T.C.
TÜRK PATENT VE MARKA KURUMU
Patent Dairesi Başkanlığı

Sayı : 39616753- 2017/20732 /
Konu : Patent

ZELİHA ÖZSOY (3 TEK PATENT MARKA DANIŞMANLIK A.Ş.)
ÇANKAYA MAH. MAHMUT YESARİ SOK. NO:8/5 ÇANKAYA/ANKARA

İlgi: 19/12/2017 tarihli patent başvurunuz.

İlgide kayıtlı başvurunuzla ilgili olarak Kurumumuz tarafından düzenlenen tekniğin bilinen durumu konusundaki Araştırma Raporu ve Ekleri ilişikte gönderilmektedir.

6769 sayılı Sınai Mülkiyet Kanununun 98 inci maddesinin birinci fıkrası ve anılan Kanunun Uygulanmasına Dair Yönetmeliğin 102 nci maddesinin birinci fıkrası hükümleri uyarınca bildirim tarihinden itibaren üç ay içinde ücretinin de ödenerek inceleme talebinde bulunulması gerekmektedir. Aksi takdirde başvurunuz geri çekilmiş sayılacaktır.

Saygılarımla.

Bilge Cennet BAŞARICI
Kurum Başkanı a.
Sınai Mülkiyet Uzman Yardımcısı

Ek: Araştırma Raporu ve Ekleri

NOTLAR:

1- Türk Patent ve Marka Kurumunun sunduğu hizmetlere ilişkin ücretlerde, ödemenin yapıldığı tarih itibariyle yürürlükte olan Ücret Tebliğinin dikkate alınması gerekmektedir.

2- Başvurunun korunması için gerekli olan yıllık ücretler üçüncü yıldan başlamak üzere her yıl vadesinde ödenir. Vade tarihi, başvuru tarihine tekabül eden ay ve gündür. Yıllık ücretler, vadesinde ödenmediği takdirde ek ücretle birlikte vadeyi takip eden altı ay içinde de ödenebilir. Yıllık ücretlerin bu süre içinde de ödenmemesi halinde başvurular geçersiz sayılır.

3- İşbu yazıya konu talebi, Kurumumuzun Elektronik Başvuru Sistemi (epats.turkpatent.gov.tr) üzerinden, Benim Sayfam panelinde Başvuru Sonrası İşlemler menüsü altında yer alan "İnceleme Talebi" işlemini seçerek gerçekleştirebilirsiniz.

ARAŞTIRMA RAPORU

Başvuru Sahibi: **TURKCELL TEKNOLOJİ ARAŞTIRMA VE GELİŞTİRME ANONİM ŞİRKETİ**		
Başvuru No: 2017/20732	Başvuru Tarihi: 19/12/2017	(İlk) Rüçhan Tarihi –
Patent Sınıfı (IPC[8]): **H04L 12/14,G06N 20/00,H04M 15/00 (2009.01)**		

GENEL GÖZLEMLER

Buluş Bütünlüğü

X Var (başvuru sadece bir buluş konusunu içermektedir)

... (başvuru birden çok buluş konusunu içermektedir) (Bakınız: Bölüm III)

Tarifname Takımı

X Rapor aşağıda belirtilen tarifname takımı esas alınarak düzenlenmiştir.

Tarifname 6 sayfa (Orijinal)

İstem 9 adet (Orijinal)

Resim 1 sayfa (Orijinal)

Açıklık

X Tüm istemler araştırılabilir niteliktedir.

... ... nolu istemler araştırılabilir nitelikte değildir. (Bakınız: Bölüm IV)

... Başvuruyla ilgili diğer görüşler (Bakınız: Bölüm II)

Raporun Tamamlandığı Tarih: **20/10/2020**

Türk Patent ve Marka Kurumu - Patent Dairesi Başkanlığı
Hipodrom Cad. No:115 06330
Yenimahalle/ANKARA
Tel: (312) 303 1182
Faks: (312) 303 1220

Araştırmayı Yapan Uzman:

Bilge Cennet BAŞARICI

ARAŞTIRMA RAPORU

Başvuru Numarası:
2017/20732

A. BULUŞUN PATENT SINIFI (IPC[8])
H04L 12/14,G06N 20/00,H04M 15/00 (2009.01)

B. ARAŞTIRILAN ALANLAR
H04M,G06N,H04L

Araştırma esnasında kullanılan elektronik veritabanları ve -uygun olduğu durumlarda- kullanılan bazı anahtar kelimeler

EPODOC, WPI, EPOQUE İngilizce ve Almanca Tüm-metin Veritabanları (TXTE, TXTDE), Türk Patent Veritabanı, Espacenet, DEPATISnet, KIPRIS, PAJ, IPDL, AIPN, C-PAT

"CDR, error, failure, charging, billing, detection, machine learning, artificial intelligence, control" ve bunların uygun kombinasyonları

C. İLGİLİ DOKÜMANLAR

Kategori	Dokümanlar	İlgili Olduğu İstem
Y	KR100815391BB1 (KT FREETEL CO LTD [KR]) 20 Mart 2008 (20.03.2008) Tüm Doküman	1-9
Y	US2017019291A1 (TUPL INC [US]) 19 Ocak 2017 (19.01.2017) Tarifname: özellikle Paragraf 54,73	1-9

☒ İlgili Dokümanlar sonraki sayfadan devam etmektedir. ☐ Patent Ailesi Üyeleri ekine bakınız.

Kategorilerin Açıklaması:

"X"	Buluşun yeni olmadığını veya buluş basamağı içermediğini tek başına gösteren doküman	"E"	Başvuru tarihinde veya başvuru tarihinden sonra yayımlanan doküman
"Y"	Buluşun buluş basamağı içermediğini başka bir dokümanla bir araya getirildiğinde gösteren doküman	"T"	Buluşun altında yatan ilke veya teoriyi anlamak için belirtilen doküman
"A"	Tekniğin bilinen durumunu belirten ama buluşla tam olarak ilgili olmayan doküman	"L"	Başka nedenlerle belirtilen doküman
"O"	Yazılı olmayan açıklama	"D"	Başvuruda belirtilen doküman
"P"	Başvuru tarihi ile rüçhan tarihi arasında yayımlanan doküman	"&"	Aynı patent ailesinin dokümanı

Türk Patent ve Marka Kurumu - Patent Dairesi Başkanlığı
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Tel: (312) 303 1182
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Araştırmayı Yapan Uzman:

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H04M 15/00 (2006.01) *H04L 12/14* (2006.01)
H04M 3/36 (2006.01)
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(56) 선행기술조사문헌
②한국공개특허KR1020060104701 A(2006.10.9)
③한국등록특허KR100182688 B1(1999.5.15)

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전체 청구항 수 : 총 12 항 심사관 : 이현홍

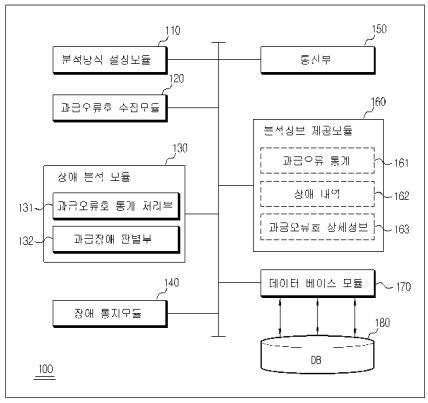
(54) 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식방법 및 장치

(57) 요 약

본 발명은 이동통신 시스템의 과금처리시의 과금오류 및 과금장애를 분석하는 방법 및 장치에 관한 것이다.

