and maintenance of VMs and virtual appliances as well as to provide high-level, distributed functionalities that involve pooling the devices of individual physical servers and migrating VMs among physical servers to achieve load balancing, fault tolerance, and high availability.

FIG. **8** shows virtual-machine components of a virtual-data-center management server and physical servers of a physical data center above which a virtual-data-center interface is provided by the virtual-data-center management server. The virtual-data-center management server **802** and a virtual-data-center database **804** comprise the physical components of the management component of the virtual data center. The virtual-data-center management server **802** includes a hardware layer **806** and virtualization layer **808**, and runs a virtual-data-center management-server VM **810** above the virtualization layer. Although shown as a single server in FIG. **8**, the virtual-data-center management server ("VDC management server") may include two or more physical server computers that support multiple VDC-management-server virtual appliances. The VM **810** includes a management-interface component **812**, distributed services **814**, core services **816**, and a host-management interface **818**. The management interface **818** is accessed from any of various computers, such as the PC **708** shown in FIG. **7**. The management interface **818** allows the virtual-data-center administrator to configure a virtual data center, provision VMs, collect statistics and view log files for the virtual data center, and to early out other, similar management tasks. The host-management interface **818** interfaces to virtual-data-center agents **824**, **825**, and **826** that execute as VMs within each of the physical servers of the physical data center that is abstracted to a virtual data center by the VDC management server.

The distributed services **814** include a distributed-device scheduler that assigns VMs to execute within particular physical servers and that migrates VMs in order to most effectively make use of computational bandwidths, data-storage capacities, and network capacities of the physical data center. The distributed services **814** further include a high-availability service that replicates and migrates VMs in order to ensure that VMs continue to execute despite problems and failures experienced by physical hardware components. The distributed services **814** also include a live-virtual-machine migration service that temporarily halts execution of a VM, encapsulates the VM in an OVF package, transmits the OVF package to a different physical server, and restarts the VM on the different physical server from a virtual-machine state recorded when execution of the VM was halted. The distributed services **814** also include a distributed backup service that provides centralized virtual-machine backup and restore.

The core services **816** provided by the VDC management server **810** include host configuration, virtual-machine configuration, virtual-machine provisioning, generation of virtual-data-center alarms and events, ongoing event logging and statistics collection, a task scheduler, and a device-management module. Each physical server **820-822** also includes a host-agent VM **828-830** through which the virtualization layer can be accessed via a virtual-infrastructure application programming interface ("API"). This interface allows a remote administrator or user to manage an individual server through the infrastructure API. The virtual-data-center agents **824-826** access virtualization-layer server information through the host agents. The virtual-data-center agents are primarily responsible for offloading certain of the virtual-data-center management-server functions specific to a particular physical server to that physical server. The virtual-data-center agents relay and enforce device allocations made by the VDC management server **810**, relay virtual-machine provisioning and configuration-change commands to host agents, monitor and collect performance statistics, alarms, and events communicated to the virtual-data-center agents by the local host agents through the interface API, and to carry out other, similar virtual-data-management tasks.

The virtual-data-center abstraction provides a convenient and efficient level of abstraction for exposing the computational devices of a cloud-computing facility to cloud-computing-infrastructure users. A cloud-director management server exposes virtual devices of a cloud-computing facility to cloud-computing-infrastructure users. In addition, the cloud director introduces a multi-tenancy layer of abstraction, which partitions VDCs into tenant-associated VDCs that can each be allocated to a particular individual tenant or tenant organization, both referred to as a "tenant." A given tenant can be provided one or more tenant-associated VDCs by a cloud director managing the multi-tenancy layer of abstraction within a cloud-computing facility. The cloud services interface (**308** in FIG. **3**) exposes a virtual-data-center management interface that abstracts the physical data center.

FIG. **9** shows a cloud-director level of abstraction. In FIG. **9**, three different physical data centers **902-904** are shown below planes representing the cloud-director layer of abstraction **906-908**. Above the planes representing the cloud-director level of abstraction, multi-tenant virtual data centers **910-912** are shown. The devices of these multi-tenant virtual data centers are securely partitioned in order to provide secure virtual data centers to multiple tenants, or cloud-services-accessing organizations. For example, a cloud-services-provider virtual data center **910** is partitioned into four different tenant-associated virtual-data centers within a multi-tenant virtual data center for four different tenants **916-919**. Each multi-tenant virtual data center is managed by a cloud director comprising one or more cloud-director servers **920-922** and associated cloud-director databases **924-926**. Each cloud-director server or servers runs a cloud-director virtual appliance **930** that includes a cloud-director management interface **932**, a set of cloud-director services **934**, and a virtual-data-center management-server interface **936**. The cloud-director services include an interface and tools for provisioning multi-tenant virtual data center virtual data centers on behalf of tenants, tools and interfaces for configuring and managing tenant organizations, tools and services for organization of virtual data centers and tenant-associated virtual data centers within the multi-tenant virtual data center, services associated with template and media catalogs, and provisioning of virtualization networks from a network pool. Templates are VMs that each contains an OS and/or one or more VMs containing applications. A template may include much of the detailed contents of VMs and virtual appliances that are encoded within OVF packages, so that the task of configuring a VM or virtual appliance is significantly simplified, requiring only deployment of one OVF package. These templates are stored in catalogs within a tenant's virtual-data center. These catalogs are used for developing and staging new virtual appliances and published catalogs are used for sharing templates in virtual appliances across organizations. Catalogs may include OS images and other information relevant to construction, distribution, and provisioning of virtual appliances.

Considering FIGS. **7** and **9**, the VDC-server and cloud-director layers of abstraction can be seen, as discussed above, to facilitate employment of the virtual-data-center concept within private and public clouds. However, this level of abstraction does not fully facilitate aggregation of single-tenant and multi-tenant virtual data centers into heterogeneous or homogeneous aggregations of cloud-computing facilities.

FIG. **10** shows virtual-cloud-connector nodes ("VCC nodes") and a VCC server, components of a distributed system that provides multi-cloud aggregation and that includes a cloud-connector server and cloud-connector nodes that cooperate to provide services that are distributed across multiple clouds. VMware vCloud™ VCC servers and nodes are one example of VCC server and nodes. In FIG. **10**, seven different cloud-computing facilities are shown **1002-1008**. Cloud-computing facility **1002** is a private multi-tenant cloud with a cloud director **1010** that interfaces to a VDC management server **1012** to provide a multi-tenant private cloud comprising multiple tenant-associated virtual data centers. The remaining cloud-computing facilities **1003-1008** may be either public or private cloud-computing facilities and may be single-tenant virtual data centers, such as virtual data centers **1003** and **1006**, multi-tenant virtual data centers, such as multi-tenant virtual data centers **1004** and **1007-1008**, or any of various different kinds of third-party cloud-services facilities, such as third-party cloud-services facility **1005**. An additional component, the VCC server **1014**, acting as a controller is included in the private cloud-computing facility **1002** and interfaces to a VCC node **1016** that runs as a virtual appliance within the cloud director **1010**. A VCC server may also run as a virtual appliance within a VDC management server that manages a single-tenant private cloud. The VCC server **1014** additionally interfaces, through the Internet, to VCC node virtual appliances executing within remote VDC management servers, remote cloud directors, or within the third-party cloud services **1018-1023**. The VCC server provides a VCC server interface that can be displayed on a local or remote terminal, PC, or other computer system **1026** to allow a cloud-aggregation administrator or other user to access VCC-server-provided aggregate-cloud distributed services. In general, the cloud-computing facilities that together form a multiple-cloud-computing aggregation through distributed services provided by the VCC server and VCC nodes are geographically and operationally distinct.