본 발명에 따르면, 이동통신 시스템에서 과금처리시 발생되는 과금오류호에 따라 실시간으로 과금처리 장애여부를 분석하는 방법으로서, (a) 운영자 단말로부터 과금오류호에 따른 과금장애 여부를 판단하는 기준을 입력받아 과금장애 분석방식을 설정하는 단계; (b) 과금 서버에서 발생한 과금오류호를 실시간으로 수신하는 단계; (c) 수신되는 과금오류호를 통계적으로 처리하며 상기 설정된 과금장애 분석방식에 근거하여 장애여부를 분석하는 단계; 및 (d) 상기 분석결과 과금장애로 판단되는 경우 상기 운영자 단말로 장애 사실을 SMS로 발송하는 단계;를 포함하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법이 개시된다.

대표도 - 도1



특허청구의 범위

청구항 1

이동통신 시스템에서 과금처리시 발생되는 과금오류호에 따라 실시간으로 과금처리 장애여부를 분석하는 방법으로서,

(a) 운영자 단말로부터 과금오류호에 따른 과금장애 여부를 판단하는 기준을 입력받아 과금장애 분석방식을 설정하는 단계;

(b) 과금 서버에서 발생한 과금오류호를 실시간으로 수신하는 단계;

(c) 수신되는 과금오류호를 통계적으로 처리하며 상기 설정된 과금장애 분석방식에 근거하여 장애여부를 분석하는 단계; 및

(d) 상기 분석결과 과금장애로 판단되는 경우 상기 운영자 단말로 장애 사실을 SMS로 발송하는 단계;를 포함하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법.

청구항 2

제 1 항에 있어서,

상기 과금장애 분석방식은 과금파일의 형식(format), 오류 유형에 따라 구분하여 설정되는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법.

청구항 3

제 1 항 또는 제 2 항에 있어서,

상기 단계 (a)에서 입력받는 장애 여부 판단 기준은, 특정기간에 발생된 과금오류호 평균건수 대비 증/감 임계치를 이용하는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법.

청구항 4

제 1 항 또는 제 2 항에 있어서,

상기 단계 (d) 이후에,

상기 운영자 단말의 요청에 따라 상기 단계 (c)에서 처리된 과금오류 통계 데이터를 제공하는 단계를 더 포함하는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법.

청구항 5

제 1 항 또는 제 2 항에 있어서,

상기 단계 (d) 이후에,

상기 운영자 단말의 요청에 따라 상기 SMS 발송에 대응하는 장애 내역의 상세한 정보를 제공하는 단계를 더 포함하는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법.

청구항 6

제 1 항 또는 제 2 항에 있어서,

상기 단계 (d) 이후에,

상기 운영자 단말의 요청에 따라 과금오류호의 오류상세내역 정보를 제공하는 단계를 더 포함하는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법.

청구항 7

이동통신 시스템에서 과금처리시 발생되는 과금오류호에 따라 실시간으로 과금처리 장애여부를 분석하는 장치로서,

운영자 단말로부터 과금오류호에 따른 과금장애 여부를 판단하는 기준을 입력받아 과금장애 분석방식을 설정하는 과금장애 분석방식 설정모듈;

과금 서버에서 발생한 과금오류호를 실시간으로 수신하는 과금오류호 수집모듈;

상기 수신된 과금오류호를 상기 설정된 분석방식에 따라 분석하여 장애여부를 판단하는 장애분석모듈; 및

상기 분석결과 과금장애로 판단되는 경우에 해당 운영자 단말로 장애 사실을 SMS 발송하는 장애 통지모듈;을 포함하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 장치.

청구항 8

제 7 항에 있어서,

상기 과금장애 분석방식 설정모듈은,

과금파일의 형식(format) 및 오류 유형에 따라 분석방식이 구분되며, 각 방식마다 임계치를 설정하는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 장치.

청구항 9

제 7 항 또는 제 8 항에 있어서,

상기 장애분석모듈은,

상기 수신된 과금오류호를 통계적으로 처리하는 과금오류호 통계처리부; 및

상기 설정된 분석방식에 따라 과금장애 여부를 분석하는 과금장애 판별부;를 포함하는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 장치.

청구항 10

제 7 항 또는 제 8 항에 있어서,

상기 장애분석모듈에서 과금오류호를 통계적으로 처리한 과금오류 통계 데이터, 과금장애로 판별시에 해당 과금장애의 상세정보인 장애내역 데이터 및 해당 과금오류호에 대한 상세정보인 과금오류호 상세내역 데이터 중 적어도 하나를 분석정보로 제공하는 분석정보 제공모듈을 더 포함하는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 장치.

청구항 11

제 7 항 또는 제 8 항에 있어서,

상기 과금오류호 수집모듈에서 수신된 과금오류호 데이터, 상기 분석방식 설정모듈에서 설정된 분석방식 설정정보 데이터 및 상기 장애분석모듈에서 분석된 분석정보 데이터를 데이터베이스에 저장하고 관리하는 데이터베이스 모듈을 더 포함하는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 장치.

청구항 12

제 1 항 또는 제 2 항에 있어서,

상기 단계 (a)에서 입력받는 장애 여부 판단 기준은, 설정한 기준 건수 대비 증/감 임계치를 이용하는 것을 특징으로 하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법.

명 세 서

발명의 상세한 설명

발명의 목적

발명이 속하는 기술 및 그 분야의 종래기술

<12> 본 발명은 이동통신 시스템의 운용 및 유지 보수에 관한 것으로서, 보다 상세하게는 이동통신 시스템의 과금처

리시의 과금오류 및 과금장애를 분석하는 방법 및 장치에 관한 것이다.

<13> 최근 이동통신 기술의 비약적인 발전은 이동통신 단말기의 대중화를 급속히 촉진시켜, 대부분의 일반인들도 핸드폰, PDA 등의 이동통신 단말기를 항상 소지하고 다니도록 우리의 생활을 변모시켰다. 이동통신 단말기는 사용자로 하여금 통신망의 접근을 보다 용이하게 하면서 종래의 전통적인 통신 시스템이 가지던 시스템 자원을 효율적으로 배분하게 하는 효과를 가져왔다.

<14> 이러한 이동통신 단말기의 대중화에 따라 이동통신 서비스의 가입자가 급증하게 되고, 해당 가입자들의 통화호에 따른 과금 처리에도 많은 시간과 비용이 발생하게 되었다. 특히, 많은 수의 가입자들에 대한 과금 처리로 인해 과금오류 발생이 증가하는 문제가 발생하고 있다.

<15> 기존에는 이러한 과금처리상에 발생되는 오류에 대해서는 운영자가 직접 과금오류호에 대한 일별 통계 데이터를 눈으로 확인하고, 각 오류별로 오류건수가 급증한 것에 대해서 세부적으로 분석작업을 실시하는 방식이 이용되었다. 그러나 이렇게 일 단위로 통계 데이터를 분석함에 따라 장애의 인지가 늦어지고 사람이 직접 눈으로 확인하는 것이다 보니 정확한 체크가 되지 못하는 실정이다.

<16> 이렇게 가입자들의 통화호는 실시간으로 발생되고 과금처리 역시 실시간으로 진행됨에 따라 과금처리에 대한 오류 및 장애 인지가 늦어져 조치가 제때 이루어지지 않는다면, 이는 재무적인 손실로 이루어지는 문제가 발생하게 된다.

발명이 이루고자 하는 기술적 과제

<17> 본 발명은 상기와 같은 문제점을 해결하기 위해 창안된 것으로서, 이동통신 시스템의 과금처리시에 발생되는 과금오류호를 분석하여 장애 발생 여부를 실시간으로 인식하고 운영자에게 신속하게 통보할 수 있도록 하는 데 목적이 있다.

<18> 또한, 과금처리시의 과금오류건에 대한 통계를 제공하고, 각 장애에 대한 분석을 용이하게 할 수 있도록 다양한 분석기능을 제공하는 데 다른 목적이 있다.

<19> 본 발명의 다른 목적 및 장점들은 하기에 설명될 것이며, 본 발명의 실시예에 의해 알게 될 것이다. 또한, 본 발명의 목적 및 장점들은 첨부된 특허 청구 범위에 나타낸 수단 및 조합에 의해 실현될 수 있다.

발명의 구성 및 작용

<20> 상기와 같은 목적을 달성하기 위해 본 발명에 따른 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법은, 이동통신 시스템에서 과금처리시 발생되는 과금오류호에 따라 실시간으로 과금처리 장애여부를 분석하는 방법으로서, (a) 운영자 단말로부터 과금오류호에 따른 과금장애 여부를 판단하는 기준을 입력받아 과금장애 분석방식을 설정하는 단계; (b) 과금 서버에서 발생한 과금오류호를 실시간으로 수신하는 단계; (c) 수신되는 과금오류호를 통계적으로 처리하며 상기 설정된 과금장애 분석방식에 근거하여 장애여부를 분석하는 단계; 및 (d) 상기 분석결과 과금장애로 판단되는 경우 상기 운영자 단말로 장애 사실을 SMS로 발송하는 단계;를 포함한다.

<21> 본 발명의 다른 측면에 따르면, 이동통신 시스템에서 과금처리시 발생되는 과금오류호에 따라 실시간으로 과금처리 장애여부를 분석하는 장치로서, 운영자 단말로부터 과금오류호에 따른 과금장애 여부를 판단하는 기준을 입력받아 과금장애 분석방식을 설정하는 과금장애 분석방식 설정모듈; 과금 서버에서 발생한 과금오류호를 실시간으로 수신하는 과금오류호 수집모듈; 상기 수신된 과금오류호를 상기 설정된 분석방식에 따라 분석하여 장애여부를 판단하는 장애분석모듈; 및 상기 분석결과 과금장애로 판단되는 경우에 해당 운영자 단말로 장애 사실을 SMS 발송하는 장애 통지모듈;을 포함하는 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 장치가 제공된다.

<22> 이하, 첨부된 도면을 참조하여 본 발명의 바람직한 실시예를 상세히 설명하기로 한다. 이에 앞서, 본 명세서 및 청구범위에 사용된 용어나 단어는 통상적이거나 사전적인 의미로 한정해서 해석되어서는 아니되며, 발명자는 그 자신의 발명을 가장 최선의 방법으로 설명하기 위해 용어의 개념을 적절하게 정의할 수 있다는 원칙에 입각하여 본 발명의 기술적 사상에 부합하는 의미와 개념으로 해석되어야만 한다. 따라서, 본 명세서에 기재된 실시예와 도면에 도시된 구성은 본 발명의 가장 바람직한 일 실시예에 불과할 뿐이고 본 발명의 기술적 사상을 모두 대변하는 것은 아니므로, 본 출원시점에 있어서 이들을 대체할 수 있는 다양한 균등물과 변형예들이 있을 수 있음을 이해하여야 한다.

<23> 도 1은 본 발명의 일 실시예에 따른 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 장치의 구성을 도시한 도면이다.

<24> 도 1을 참조하면, 본 발명에 따른 장애 인식 장치(100)는, CPU, RAM, 운영체제 등을 구비한 서버장치로서, 운영자 단말 및 과금 서버와의 데이터 통신을 수행하는 통신부(150), 운영자로부터 과금오류를 분석하기 위한 설정값을 입력받아 분석방식을 설정하는 분석방식 설정모듈(110), 과금 서버에서 발생되는 과금오류호를 수신하는 과금오류호 수집모듈(120), 수집된 과금오류호를 설정된 분석방식에 따라 과금장애를 분석하는 장애 분석모듈(130), 과금 장애 발생시에 운영자에게 통지하는 장애 통지모듈(140), 장애 분석에 따른 다양한 분석정보를 제공하는 분석정보 제공모듈(160) 및 데이터베이스(180)에 다양한 데이터 및 정보들을 저장 관리하는 데이터베이스 모듈(170)을 포함한다.

<25> 통신부(150)는 시스템을 운영하는 운영자가 단말을 이용하여 본 발명의 장애 인식 장치(100)에 접속하여 데이터를 통신할 수 있도록 하는 기능을 수행한다. 또한 과금 서버로부터 데이터를 수신하는 기능을 수행한다.

<26> 과금오류호 수집모듈(120)은 상기 통신부(150)를 통해 상기 과금 서버에서 발생되는 과금오류호를 수신한다. 이때에는 다양한 과금파일 형식과 오류유형의 과금오류호를 실시간으로 수신하여 해당 형식과 유형별로 구분하여 수집한다. 또한 상기 과금오류호 수집모듈(120)은 이렇게 수집된 과금오류호를 후술할 데이터베이스 모듈(170)을 통해 데이터베이스(180)에 저장한다.

<27> 분석방식 설정모듈(110)은 과금장애 분석을 위한 각종 설정값을 운영자로부터 입력받아 분석방식을 설정하는 역할을 수행한다. 상기 설정값은 과금장애 여부를 판단하는 기준이 되는 값이다. 상기 설정값은 운영자에 의해 정해지며, 이를 위해 운영자 단말로 설정값 입력 인터페이스를 제공한다. 상기 분석방식 설정모듈(110)에서는 과금 서버에서 제공되는 과금파일의 형식(format) 및 오류 유형에 따라 분석방식을 구분한다. 또한, 이렇게 구분된 각 방식에 따라 임계치를 설정할 수 있다. 각 방식에 따른 임계치 설정은 과금 서버로부터 수신한 과금오류호를 분석하여 과금장애 여부를 판단할 시에 근거가 되는 수치이다. 이러한 임계치는 특정기간에 발생된 과금오류호 평균건수 대비 증/감을 판단하는 기준 값이고, 또는 설정한 건수 대비 증/감을 판단하는 기준 값이다. 이렇게 상기 분석방식 설정모듈(110)에서 수행되는 절차는 상기 설정값 입력 인터페이스를 통하여 진행된다. 상기 설정값 입력 인터페이스는 도 4에서 도시한 바와 같은 분석방식 설정창으로 출력되어 운영자 단말로 제공한다.