Containers and Containers Supported by Virtualization Layers

As mentioned above, while the virtual-machine-based virtualization layers, described in the previous subsection, have received widespread adoption and use in a variety of different environments, from personal computers to enormous distributed computing systems, traditional virtualization technologies are associated with computational overheads. While these computational overheads have steadily decreased, over the years, and often represent ten percent or less of the total computational bandwidth consumed by an application running above a guest operating system in a virtualized environment, traditional virtualization technologies nonetheless involve computational costs in return for the power and flexibility that they provide.

While a traditional virtualization layer can simulate the hardware interface expected by any of many different operating systems, OSL virtualization essentially provides a secure partition of the execution environment provided by a particular operating system. As one example, OSL virtualization provides a file system to each container, but the file system provided to the container is essentially a view of a partition of the general file system provided by the underlying operating system of the host. In essence, OSL virtualization uses operating-system features, such as namespace isolation, to isolate each container from the other containers running on the same host. In other words, namespace isolation ensures that each application is executed within the execution environment provided by a container to be isolated from applications executing within the execution environments provided by the other containers. A container cannot access files not included the container's namespace and cannot interact with applications running in other containers. As a result, a container can be booted up much faster than a VM, because the container uses operating-system-kernel features that are already available and functioning within the host. Furthermore, the containers share computational bandwidth, memory, network bandwidth, and other computational resources provided by the operating system, without the overhead associated with computational resources allocated to VMs and virtualization layers. Again, however, OSL virtualization does not provide many desirable features of traditional virtualization. As mentioned above, OSL virtualization does not provide a way to run different types of operating systems for different groups of containers within the same host and OSL-virtualization does not provide for live migration of containers between hosts, high-availability functionality, distributed resource scheduling, and other computational functionality provided by traditional virtualization technologies.

FIG. **11** shows an example server computer used to host three containers. As discussed above with reference to FIG. **4**, an operating system layer **404** runs above the hardware **402** of the host computer. The operating system provides an interface, for higher-level computational entities, that includes a system-call interface **428** and the non-privileged instructions, memory addresses, and registers **426** provided by the hardware layer **402**. However, unlike in FIG. **4**, in which applications run directly above the operating system layer **404**, OSL virtualization involves an OSL virtualization layer **1102** that provides operating-system interfaces **1104-1106** to each of the containers **1108-1110**. The containers, in turn, provide an execution environment for an application that runs within the execution environment provided by container **1108**. The container can be thought of as a partition of the resources generally available to higher-level computational entities through the operating system interface **430**.

FIG. **12** shows an approach to implementing the containers on a VM. FIG. **12** shows a host computer similar to that shown in FIG. **5**A, discussed above. The host computer includes a hardware layer **502** and a virtualization layer **504** that provides a virtual hardware interface **508** to a guest operating system **1102**. Unlike in FIG. **5**A, the guest operating system interfaces to an OSL-virtualization layer **1104** that provides container execution environments **1206-1208** to multiple application programs.

Note that, although only a single guest operating system and OSL virtualization layer are shown in FIG. **12**, a single virtualized host system can run multiple different guest operating systems within multiple VMs, each of which supports one or more OSL-virtualization containers. A virtualized, distributed computing system that uses guest operating systems running within VMs to support OSL-virtualization layers to provide containers for running applications is referred to, in the following discussion, as a "hybrid virtualized distributed computing system."

Running containers above a guest operating system within a VM provides advantages of traditional virtualization in addition to the advantages of OSL virtualization. Containers can be quickly booted in order to provide additional execution environments and associated resources for additional application instances. The resources available to the guest operating system are efficiently partitioned among the containers provided by the OSL-virtualization layer **1204** in FIG. **12**, because there is almost no additional computational overhead associated with container-based partitioning of computational resources. However, many of the powerful and flexible features of the traditional virtualization technology can be applied to VMs in which containers run above guest operating systems, including live migration from one host to another, various types of high-availability and distributed resource scheduling, and other such features. Containers provide share-based allocation of computational resources to groups of applications with guaranteed isolation of applications in one container from applications in the remaining containers executing above a guest operating system. Moreover, resource allocation can be modified at run time between containers. The traditional virtualization layer provides for flexible and scaling over large numbers of hosts within large distributed computing systems and a simple approach to operating-system upgrades and patches. Thus, the use of OSL virtualization above traditional virtualization in a hybrid virtualized distributed computing system, as shown in FIG. **12**, provides many of the advantages of both a traditional virtualization layer and the advantages of OSL virtualization.

Methods to Quantize and Compress Time Series Data

FIG. **13** shows example sources of time series data in a physical data center. The physical data center **1302** comprises a management server computer **1304** and any of various computers, such as PC **1306**, on which a virtual-data-center management interface may be displayed to system administrators and other users. The physical data center **1302** additionally includes server computers, such as server computers **1308-1315**, that are coupled together by local area networks, such as local area network **1316** that directly interconnects server computers **1308-1315** and a mass-storage array **1318**. The physical data center **1302** includes three local area networks that each directly interconnects a bank of eight server computers and a mass-storage array. Different physical data centers may include many different types of computers, networks, data-storage systems and devices connected according to many different types of connection topologies. A virtual-interface plane **1322** separates a virtualization layer **1320** from the physical data center **1804**. The virtualization layer **1320** includes virtual objects, such as VMs and containers, hosted by the server computers in the physical data center **1302**. Certain server computers host VMs as described above with reference to FIGS. **5**A-**5**B. For example, server computer **1324** is a host for six VMs **1326** and server computer **1328** is a host for two VMs **1330**. Other server computers may host containers as described above with reference to FIGS. **11** and **12**. For example, server computer **1314** is a host for six containers **1832**. The virtual-interface plane **1322** abstracts the physical data center **1302** to one or more VDCs comprising the virtual objects and one or more virtual data stores, such as virtual data stores **1334** and **1336**, and one or more virtual networks. For example, one VDC may comprise VMs **1326** and virtual data store **1334** and another VDC may comprise VMs **1330** and virtual data store **1336**.

FIG. **13** also shows a management server **1338** located in the virtualization layer **1320** and hosted by the management server computer **1304**. The management server **1338**

receives and stores time series data generated by various physical and virtual resources. The physical resources include processors, memory, network connections, and storage of each computer system, mass-storage devices, and other physical components of the physical data center **1804**. Virtual resources also include virtual processors, memory, network connections and storage of the virtualization layer **1320**. The management server **1338** monitors physical and virtual resources by collecting time series data from the physical and virtual objects. Time series data includes physical and virtual CPU usage, amount of memory, network throughput, network traffic, and amount of storage. CPU usage is a measure of CPU time used to process instructions of an application program or operating system as a percentage of CPU capacity. High CPU usage may be an indication of usually large demand for processing power, such as when an application program enters an infinite loop. Amount of memory is the amount of memory (e.g., GBs) an object uses at a given time. Because time series data is collected with such high frequency, the data sets are extremely large and occupy large volumes of storage space within the physical data center **1302**. In addition, because the data sets are large and each data set alone comprises a large amount of time series data points, the management server **1338** is typically overloaded and unable to timely detect anomalies, problems, and characterize each time series data set.

FIG. **14** shows a flow diagram of a method to optimize and compress the time series data stored in a data-storage device. The time series data **1402** may be time series metric data generated by a physical or virtual object of a distributed computing system. The time series data **1402** may be stored in a data-storage device, such as a mass-storage array, of the physical data center **1302**. In block **1404**, the time series data **1402** is quantized to generate quantized time series data. In general, quantization causes a loss of information recorded in the time series data. In block **1406**, the quantized time series data is compressed to reduce the number of consecutive duplicate quantized data points in the quantized time series data. Quantization **1404** and compression **1406** are performed subject to an optimization configuration **1406** that comprises a user selected limitation on loss of information or limitation on a compression rate. The user can put a limitation on the accuracy of information loss created by quantization or put a limitation on the compression rate. For example, the user may choose to maximize the accuracy (i.e., minimize data loss) and put a constraint on the compression rate. Alternatively, the user may choose to maximize the compression rate and put a constraint on the accuracy. Compressed time series data **1410** is output and used to replace the original time series data **1402** in the data-storage device. For example, the time series data may be deleted from the data-storage device and the compressed time series data written to the data-storage device. Alternatively, the time series data may be over written by the compressed time series data. The compressed time series data **1410** occupies far less storage space than the original time series data **1402**, freeing storage space in the data-storage device. The smaller data set of compressed time series data **1410** enables faster and more timely analysis by the management server **1338** to detect anomalies and problems at the resource.

A sequence of time series data is denoted by

$$x_k = x(t_k), k = 1, \ldots, N \tag{1}$$

where

subscript k is a time index;

N is the number of data points;

$x(t_k)$ is a data point; and

t_k is a time stamp that represents when the data point is recorded.

The collection of time series data in Equation (1) may be also be represented as a sequence $X=\{x_k\}_{k=1}^N$.

FIG. **15** shows a plot of example time series data. Horizontal axis **1502** represents time. Vertical axis **1504** represents a range of metric data values. Dots represent individual data points recorded at corresponding time stamps. For example, dot **1506** represents a data point x_k recorded at a time stamp t_k. The time series data may represent metric data generated by a physical or a virtual object. For example, the time series data may represent CPU usage of a core in a multicore processor of a server computer at each time stamp. Alternative, the time series data may represent the amount of virtual memory a VM uses at each time stamp.

Quantization is carried by partitioning time series data according to a selected number n of quantiles denoted by $q_1, q_2, \ldots, q_n$. The set of quantiles $\{q_i\}_{i=1}^n$ divides a data range of time series data into n+1 groups of data points based on the values of the data points in the time series data. Each group contains about the same fraction, or number, of data points of the time series data. For example, each group may contain N/(n+1) data points, where n+1 evenly divides N. On the other hand, n+1 may not divide N evenly and certain groups may contain one or more data points than other groups. The number of quantiles n may be selected in accordance with a user selected accuracy or compression rate as described below.

FIG. **16** shows the example sequence of time series data of FIG. **15** partitioned into ten groups of data points with nine example quantiles. The nine quantiles are denoted by $q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8$, and q_9. Horizontal dashed lines represent the nine quantiles that divide the values of the time series data into ten groups, each group containing two data points. For example, adjacent pairs of dashed lines **1602** and **1604** represent adjacent quantiles q_5 and q_6, respectively, that partition two data points **1606** and **1506** from other data points in the time series data. End dashed line **1608** represents the smallest quantile q_1 that partitions two data points **1610** and **1612** from the time series data. End dashed line **1614** represents the largest quantile q_9 that partitions two data points **1616** and **1618** from the time series data.

Quantization **1404** of time series data **1402** of FIG. **14** is carried by determining quantized time series data from the time series data and the n quantiles. Let

$$x_k^q=x^q(t_k), k=1, \ldots, N \tag{2}$$

represent the quantized time series data. The sequence of quantized time series data is represented by

$$X^q=\{x_k^q\}_{k=1}^N.$$

The quantized time series data X^q is created from the time series data X^q and the n quantiles as follows. Each quantized data point x_k^q in the quantized time series data X^q has a corresponding data point x_k in the time series data X. Each quantized data point x_k^q is assigned the value of the quantile in the set of quantiles $\{q_i\}_{i=1}^n$ that is closest to the corresponding data point x_k. For a data point x_k in X, the closest unique quantile is given by

$$\underset{i=1,\ldots,n}{\operatorname{argmin}}|x_k-q_i|=q_{i_0} \tag{3}$$

where $q_{i_0}\in\{q_i\}_{i=1}^n$ is the closest unique quantile to the data point x_k.

The corresponding quantized data point x_k^q of the quantized time series data X^q is assigned the value of the quantile q_{i_0} closest to the data point x_k. A data point x_k in X that is located midway between two quantiles, has two closest non-unique quantiles given by:

$$\operatorname{argmin}_{i=1,\ldots,n}|x_k-q_i|=q_{i_0} \text{ and } \operatorname{argmin}_{i=1,\ldots,n}|x_k-q_i|=q_{i_0+1} \tag{4}$$

where $q_{i_0}, q_{i_0+1}\in\{q_i\}_{i=1}^n$ are adjacent quantiles.

The data point x_k is located midway between two adjacent quantiles q_{i_0} and q_{i_0+1}. In this case, when the preceding quantized data point x_{k-1}^q equals either q_{i_0} and q_{i_0+1}, the quantized data point x_k^q is assigned the value of x_{k-1}^q. Otherwise, when the preceding quantized data point x_{k-1}^q does not equal either q_{i_0} and q_{i_0+1}, then x_k^q is assigned the larger of q_{i_0} and q_{i_0+1}. Alternatively, x_k^q is assigned the smaller of q_{i_0} and q_{i_0+1}.

Accuracy of quantization of time series data can be measured using any one of the following loss functions ("LFs"):

$$LF=l_1=\frac{1}{N}\sum_{k=1}^N|x_k-x_k^q| \tag{5}$$

$$LF=l_2=\frac{1}{N}\sum_{k=1}^N|x_k-x_k^q|^2 \tag{6}$$

and

$$LF=l_{med}=\operatorname{median}|x_k-x_k^q| \tag{7}$$

The value of a loss function is a measure of how much the quantized time series data X^q differs from the time series data X. The larger a loss function value is, the farther, or more distant, the quantized time series data X^q is from the time series data X.