<28> 도 4는 분석방식 설정모듈(110)에서 제공하는 설정값 입력 인터페이스의 일 예인 윈도우 화면을 캡처한 도면이다. 도 4를 참조하면, 상기 분석방식 설정창에는 과금장애 여부를 판단하기 위한 설정값들을 운영자로부터 선택 혹은 입력받을 수 있도록 구성되어 있다. 도면에서의 포맷(format)란과 오류코드란에서는 분석의 대상을 설정할 수 있다. 즉, 과금 서버에서의 과금파일 포맷과 발생되는 오류코드의 유형을 선택하여 설정할 수 있다. 다음, 과금장애 여부 판단의 조건이 되는 항목인 증가선택과 건수기준선택을 체크하여 활성화하면 과금장애 분석에 해당 조건이 적용된다. 상기 증가선택란은 특정기간을 설정하고 해당 기간의 과금오류호 평균발생량 대비 증가한 비율 또는 값을 임계치로 설정한다. 상기 건수기준선택란은 해당하는 과금오류호 발생건수 임계치를 설정한다. 조건조합란은 상기 두 조건이 활성화 되었을 때 AND 조합 또는 OR 조합을 선택할 수 있다. 이와 같이 운영자는 상기 분석방식 설정창과 같은 인터페이스를 통하여 과금장애 판단의 주요 기준과 방식을 설정하게 된다.

<29> 상기 장애 분석모듈(130)은 상기 과금오류호 수집모듈(120)에서 수신한 과금오류호를 통계적으로 처리하고 상기 분석방식 설정모듈(110)에서 설정된 분석방식에 따라 분석하여 과금장애 여부를 판단하는 역할을 수행한다. 상기 장애 분석모듈(130)은 과금오류호 통계처리부(131) 및 과금장애 판별부(132)를 포함한다. 상기 과금오류호 통계처리부(131)는 과금서버로부터 수신한 과금오류호를 수집하고 통계처리한다. 상기 수신한 과금오류호는 형식과 오류유형에 따라 구분되어 수집되며, 통계처리하여 데이터베이스에 저장된다. 상기 과금장애 판별부(132)는 상기 분석방식 설정모듈(110)에서 설정된 분석방식에 따라 수신된 과금오류호와 상기 과금오류호 통계처리부(131)에서 통계처리한 데이터를 이용하여 과금장애 여부를 판별한다. 예를 들어, 도 4에서 도시된 바와 같은 설정의 분석방식이라면, 상술한 바와 같은 포맷과 오류코드의 과금오류호가 1000건 이상 발생하게 되면 이를 과금장애로 판단하게 된다. 또는 3일 평균 과금오류호 발생건 보다 20% 증가한 수의 과금오류호가 발생하면 이를 과금장애로 판단하게 된다.

<30> 상기 장애 통지모듈(140)은 상기 장애 분석모듈(130)에서 과금장애로 판별된 경우 해당 운영자 단말로 장애발생 사실을 통보하는 역할을 수행한다. 상기 장애발생 통보는 SMS를 이용하여 해당 내용을 발송한다. 또한, 장애발생 사실을 통보받을 운영자는 미리 지정해 놓을 수 있으며, 해당 운영자 단말의 착신번호를 입력하여 지정할 수 있다. 특히, 다수의 운영자 단말을 지정하여 동시에 다수의 운영자에게 장애발생 사실을 SMS로 발송할 수도 있

다.

<31> 상기 분석정보 제공모듈(160)은 상기 장애 분석모듈(130)에서 분석한 정보와 통계처리한 정보 등의 다양한 정보를 조회할 수 있도록 분석정보를 제공한다. 상기 분석정보 제공모듈(160)에서 제공되는 정보로는 과금오류 통계데이터(161), 장애 내역 상세 데이터(162), 과금오류호 상세정보 데이터(163) 등이 포함된다. 상기 과금오류 통계데이터(161)는 상기 장애 분석모듈(140)의 과금오류호 통계처리부(131)에서 통계처리한 정보가 포함되어 있다. 상기 과금오류 통계데이터는 과금오류 통계 제공 인터페이스를 통하여 정보를 제공한다.

<32> 도 5는 장애내역 상세정보 제공 인터페이스의 일 예인 장애내역 상세정보 윈도우의 화면을 캡처한 도면이다. 도 5를 참조하면, 포맷, 오류코드 등으로 장애내역을 검색하고, 도면에서와 같이 검색된 장애내역 목록을 통하여 분석방식 설정모듈(110)에서 설정한 임계치 및 조건 등의 분석방식 정보를 조회할 수 있다. 상기 과금오류호 상세정보 데이터는 과금오류호 상세정보 제공 인터페이스를 통하여 정보를 제공한다.

<33> 도 6은 과금오류 통계 제공 인터페이스의 일 예인 과금오류 통계분석 윈도우의 화면을 캡처한 도면이다. 도 6을 참조하면, 통계기준, 조회기간, 업무구분, 과금포맷, 오류코드 등의 항목을 입력할 수 있는 인터페이스가 구성되어 있다. 이러한 인터페이스를 통하여 조회를 요청받으면, 통계처리된 과금오류 통계데이터에서 해당하는 정보가 도 6에서와 같이 화면에 출력된다. 이를 이용하면 각 과금포맷에 대한 오류코드별 건수 및 상세 내역의 확인이 가능하다. 또한 엑셀과도 연동하고 그래프를 제공하여 오류 추이 분석이 용이하도록 한다. 상기 장애내역 상세정보 데이터는 장애내역 상세정보 제공 인터페이스를 통하여 정보를 제공한다.

<34> 도 7은 과금오류호 상세정보 제공 인터페이스의 일 예인 과금오류호 분석정보 윈도우의 화면을 캡처한 도면이다. 도 7을 참조하면, 선택된 과금서버에서 발생한 과금오류호의 상세한 정보가 화면에 출력된다. 이를 이용하여 과금오류호의 상세정보를 확인할 수 있게 되어 오류의 발생 원인을 용이하게 분석할 수 있다.

<35> 상기 데이터베이스 모듈(170)은 상기 장애 분석모듈(130)에서 분석된 분석정보 데이터, 상기 과금오류호 수집모듈(120)에서 수신된 과금오류호 데이터, 상기 분석방식 설정모듈(110)에서 설정된 분석방식 설정정보 데이터 등을 데이터베이스(180)에 저장하고 관리하는 역할을 수행한다. 상기 데이터베이스 모듈(170)은 상기 분석방식 설정모듈(110), 상기 과금오류호 수집모듈(120), 상기 장애 분석모듈(130) 및 상기 분석정보 제공모듈(160)에 연동하여 데이터베이스(180)에 데이터를 저장 및 액세스할 수 있게 한다. 상기 데이터베이스 모듈(170)에 의해 운용되는 데이터베이스(180)의 구성 및 그 데이터베이스에 저장되는 정보와 데이터들의 예시를 도 2에 도시하였다.

<36> 도 2는 본 발명의 일 실시예에 따른 장애 인식 장치(100)에 구비된 데이터베이스(180)의 구성예를 나타낸 도면이다. 도 2에서와 같이, 상기 데이터베이스(180)는 둘로 구분할 수 있으며, 분석정보 데이터베이스(181)와 설정정보 데이터베이스(182)로 구분된다. 상기 분석정보 데이터베이스(181)에는 과금오류 통계데이터, 장애 내역 데이터, 과금오류호 상세 데이터 등이 데이터베이스화하여 저장되어 있다. 상기 설정정보 데이터베이스(182)에는 상기 분석방식 설정모듈(110)에서 설정된 분석방식이 저장되며, 과금파일 형식과 오류 유형별로 조건 정보와 임계치들이 저장되어 있다.

<37> 다음으로, 본 발명의 일 실시예에 따른 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 처리가 진행되는 절차를 설명하기로 한다.