Compression **1406** of the quantized time series data of FIG. **14** is created by elimination of sequential repetitions, or consecutive duplications, of quantized data points x_k^q from the quantized time series data X^q. The remaining quantized time series data forms compressed time series data denoted by:

$$x_k^c=x^c(t_k), k=1, \ldots, M \tag{8}$$

where M≤N.

The sequence of compressed time series data is represented by $X^c=\{x_k^c\}_{k=1}^M$.

The compression rate is given by:

$$CR=100\frac{N-M}{N} \tag{9}$$

The compression rate is a measure of how much of the time series data X has been reduced to obtain the compressed time series data X^c A large compression rate corresponds to large amount of the quantized time series data having been removed as a result of compression. A small compression rate corresponds to small amount of the quantized time series data having been removed as a result of compression.

Quantization creates a loss of information from the time series data. As the number of quantiles n is increased, the amount of information lost is decreased, as represented in

FIG. **17**. FIG. **17** shows a plot of a loss function versus quantiles. Horizontal axis **1702** represents a range of quantiles. Vertical axis **1704** represents a range of loss function values. Dashed curve **1706** represents the value of the loss function over the range quantiles. Note that as the number of quantiles increases, the loss function decreases. The asymptotic portion of the loss function indicates that continued increases in the number of quantiles achieves only a marginal decrease or insignificant decrease in the loss of information from the time series data.

Compression, on the other hand, is a lossless transformation of the quantized time series data. In other words, information is not lost from compressing the quantized time series data. The compression rate is a linear function of the number M of quantized data points in the compressed time series data. FIG. **18** shows a plot of the compression rate as a function M. Horizontal axis **1802** represents a range of values for M between 0 and N. Vertical axis **1804** presents the range of compression rate values between 0 and 100. Negatively sloped line **1806** represents the compression rate. A small compression rate (i.e., large M) indicates that compression has resulted in a small reduction in the amount of data stored. In other words, as the number M approaches the number N, the amount of data storage used to store the compressed time series data X^c approaches the amount of data storage used to store the original time series data X. As the number M approaches zero, the amount of data storage used to store the compressed time series data X^c is far less than the storage used to store the original time series data X.

The number of quantiles, n, is ideally selected such that the loss function reaches a minimum:

$$LF\rightarrow\min \tag{10}$$

and the compression rate is maximized:

$$CR\rightarrow\max \tag{11}$$

However, simultaneously minimization of the loss function and maximization of the compression rate is not feasible. Maximization of the compression rate corresponds to an increase in the loss function. On the other hand, minimization of the loss function corresponds to a decrease in the compression rate. A user selects which of these optimization conditions to use in reducing the size of time series data.

This inability to simultaneously maximize the compression rate and minimize the loss function is resolved by allowing the user an opportunity to select from two optimization conditions. A first optimization condition allows a user to set an upper bound on the loss function while maximizing the compression rate as follows:

$$\begin{gathered} CR\rightarrow\max \\ LF\le\Delta \end{gathered} \tag{12}$$

where Δ is a loss function upper bound.

A second optimization condition allows a user to set a lower bound on the compression rate while minimizing the loss function as follows:

$$\begin{gathered} CR\ge r \\ LF\rightarrow\min \end{gathered} \tag{13}$$

where r is a compression rate lower bound.

A user selects one of the above optimization conditions represented by Equations (12) and (13) to solve for a given number of quantiles n. In other implementations, the number of quantiles may be varied to determine an optimal number of quantiles n for either of the optimization conditions represented by Equations (12) and (13).

Optimization according to the condition in Equation (12) or the condition in Equation (13) is accomplished by iteratively quantizing and compressing the time series data for a given number of quantiles $q_1, q_2, \ldots, q_n$. In a first iteration, the time series data is separately quantized to each of the n quantiles to obtain n sequences of quantized time series data. Each sequence of quantized time series data is compressed to obtain n sets of compressed time series data. A loss function value and compression rate are computed for each set of the n sets of compressed time series data. The compressed time series data with corresponding loss function value and compression rate that best satisfies the optimization condition (12) or (13) is used to replace the original time series data. If none of the loss function values and corresponding compression rates satisfies the selected optimization condition, the method proceeds to a second iteration. In the second iteration, quantization and compression are carried out on the time series data for each combination of two of the quantiles $q_1, q_2, \ldots, q_n$ to obtain sets of compressed time series data and corresponding loss function values and compression rates. The compressed time series data with corresponding loss function value and compression rate that satisfies the selected optimization condition is used to replace the original time series data. If none of the loss function values and corresponding compression rates satisfies the selected optimization condition, the method proceeds to a third iteration.

With each iteration, the number of combinations of quantiles used to quantize the original time series data is given by:

$$C(n, m) = \frac{n!}{m!(n-m)!} \tag{14}$$

where

m<n; and

m is the m-th iteration and corresponds to the number of quantiles in the set of n quantiles used to quantize and compress the original time series data.

The number of compressed time series data is C(n, m). A loss function value and compression rate is computed for each compressed time series data. As a result, each compressed time series data has an associated loss function value and compression rate represented by:

$$X^c\rightarrow(CR,LF) \tag{15}$$

When a compression rate and loss function value satisfy the selected optimization condition of Equation (12) or (13), the process stops and the associated compressed time series data is used to replace the original time series data.

FIGS. **19-23** illustrate the first and second iterations of quantization and compression of the time series data shown in FIG. **15** using the nine quantiles shown in FIG. **16**. In the first iteration, combinations index m equals 1 and the number of combinations of the nine quantiles is C(9,1)=1. In other words, quantization and compression are carried out in the same manner for each of the quantiles q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8, and q_9.

FIGS. **19**A-**19**C show an example of quantizing and compressing the example sequence of time series data shown in FIG. **15** to the quantile q_2 of a first iteration. FIG.

19A shows directional arrows that represent quantization of the time series data to the quantile q_2. Note that because only one quantile is considered at a time in the first iteration, the data points of the time series data are all quantized to the same quantile, which in this case is the quantile q_2. FIG. **19**B shows the quantized time series data that result from quantization to the quantile q_2. The quantized time series data is represented by $x_k=q_2$, for k=1, . . . , 20. Compression eliminates sequential repetitions in the quantized time series data. In one implementation, the first data point in a sequential repetition of the quantized time series data is retained and the other data points in the sequence are deleted. In another implementation, the first and the last data points in a sequential repetition of the quantized time series data are retained and the data points between the first and last data points are deleted. For example, compression reduces the quantized time series data of FIG. **19**B to a single data point $x_1^c=q_2$ **1902**, as represented in FIG. **19**C. Alternatively, compression reduces the quantized time series data of FIG. **19**B to a two data points $x_1^c=q_2$ and $x_{20}^c=q_2$ as represented in FIG. **19**C by data points **1902** and **1904**, respectively. Any one of the loss functions given by Equations (5), (6), and (7) can be used to compute a loss function value to obtain a measure of the amount of lost information in performing the quantization step. The compression rate calculated according to Equation (9) is 100((20−1)/20)=95%.

For the first iteration, quantization and compression are carried out in the same manner as represented in FIGS. **19**A-**19**C for each of the remaining quantiles q_1, q_3, q_4, q_5, q_6, q_7, q_8, and q_9. A loss function value and compression rate is computed for each quantile. FIG. **20** shows a plot of example loss function values computed for each of the nine quantiles. The loss function values may be computed using one of the loss functions given by Equations (5), (6), and (7). Horizontal axis **2002** represents a range of quantiles. Vertical **2004** represents a range of loss function values. Open dots represent loss function values calculated for each of the quantized time series data obtained by quantization of the time series data to one of the quantiles. For example, dot **2006** represents the loss function value obtained from quantizing the time series data to the quantile q_2, as described above with reference to FIGS. **19**A-**19**B. Note that loss function values **2008** and **2010** are largest for the quantiles q_1 and q_9, respectively, because these quantiles are farthest from most of the time series data. On the other hand, the loss function value **2012** for the quantile q_5 is the smallest, because the quantile q_5 is the median of the time series data and the closest quantile to all the data points.

Because quantized time series data includes sequential repeats of the data values, as shown in FIG. **19**B, compression reduces each repeated sequence of quantized data points to a single value. Thus, the compressed time series data have the same compression rate of 95%. FIG. **21** shows a plot of the loss function values of FIG. **20** versus the compression rate. Horizontal axis **2102** represents a range of compression rates. Vertical axis **2104** represents a range of loss function values. Dots represent the loss function values for the same compression rate of 95%. For example, loss function values **2106**, **2108**, **2110**, and **2112** correspond to the loss function values **2006**, **2008**, **2010**, and **2012** in FIG. **20**. Because the compressed time series data all have the same compression rate of 95%, the smallest loss function value is used to identify which compressed time series data best represents the original time series data for the first iteration. In this example, compressed time series data is $x_k^q=q_5$ has the smallest loss function value.

If a user has selected a loss function upper bound Δ for the optimization condition of the Equation (12) and the loss function values are greater than Δ, then the method proceeds to the next iteration. If a user has selected a compression rate minimum r=96% for the optimization condition of Equation (13), the method proceeds to the next iteration because the compression rate for the quantiles is 95%.

In the second iteration, the combination index in equals 2 and the number of combinations of the nine quantiles is C(9,2)=36. In other words, quantization and compression are carried out for 36 combinations of two quantiles of the nine quantiles q_2, q_3, q_4, q_5, q_6, q_7, q_8, and q_9.

FIGS. **22**A-**22**C show an example of quantization and compression carried out on the example sequence of time series data shown in FIG. **15** using the two quantiles q_2 and q_7 in a second iteration. In FIG. **22**A, none of the data points are located midway between the two quantiles q_2 and q_7. Unlike the case where there is only one quantile to quantize the time series data as described above with reference to FIGS. **19**A-**19**C, the quantile closest to each data point x_k **1506** is determined by

$$\underset{i=2,7}{\operatorname{argmin}}|x_k - q_i|$$

Dashed line **2202** is the distance $|x_k-q_7|$ between the data point **1506** and the quantile q_7 and dashed line **2204** is the distance $|x_k-q_2|$ between the data point **1506** and the quantile q_2. The quantized data point x_k^q is assigned the quantile value q_7, because $|x_k-q_7|<|x_k-q_2|$. FIG. **22**B shows directional arrows that represent quantization of the time series data to the closest of the two quantiles q_2 and q_7. FIG. **22**C shows the quantized time series data that results from quantization to the two quantiles q_2 and q_7. The quantized time series data is represented by $x_k=q_2$ for time stamps **2206**, and $x_k=q_7$ for time stamps **2208**. Compression eliminates sequential repetitions in the quantized time series data. In one implementation, FIG. **22**D shows how compression may be used to reduce a sequence of the quantized time series data that repeats the quantile q_2 for consecutive time stamps **2206** to a single value $x_1^c=q_2$ and reduce a sequence of the quantized time series that repeats the quantile q_7 for the consecutive time stamps **2207** to a single value $x_1^c=q_2$. Alternatively, compression may be used to reduce the sequence of the quantized time series that repeats the quantile q_2 for the consecutive time stamps **2206** to two data points q_2 and $x_{10}^c=q_2$ as represented in FIG. **22**D by data points **2210** and **2214**, respectively. Compression may be used to reduce the sequence of the quantized time series that repeats the quantile q_7 for the consecutive time stamps **2207** to two data points $x_{11}^c=q_7$ and $x_{20}^c=q_7$ as represented in FIG. **22**D by data points **2212** and **2216**, respectively. Any one of the loss functions given by Equations (5), (6), and (7) is used to compute a loss function value to obtain a measure of the amount of lost information in performing the quantization step. The compression rate calculated according to Equation (9) is 100((20−2)/20)=90%. Although the compression rate has not been reduced, the compresses time series data more closely matches the two clusters of data points in the original time series data and would have a lower loss function value than the loss function value for $x_k^q=q_5$, for k=1.

A loss function value and compression rate are computed for each combination of different pairs of the quantiles. The resulting set of loss function values and associated compression rates are subject to one of the selected optimization conditions given by Equation (12) or (13). The compressed time series data that correspond to the loss function value and compression rate that satisfies the selected condition is used to replace the original time series data in data storage.

FIG. **23** shows a plot of example loss function values versus compression rates for 36 combinations of different pairs of quantiles used to quantize and compress time series data. Each open point represents a loss function value and corresponding compression rate (CR, LF) computed for a pair of quantiles, as described above with reference to FIGS. **22**A-**22**D. Suppose a user selected optimization of the loss function for a user selected lower bound r on the compression rate represented by dashed line **2302**. According to the optimization condition in Equation (13), point **2304** has the minimum loss function value with a corresponding compression rate greater than the lower bound compression rate r. In this example, because the optimization condition in Equation (13) is satisfied, quantization and compression process stops and the compressed time series data associated with the point **2304** would be used to replace the original time series data. Suppose a user selected optimization of the compression rate for a selected upper bound Δ on loss function represented by dashed line **2306**. According to the optimization condition in Equation (12), point **2308** has the maximum compression rate with a corresponding loss function values less than the upper bound Δ. In this example, because the optimization condition in Equation (12) is satisfied, the quantization and compression process would also stop and the compressed time series data associated with the point **2308** would be used to replace the original time series data.

The example upper and lower bounds in FIG. **23** illustrate how the compressed time series data used to replace the original time series data may be different depending on which of the two optimization conditions are selected by the user. The compressed time series data associated with the point **2304** minimizes the amount of information lost due to quantization with a lower compression rate. While the compressed time series data associate with the point **2308** maximizes the amount of compressed data while giving up some loss in information content due to quantization.

If a user selected an upper bound Δ for the optimization condition of Equation (12) and the loss function values are greater than Δ, then the method proceeds to a third iteration. If a user selected a lower bound r for the optimization condition of Equation (13), the method proceeds to the third iteration because the compression rate for the quantiles is less the r. In the third iteration, the combination index m is equal to 3 and the number of combinations of the nine quantiles is C(9,3)=84. In other words, quantization and compression are carried out for 84 combinations of three quantiles of the nine quantiles q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8, and q_9.