<38> 도 3은 본 발명의 일 실시예에 따른 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법이 진행되는 절차를 도시한 순서도이다.

<39> 도 3을 참조하면, 먼저 운영자로부터 미리 과금장애 분석을 위한 분석방식을 설정하게 된다. 이때에는 해당 운영자 단말로 분석방식 설정 입력을 위한 분석방식 설정 인터페이스를 제공하여 과금파일 형식과 오류 유형에 따른 조건 및 임계치 값을 입력하도록 한다.(S 10)

<40> 이동통신 시스템의 과금 서버에서 가입자의 통화호에 따른 과금처리를 수행하다가 과금오류호가 발생하면, 이를 실시간으로 수신하며 이러한 과금오류호 수집활동은 계속적으로 진행이 된다. 또한, 복수의 과금서버가 존재할 경우에는 모든 과금서버로부터 발생하는 과금오류호를 수신하여 수집한다.(S 20)

<41> 이렇게 수집된 과금오류호는 데이터베이스에 통계적으로 처리되어 저장한다. 또한 수신된 과금오류호는 축적된 통계 데이터와 상기 단계 S 10에서 설정된 분석방식에 따라 분석하여 과금장애인지 여부를 판단하게 된다.(S 30)

<42> 상기 판단 결과 과금장애로 판단되는 경우에는 미리 설정된 운영자 단말로 해당 사실을 SMS를 통하여 발송하게

된다. 이러한 절차는 실시간으로 진행되어 과금장애로 판단되는 동시에 운영자 단말로 SMS가 발송된다. 이 SMS에는 상기 과금장애 발생 사실과 해당 내용이 포함될 수 있다. 이렇게 과금장애가 발생하면 해당 운영자에게 그 사실을 실시간으로 통보하게 된다. 반면에 상기 판단 결과 과금장애가 아닌 것으로 판단되면 정상 상태로 간주하고 운영자에게 통지는 생략한다.(S 40, S 50)

<43> 과금장애 통지를 수신한 운영자 단말 또는 평상시의 운영자 단말로부터 분석정보 조회 요청이 수신되면, 도 5 내지 도 7을 참조하여 상술한 바와 같은 정보 제공 인터페이스를 제공하고, 운영자 단말로부터 해당 인터페이스를 통하여 조회 조건 및 값을 입력받는다.(S 60)

<44> 해당 조회 인터페이스를 통하여 입력받은 데이터와 조회 요청정보를 근거로 하여 상기 운영자가 요청하는 것에 대응하는 정보를 데이터베이스에서 추출하여 제공하게 된다.(S 70)

<45> 이상과 같이, 실시간으로 과금오류호를 수신하고 분석함으로써 장애 발생 즉시 이를 운영자에게 통지할 수 있다. 또한, 운영자로부터 과금장애 여부 판단의 기준이 되는 조건 및 임계치 값을 미리 설정하게 함으로써 장애 판단율을 조절할 수 있고, 각 오류유형별로 설정기준을 다르게 정의할 수도 있다.

<46> 상술한 바와 같은 본 발명의 방법은 프로그램으로 구현되어 컴퓨터로 읽을 수 있는 형태로 기록매체(시디롬, 램, 롬, 플로피 디스크, 하드 디스크, 광자기 디스크 등)에 저장될 수 있다. 이러한 과정은 본 발명이 속하는 기술 분야에서 통상의 지식을 가진 자가 용이하게 실시할 수 있으므로 더 이상 상세히 설명하지 않기로 한다.

<47> 본 명세서 및 청구범위에 사용된 용어나 단어는 통상적이거나 사전적인 의미로 한정해서 해석되어서는 아니 되며, 발명자는 그 자신의 발명을 가장 최선의 방법으로 설명하기 위해 용어의 개념을 적절하게 정의할 수 있다는 원칙에 입각하여 본 발명의 기술적 사상에 부합하는 의미와 개념으로 해석되어야만 한다.

<48> 따라서, 본 명세서에 기재된 실시예와 도면에 도시된 구성은 본 발명의 가장 바람직한 일 실시예에 불과할 뿐이고 본 발명의 기술적 사상을 모두 대변하는 것은 아니므로, 본 출원시점에 있어서 이들을 대체할 수 있는 다양한 균등물과 변형예들이 있을 수 있음을 이해하여야 한다.

발명의 효과

<49> 본 발명에 따르면, 이동통신 시스템에서 과금처리시에 각 오류유형별로 정의해 놓은 기준에 의해 검출된 과금장애는 실시간으로 운영자에게 통지(SMS)됨에 따라 장애 사실을 신속하여 인식할 수 있고 또한 즉각적인 대응을 진행할 수 있어 장애에 따른 손실을 최소화할 수 있는 효과를 제공한다.

<50> 또한, 장애여부 판단을 위한 기준의 설정시에 개선된 인터페이스로 인하여 보다 용이하고 신속하게 설정 및 변경이 가능한 효과를 제공한다.

<51> 또한, 다양한 분석정보 제공툴을 제공하여 오류 및 문제 발생의 원인 추적과 분석을 용이하게 할 수 있는 효과를 제공한다.

도면의 간단한 설명

<1> 본 명세서에 첨부되는 다음의 도면들은 본 발명의 바람직한 실시예를 예시하는 것이며, 후술하는 발명의 상세한 설명과 함께 본 발명의 기술사상을 더욱 이해시키는 역할을 하는 것이므로, 본 발명은 그러한 도면에 기재된 사항에만 한정되어 해석되어서는 아니된다.

<2> 도 1은 본 발명의 일 실시예에 따른 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 장치의 구성을 도시한 도면이다.

<3> 도 2는 본 발명의 일 실시예에 따른 장애 인식 장치에 구비된 데이터베이스의 구성예를 나타낸 도면이다.

<4> 도 3은 본 발명의 일 실시예에 따른 이동통신 시스템의 실시간 과금오류 분석을 통한 장애 인식 방법이 진행되는 절차를 도시한 순서도이다.

<5> 도 4는 분석방식 설정모듈에서 제공하는 설정값 입력 인터페이스의 일 예인 윈도우 화면을 캡처한 도면이다.

<6> 도 5는 장애내역 상세정보 제공 인터페이스의 일 예인 장애내역 상세정보 윈도우의 화면을 캡처한 도면이다.

<7> 도 6은 과금오류 통계 제공 인터페이스의 일 예인 과금오류 통계분석 윈도우의 화면을 캡처한 도면이다.

<8> 도 7은 과금오류호 상세정보 제공인터페이스의 일 예인 과금오류호 분석정보 윈도우의 화면을 캡처한 도면이다.