In other implementation, the number of quantiles considered in each iteration may be reduced by using the quantiles that are closest to satisfying the optimization condition from the previous iteration combined with another quantile. For example, suppose the quantiles q_2 and q_7 fail to satisfy the user selected optimization condition of Equation (12) or (13) but are closest to satisfying the select quantization condition. The third iteration may be carried out with the quantiles q_2 and q_7 combined separately with each of the remaining quantiles q_1, q_3, q_4, q_5, q_6, q_8, and q_9 until the selected optimization condition is satisfied.

FIG. **24** shows a control-flow diagram of a method to quantize and compress time series data. In block **2401**, a sequence of time series data is read from a database or

data-storage device. In block **2402**, the time series data is partitioned according to n quantiles as described above with reference to FIG. **16**. A loop beginning with block **2403** repeats the computational operations represented by blocks **2404**-**2414** for each value of the combination index m described above with reference to Equation (14). A loop beginning with block **2404** repeats the computational operations represented by blocks **2405**-**2407** for each combination of in quantiles of the set of n quantiles. In block **2405**, a routine "quantize time series data" is called. In block **2406**, a routine "compressed quantized time series data" is called. In block **2407**, a routine "compute compression rate and loss function" is called. In decision block **2408**, when the combinations of m quantiles. have been exhausted, control flows to decision block **2409**. In decision block **2409**, if the user selected the optimization condition represented by Equation (13), control flows to block **2410**. If the user selected the optimization condition represented by Equation (12), control flows to block **2411**. In block **2410**, a routine "determine if any compression rates and loss functions satisfy first optimization condition" is called. In block **2411**, a routine "determine if any compression rates and loss functions satisfy second optimization condition" is called. Blocks **2410** and **2411** return a constant SC that can be "0" or "1." In decision block **2412**, when the value of the constant SC returned from block **2410** or block **2411** equals "0," none of the combination rates and loss function values satisfies the conditions represented by Equations (12) or (13) and control flows to decision block **2414**. Otherwise, when the value of the constant SC returned from block **2410** or block **2411** equals "1," a combination rate and loss function value that satisfies the conditions represented by Equations (12) or (13) has been determined and control flows to block **2413**. In block **2413**, the time series data is replaced with the compressed time series data associated with the compression rate and loss function value that satisfied the user selected optimization condition. In block **2414**, when the number of combinations m is less than or equal to n/2, control flows to block **2415**. In block **2415**, the number of combinations index in is incremented.

FIG. **25** shows a control-flow diagram of the routine "quantize time series data" called in block **2405** of FIG. **24**. A loop beginning with block **2501** repeats the computational operations represented by blocks **2502** and **2503** for each data point in the sequence of time series data. In block **2502**, the closest quantile of the m quantiles to the data point x_k is determined as described above with reference to Equation (3) is determined. In decision block **2503**, if the closest quantile is unique (i.e., the data point x_k is not midway between two quantiles q_{i_0} and q_{i_0+1} as described above with reference to Equation (3)), control flows to block **2504**. In block **2504**, the corresponding quantized data point x_k^q is assigned the value of the closest quantile q_{i_0} to the data point x_k and added to the quantized time series data X^q, as described above with reference to FIGS. **19**B and **22**C. In decision block **2505**, when the preceding quantized data point x_{k-1}^q is equal to either of the two quantiles q_{i_0} and q_{i_0+1}, control flows to block **2506**. In block **2506**, the quantized data point x_k^q is assigned the value of the preceding quantized data point In decision block **2507**, when q_{i_0} is less than q_{i_0+1}, control flows to block **2508** and the quantized data point x_k^q is assigned the larger value q_{i_0+1}. In decision block **2509**, when k is not equal to N, control flows to block **2510** in which k is incremented.

FIG. **26** shows a control-flow diagram of the routine "compress quantized time series data" called in block **2406** of FIG. **24**. In block **2601**, the parameters k and M are initialized to "1." In block **2602**, the quantized data point x_k^q is read from the quantized time series data X^q. In block **2603**, the parameter p is set equal to k+1. In block **2604**, the quantized data point x_k^q is read from the quantized time series data X^q. In decision block **2605**, when the quantized data points x_k^q and x_p^q, control flows to block **2606**. Otherwise, control flows block **2609**. In block **2606**, the quantized data point x_p^q is removed from the quantized time series data X^q. In decision block **2607**, when p is less than N control flows to block **2608** in which p is incremented. In block **2609**, the parameter M is incremented. In decision block **2610**, when p is less than N control flows to block **2611** in which k is assigned the value of p.

FIG. **27** shows a control-flow diagram of the routine "compute compression rate and loss function" called in block **2407** of FIG. **24**. In block **2701**, the loss function LF is computed for the quantized time series data using any one of the loss functions described above with reference to Equations (5), (6), and (7). In block **2702**, the compression rate CR is computed using the value of the parameter M determined in the compression routine of block **2406** as described above with reference to Equation (9). In block **2703**, the compression rate and loss function value, (CR, LF), for the compressed time series data obtained in block **2406** of FIG. **24** is stored in a data-storage device.

FIG. **28** shows a control-flow diagram of the routine "determine if any compression rates and loss functions satisfy first optimization condition" called in block **2410** of FIG. **24**. In block **2801**, the parameter SC is initialized "0" and the minimum loss function value LF_{min} is initialized. The initial value of zero for the parameter SC indicates that no compression rate and loss function value satisfies the optimization condition represented by Equation (13). A loop beginning with block **2802** repeats the computational operations represented by blocks **2803-2806** for each compression rate and loss function value (CR, LF) associated with a sequence of compressed time series data in X^c. In decision block **2803**, when the compression rate CR is greater than a user selected lower bound r for the compression rate, control flows to decision block **2804**. In decision block **2804**, when the loss function value LF is greater than a user selected lower bound r for the compression rate, control flows to block **2805**. In block **2805**, the compression rate and loss function value that satisfies the conditions in blocks **2803** and **2804** is stored as (CR_h, LF_h). In block **2806**, the parameter SC is set equal to "1," which indicates that a compression rate and loss function value that satisfies the optimization condition represented by Equation (13) has been found. In decision block **2807**, if other compression rates and loss function values (CR, LF) are have not processed, control flows to block **2808**, in order to determine if there exists another compression rate and loss function value that minimizes the loss function. In block **2808**, the minimum loss function value LF_{min} is set to the current loss function value LF.

FIG. **29** shows a control-flow diagram of the routine "determine if any compression rates and loss functions satisfy second optimization condition" called in block **2411** of FIG. **24**. In block **2901**, the parameter SC is initialized "0" and the maximum compression rate CR_{max} is initialized. The initial value of zero for the parameter SC indicates that no compression rate and loss function value satisfies the optimization condition represented by Equation (12). A loop beginning with block **2902** repeats the computational operations represented by blocks **2903-2906** for each compression rate and loss function value (CR, LF) associated with a sequence of compressed time series data in X'. In decision

block **2903**, when the loss function value LF is less than or equal to a user selected upper bound Δ for the loss function, control flows to decision block **2904**. In decision block **2904**, when the compression rate CR is greater than maximum compression rate CR_{max}, control flows to block **2905**. In block **2905**, the compression rate and loss function value that satisfies the conditions in blocks **2903** and **2904** is stored as (CR_h, LF_h). In block **2906**, the parameter SC is set equal to "1," which indicates that a compression rate and loss function value that satisfies the optimization condition represented by Equation (12) has been found. In decision block **2907**, if other compression rates and loss function values (CR, LF) are have not processed, control flows to block **2908**, in order to determine if there exists another compression rate and loss function value that minimizes the loss function. In block **2908**, the maximum compression rate CR_{max} is set to the current compression rate CR.

In other implementation, the operations represented by blocks **2405-2407** may be carried using the quantiles that are closest to satisfying the optimization condition from the previous iteration combined with another quantile. For example, suppose that after the first iteration, the quantiles q_i is closest to satisfying the selected optimization condition of Equation (12) or (13). A second iteration may be carried out for different combinations of the quantile q_i and the quantiles q_j, where j=1, . . . , n. If a combination of quantiles q_i and q_j are determined are closest but still do not satisfy the optimization condition of Equation (12) or (13), a third iteration is carried out with the combination of quantiles q_i, q_j, and q_l, where l=1, . . . , n. The process of using the quantiles from a previous iteration continues until the selected optimization condition is satisfied as described above with reference to **28** and **29**.

The method of FIGS. **24-29** automates the task of quantizing and compressing time series data stored in data-storage devices of a distributed computing system. The compressed time series data used to replace the original time series data in block **2413** of FIG. **24** occupies far less storage space than the original time series data, freeing storage space in the data-storage device. The time series data may be replaced by deleting the time series data from the data-storage device and writing the compressed time series data to the data-storage device. Alternatively, the time series data may be overwritten by the compressed time series data. The smaller set of compressed time series data also enables faster and more timely analysis by a management server. For example, the management server can process the compressed time series data in real time or near real time to search for anomalous behavior of a resource or object, identify problems with the resource, and characterize the compressed time series data. For example, an anomaly or problem may be identified when compressed data points violate a threshold. When an anomaly or problem is detected, the management server may generate an alert identifying the anomaly or problem, and because there is no significant delay, a system administrator is better able to respond accordingly.

FIGS. **30**A-**35**B show examples of quantization and compression applied to actual high-variability and low-variability sets of time series data. FIG. **30**A shows a plot of a high-variability set of time series data comprising 2340 data points. The minimum data value is min(data)=8.9. The maximum data value is max(data)=85.9. A set of 100 quantiles was applied to the time series data as described above with reference to Equation (3). FIG. **30**B shows a plot of error values versus quantiles for the time series data shown in FIG. **30**A. The error values were computed for each of the 100 quantiles using Equation (5) and are given by l_1/mean(data). Line **3002** in FIG. **30**A represents the quantile value of 29.3, which is the median value of the time series data and corresponds to the 0.5-th quantile. The compression rate of CR=100% is the same for each quantile of the 100 quantiles. FIG. **30**C shows the original time series data of FIG. **30**A represented by a gagged curve **3004** and the quantized time series data for quantile value of 29.3 represented by dashed line **3006**.

FIG. **31**A shows a plot of the time series data with two quantiles of the 100 represented by lines **3102** and **3104**. Line **3102** corresponds to the 75-th quantile with a value of 31.53. Line **3104** corresponds to the 25-th quantile with a value of 27. FIG. **31**B shows the time series data represented by gagged curve **3106**. Dashed line curve **3108** represents the quantized time series data for the 25-th and 75-th quantiles. The corresponding compression rate is 66.6% and the error is l_1/mean(data)=0.0608. The compression rate was increased by increasing the error. A lower bound of 90% was placed on the compression rate. FIG. **31**C shows a plot of error (i.e., loss function/mean(data)) versus compression rate for 10,201 pairs of the 100 quantiles applied to the time series data. The two quantiles of 19.7 and 29.7 of the 100 quantiles gave a minimum error of 0.086 and a compression rate of 90.7%. The quantized time series data obtained with the quantiles 19.7 and 29.7 are represented in FIG. **31**D by dashed curve **3110**.

FIG. **32**A shows a plot of low-variability time series data comprising 2346 data points. FIG. **32**B shows a plot of error versus 30 quantiles applied to the time series data. Each dot represents an error value computed for one of 30 quantiles. Line **3202** in FIG. **32**A is the 0.5-th quantile equal to 75, which gave a minimum error of l_1/mean(data)=0.24.

FIG. **33**A shows a plot of the time series data with two of the 30 quantiles represented by lines **3302** and **3304**. The quantile **3302** is 31 (0.14-th quantile) and the quantile **3304** is 76 (0.53-th quantile). These two quantiles gave minimize error of l_1/mean(data)=0.051 and a compression rate of 99.7%. FIG. **33**B shows the time series data represented gagged curve **3306** and the quantized time series data obtained from the quantiles **3302** and **3304** represented by dashed curve **3308**.

FIG. **34**A shows a plot of the time series data with three of the 30 quantiles represented by lines **3402**, **3404**, and **3406**. The quantile **3402** is 31 (0.14-th quantile), the quantile **3404** is 73 (0.38-th quantile), and the quantile **3406** is 78 (0.66-th quantile). These three quantiles gave a minimize error of l_1/mean(data)=0.036 and a compression rate of 98.9%. FIG. **33**B shows the time series data represented by gagged curve **3408** and the quantized time series data obtained from the quantiles **3402**, **3404**, and **3406** represented by dashed curve **3410**.

FIG. **35**A shows a plot of the time series data with four of the 30 quantiles represented by lines **3502**, **3504**, **3506**, and **3508**. The quantile **3502** is 25 (0.06-th quantile), the quantile **3504** is 33 (0.2-th quantile), the quantile **3504** is 73 (038-th quantile), and the quantile **3508** is 78 (0.66-th quantile). These four quantiles gave a minimize error of l_1/mean(data) =0.026 and a compression rate of 98.6%. FIG. **35**B shows the time series data represented by gagged curve **3510** and the quantized time series data obtained from the quantiles **3502**, **3504**, **3506**, and **3508** represented by dashed curve **3510**.

The results of FIG. **30-35** indicate that, in general, for low-variability data increasing the number of quantiles to quantize the time series data decrease the error without significant impact on the compression rate. The same is not true for high-variability data.

It is appreciated that the previous description of the disclosed embodiments is provided to enable any person skilled in the art to make or use the present disclosure. Various modifications to these embodiments will be apparent to those skilled in the art, and the generic principles defined herein may be applied to other embodiments without departing from the spirit or scope of the disclosure. Thus, the present disclosure is not intended to be limited to the embodiments shown herein but is to be accorded the widest scope consistent with the principles and novel features disclosed herein.

The invention claimed is:

1. A method stored in one or more data-storage devices and executed using one or more processors of a management server computer to quantize and compress time series data generated by an object of a distributed computing system, the method comprising:

- partitioning the time series data stored in a data-storage device into groups of time series data for a set of quantiles that divides a range of values of the time series data such that each group contains a subset of the time series data;
- for each different combination of one or more quantiles of the set of quantiles
  - computing quantized time series data from the time series data and the combination of one or more quantiles,
  - compressing the quantized time series data to generate compressed time series data,
  - computing a loss function value based on the quantized time series data and the time series data, the loss function value representing an amount of information lost in computing the quantized time series data, and
  - computing a compression rate based on a count of data points in the time series data and a count of data points in the compressed time series data; and
- replacing the time series data in the data-storage device with the compressed time series data when an associated loss function value and compression rate satisfy an optimization condition.