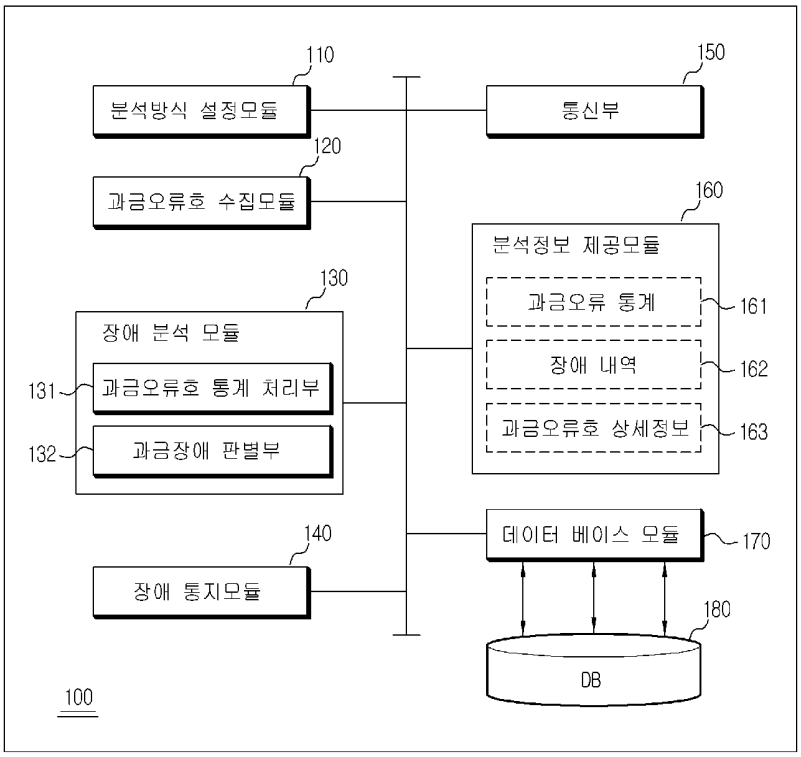
<9> <도면의 주요 부분에 대한 부호의 설명>

<10> 110: 분석방식 설정모듈 120: 과금오류호 수집모듈

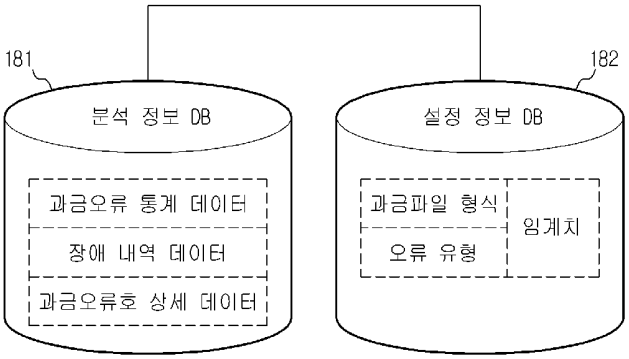
<11> 130: 장애 분석모듈 140: 장애 통지모듈

도면

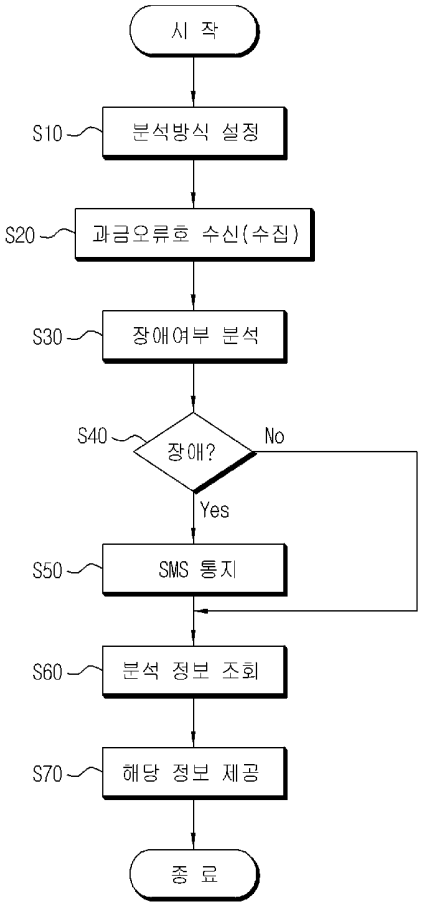
도면1



도면2



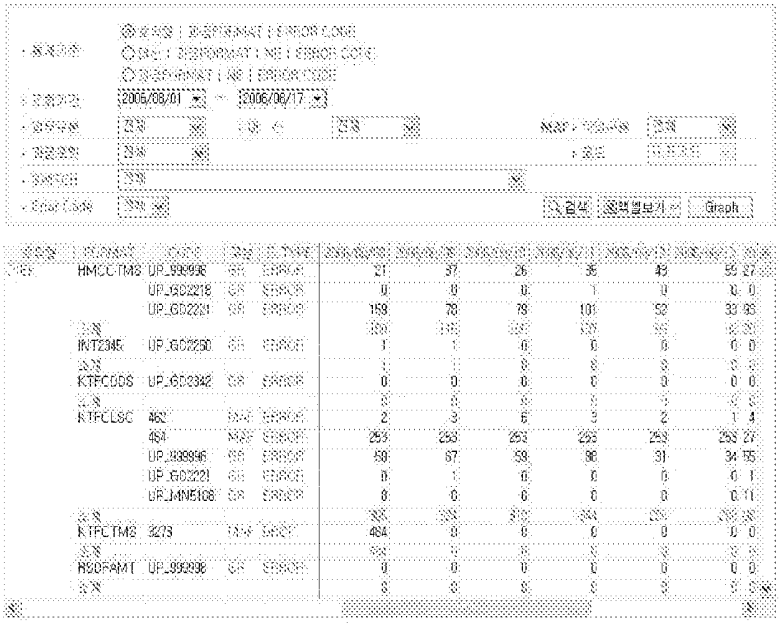
도면3


시 작
S10
분석방식 설정
S20
과금오류호 수신(수집)
S30
장애여부 분석
S40
장애?
No
Yes
S50
SMS 통지
S60
분석 정보 조회
S70
해당 정보 제공
종 료

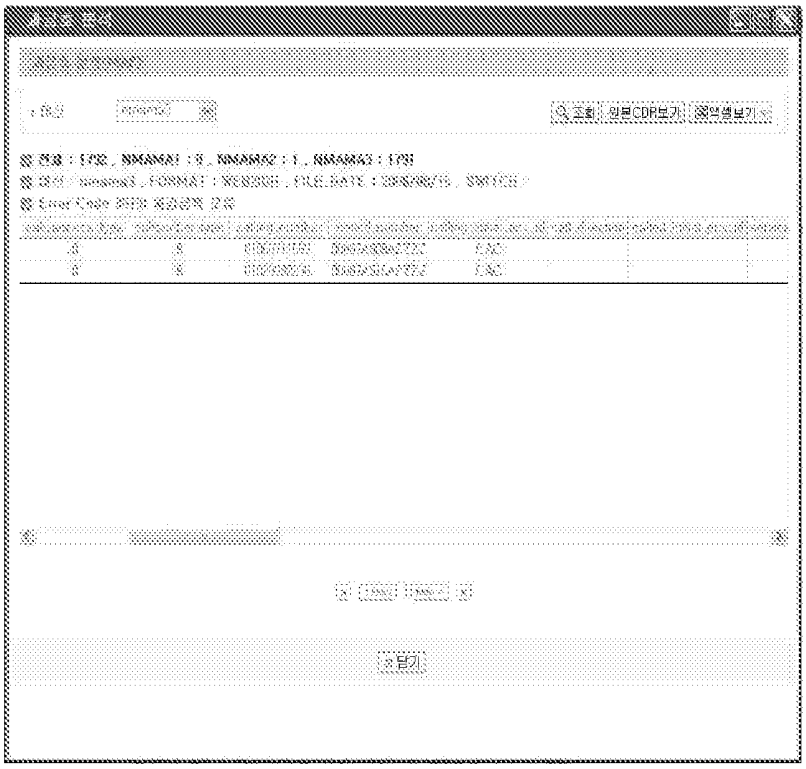
도면4

도면5

도면6



도면7



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Tapia et al.

(54) **WIRELESS CARRIER NETWORK PERFORMANCE ANALYSIS AND TROUBLESHOOTING**

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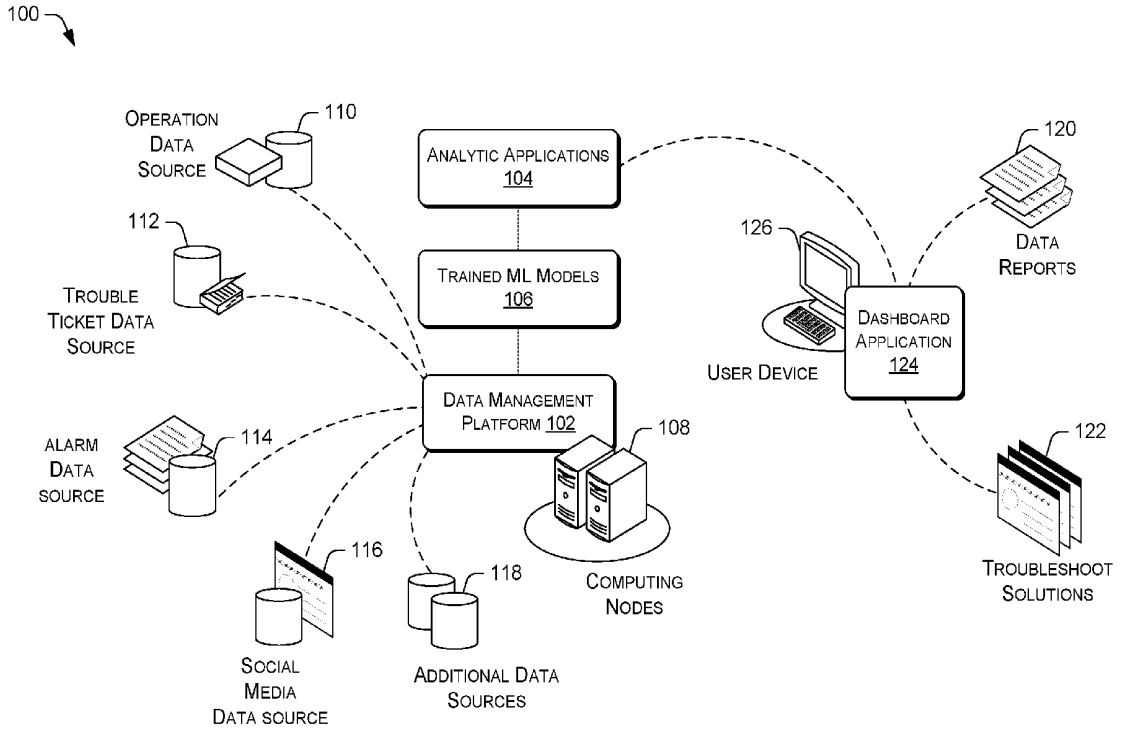
CPC ***H04L 41/0631*** (2013.01); ***H04W 24/08*** (2013.01); ***H04L 41/5074*** (2013.01); *H04W 24/10* (2013.01)

(57) **ABSTRACT**

An analytic application may provide analysis of performance data for a wireless carrier network to determine root causes of issues. Performance data for network components of the wireless carrier network and device components of user devices that use the network may be obtained. The performance data is processed by aggregating multiple datasets of the performance data into aggregated performance data according to one or more grouping parameters or converge a plurality of datasets of the performance data into converged performance data according to a unitary storage schema. Analysis may be performed on the aggregated performance data or the converged performance data to detect an issue affecting the wireless carrier network or to generate a solution to the issue. The aggregate performance data and the converged performance data may include non-real time data or real time data. Accordingly, the issue or the solution to the issue may be provided for presentation.



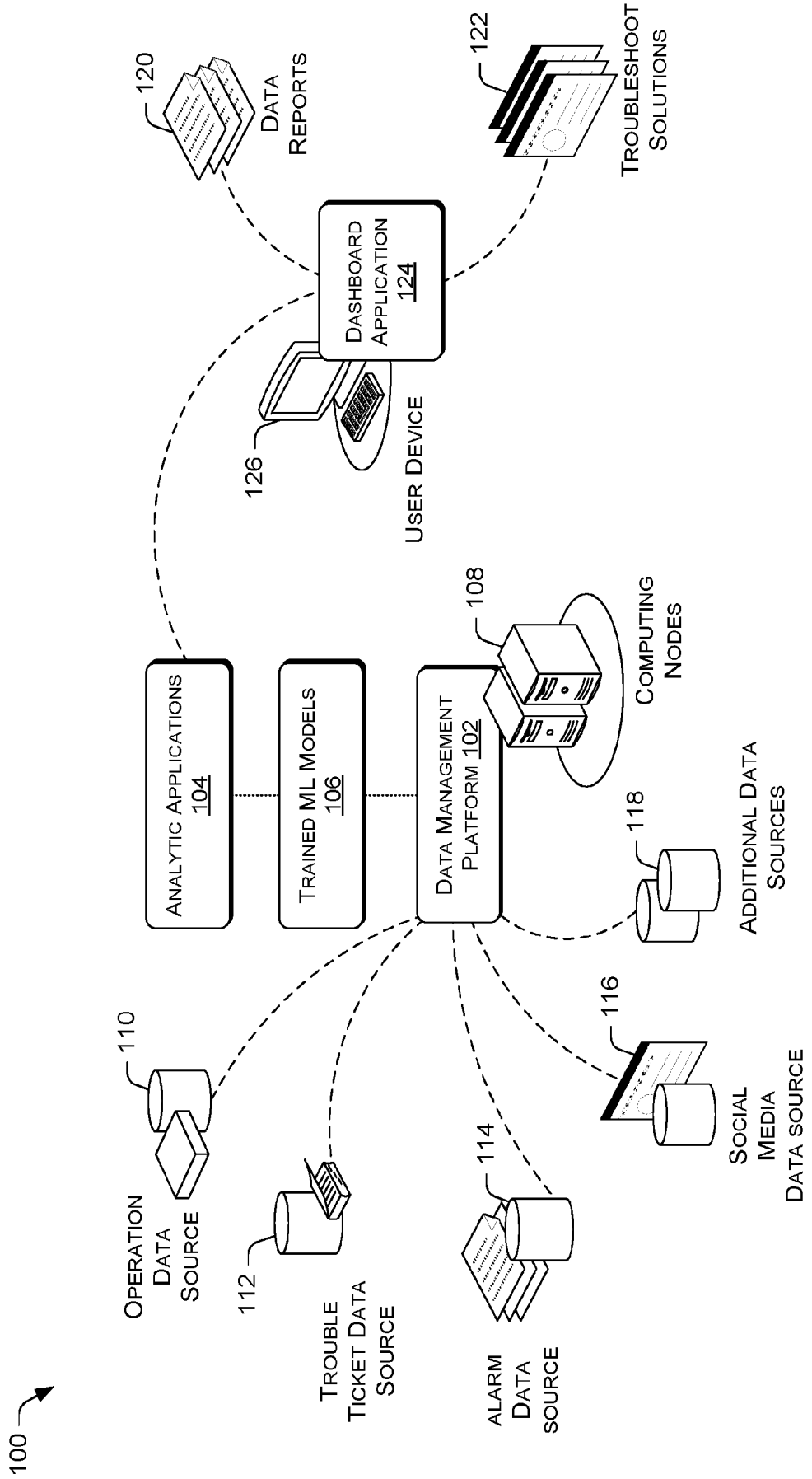

100
120
DATA REPORTS
122
TROUBLESHOOT SOLUTIONS
DASHBOARD APPLICATION 124
126
USER DEVICE
ANALYTIC APPLICATIONS 104
TRAINED ML MODELS 106
DATA MANAGEMENT PLATFORM 102
108
COMPUTING NODES
118
ADDITIONAL DATA SOURCES
110
OPERATION DATA SOURCE
112
TROUBLE TICKET DATA SOURCE
114
ALARM DATA SOURCE
116
SOCIAL MEDIA DATA SOURCE