2. The method of claim **1** wherein computing the quantized time series data comprises:

- for each data point of the time series data,
  - determining a closest quantile of the combination of one or more quantiles to the data point; and
  - assigning a value of the closest quantile to the data point to a corresponding quantized data point in the quantized time series data.

3. The method of claim **1** wherein compressing the quantized time series data comprises:

- determining each sequence of repeated quantized data points of the quantized time series data;
- deleting repeated quantized data points in each sequence of repeated quantized data points, leaving one quantized data point from each sequence.

4. The method of claim **1** wherein computing the loss function value comprises computing a distance between the quantized time series data and the time series data.

5. The method of claim **1** wherein computing the compression rate comprises computing the compression rate based on a difference between the count of data points in the time series data and the count of data points in the compressed time series data divided by the count of data points in the time series data.

6. The method of claim **1** wherein replacing the time series data in the data-storage device with the compressed time series data when an associated loss function value and compression rate satisfy an optimization condition comprises replacing the time series data in the data-storage device with the compress time series data when the compress rate is at a maximum for an upper bound on the loss function value.

7. The method of claim **1** wherein replacing the time series data in the data-storage device with the compressed time series data when an associated loss function value and compression rate satisfy an optimization condition comprises replacing the time series data in the data-storage device with the compress time series data when the loss function value is at a minimum for a lower bound on the loss function value.

8. The method of claim **1** further comprises when the associated loss function value and compression rate fail to satisfy the optimization condition each combination of the same number of one or more quantiles repeating computing quantized time series data, compressing the quantized time series data, computing a loss function value, and computing a compression rate for each combination of a different number of one or more quantiles.

9. The method of claim **1** further comprising analyzing the compressed time series data stored in the data-storage device to determine an anomaly or problem with an object that generated the time series data.

10. A system to quantize and compress time series data generated by an object of a distributed computing system, 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 perform operations comprising:

partitioning the time series data stored in a data-storage device into groups of time series data for a set of quantiles that divides a range of values of the time series data such that each group contains a subset of the time series data;

for each different combination of one or more quantiles of the set of quantiles

computing quantized time series data from the time series data and the combination of quantiles,

compressing the quantized time series data to generate compressed time series data,

computing a loss function value based on the quantized time series data and the time series data, the loss function value representing an amount of information lost in computing the quantized time series data, and

computing a compression rate based on a count of data points in the time series data and a count of data points in the compressed time series data; and

replacing the time series data in the one or more data-storage device with the compressed time series data when an associated loss function value and compression rate satisfy an optimization condition.

11. The system of claim **10** wherein computing the quantized time series data comprises:

for each data point of the time series data,

determining a closest quantile of the combination of one or more quantiles to the data point; and

assigning a value of the closest quantile to the data point to a corresponding quantized data point in the quantized time series data.

12. The system of claim **10** wherein compressing the quantized time series data comprises:

determining each sequence of repeated quantized data points of the quantized time series data;

deleting repeated quantized data points in each sequence of repeated quantized data points, leaving one quantized data point from each sequence.

13. The system of claim **10** wherein computing the loss function value comprises computing a distance between the quantized time series data and the time series data.

14. The system of claim **10** wherein computing the compression rate comprises computing the compression rate based on a difference between the count of data points in the time series data and the count of data points in the compressed time series data divided by the count of data points in the time series data.

15. The system of claim **10** wherein replacing the time series data in the data-storage device with the compressed time series data when an associated loss function value and compression rate satisfy an optimization condition comprises replacing the time series data in the data-storage device with the compress time series data when the compress rate is at a maximum for an upper bound on the loss function value.

16. The system of claim **10** wherein replacing the time series data in the data-storage device with the compressed time series data when an associated loss function value and compression rate satisfy an optimization condition comprises replacing the time series data in the data-storage device with the compress time series data when the loss function value is at a minimum for a lower bound on the loss function value.

17. The system of claim **10** further comprises when the associated loss function value and compression rate fail to satisfy the optimization condition each combination of the same number of one or more quantiles repeating computing quantized time series data, compressing the quantized time series data, computing a loss function value, and computing a compression rate for each combination of a different number of one or more quantiles.

18. The system of claim **10** further comprising analyzing the compressed time series data stored in the data-storage device to determine an anomaly or problem with an object that generated the time series data.

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 operations comprising:

partitioning the time series data stored in a data-storage device into groups of time series data for a set of quantiles that divides a range of values of the time series data such that each group contains a subset of the time series data;

for each different combination of one or more quantiles of the set of quantiles

computing quantized time series data from the time series data and the combination of one or more quantiles,

compressing the quantized time series data to generate compressed time series data,

computing a loss function value based on the quantized time series data and the time series data, the loss function value representing an amount of information lost in computing the quantized time series data, and

computing a compression rate based on a count of data points in the time series data and a count of data points in the compressed time series data; and

replacing the time series data in the data-storage device with the compressed time series data when an associated loss function value and compression rate satisfy an optimization condition.

20. The medium of claim **19** wherein computing the quantized time series data comprises:

for each data point of the time series data,

determining a closest quantile of the combination of one or more quantiles to the data point; and

assigning a value of the closest quantile to the data point to a corresponding quantized data point in the quantized time series data.

21. The medium of claim **19** wherein compressing the quantized time series data comprises:

determining each sequence of repeated quantized data points of the quantized time series data;

deleting repeated quantized data points in each sequence of repeated quantized data points, leaving one quantized data point from each sequence.

22. The medium of claim **19** wherein computing the loss function value comprises computing a distance between the quantized time series data and the time series data.

23. The medium of claim **19** wherein computing the compression rate comprises computing the compression rate based on a difference between the count of data points in the time series data and the count of data points in the compressed time series data divided by the count of data points in the time series data.

24. The medium of claim **19** wherein replacing the time series data in the data-storage device with the compressed time series data when an associated loss function value and compression rate satisfy an optimization condition comprises replacing the time series data in the data-storage device with the compress time series data when the compress rate is at a maximum for an upper bound on the loss function value.

25. The medium of claim **19** wherein replacing the time series data in the data-storage device with the compressed time series data when an associated loss function value and compression rate satisfy an optimization condition comprises replacing the time series data in the data-storage device with the compress time series data when the loss function value is at a minimum for a lower bound on the loss function value.

26. The medium of claim **19** further comprises when the associated loss function value and compression rate fail to satisfy the optimization condition each combination of the same number of one or more quantiles repeating computing quantized time series data, compressing the quantized time series data, computing a loss function value, and computing a compression rate for each combination of a different number of one or more quantiles.

27. The medium of claim **19** further comprising analyzing the compressed time series data stored in the data-storage device to determine an anomaly or problem with an object that generated the time series data.

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