FIG. 1

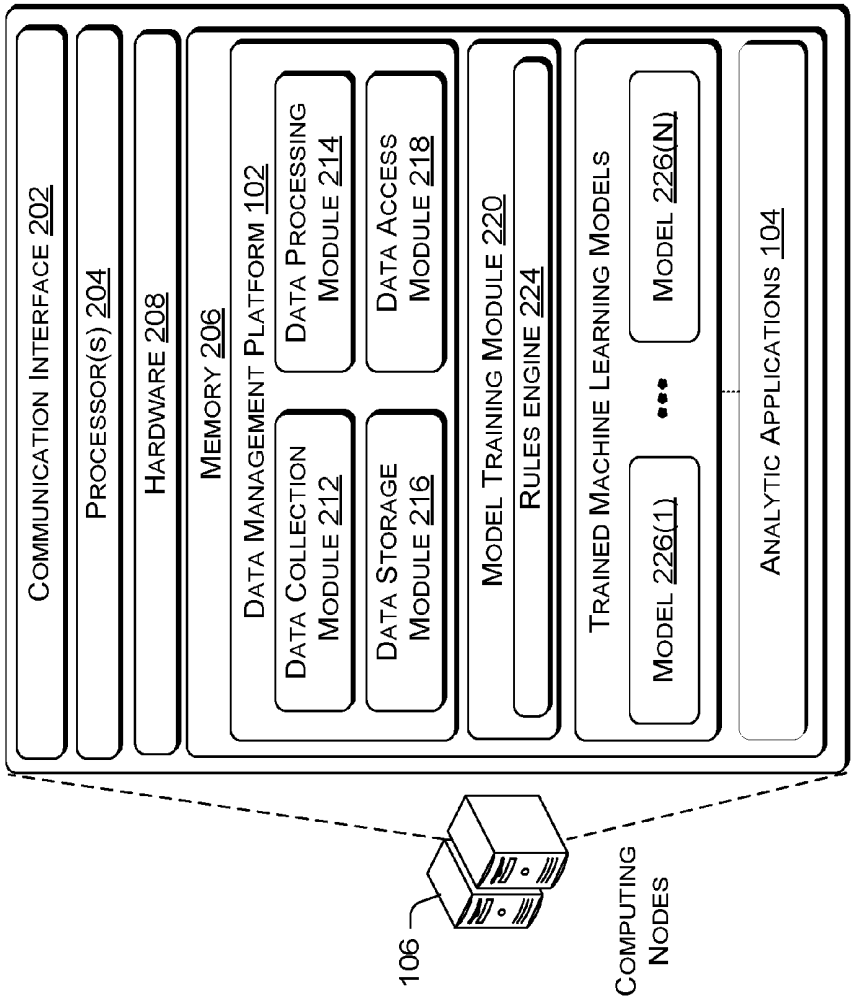

Communication Interface 202
Processor(s) 204
Hardware 208
Memory 206
Data Management Platform 102
Data Collection Module 212
Data Processing Module 214
Data Storage Module 216
Data Access Module 218
Model Training Module 220
Rules engine 224
Trained Machine Learning Models
Model 226(1)
Model 226(N)
Analytic Applications 104
106
Computing Nodes

FIG. 2

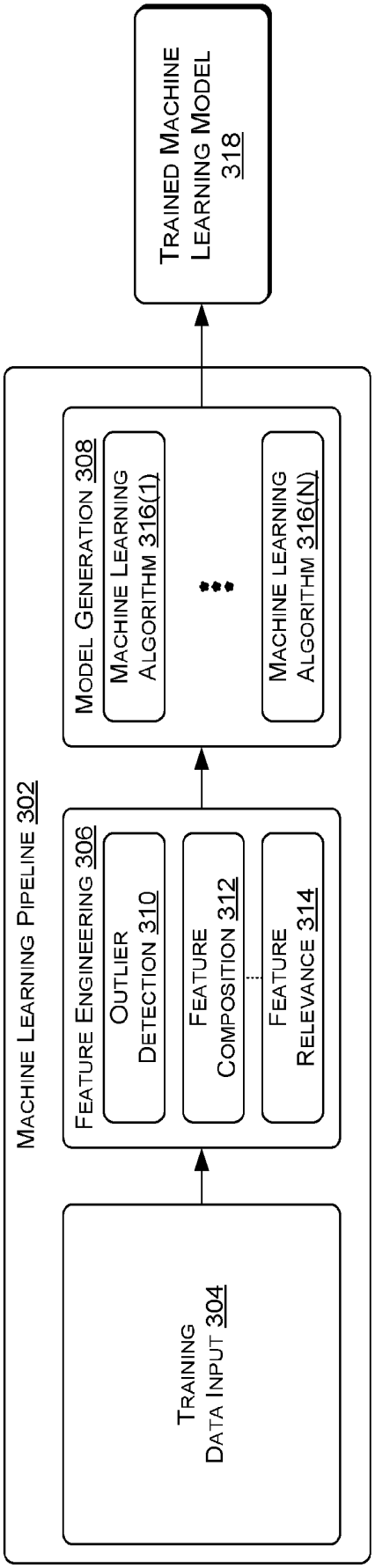

Machine Learning Pipeline 302
Training Data Input 304
Feature Engineering 306
Outlier Detection 310
Feature Composition 312
Feature Relevance 314
Model Generation 308
Machine Learning Algorithm 316(1)
Machine Learning Algorithm 316(N)
Trained Machine Learning Model 318

FIG. 3

400

ACCR – Root Cause Analysis

402

Overview | Customer Tickets | Node Tickets | Alarms | Network Performance | Call Performance

404

DATE 07/07/2016 RANGE 7 days back

Customer Tickets

Ticket	Timestamp	Site ID	Mobile No.	Status	Category	Resolution	Assignee	Closed by	Complaint	Log
1123	10:35 AM	4A56	(221)123-1234	Closed	Voice Services	Coverage Problem Corrected	J. Doe	A. Jones	Dropped Call	Show

406

Ticket Details

Service Complaint Dropped Call

Ticket Description Subscriber has been experiencing dropped calls since getting Phone X. Issue is not location specific, drops calls several times a day, issue for over a month.

Field	Value
Assignee Group	D34351
Date	07/07/2016
Coverage Level	Very Strong
Customer Type	Post Paid
Device Make	Company A
Device Model	Phone X
IMEI	33434672797

Resolution Validation

Current Resolution	Coverage Problem Corrected
Suggest Resolution	Mobility
Suggested Comment	High HO Failure Ratio SE01641A (top offender) for IF Data No WiFi Call (rid=22)
Reliability	High
Engineer Validation	Pending

FIG. 4

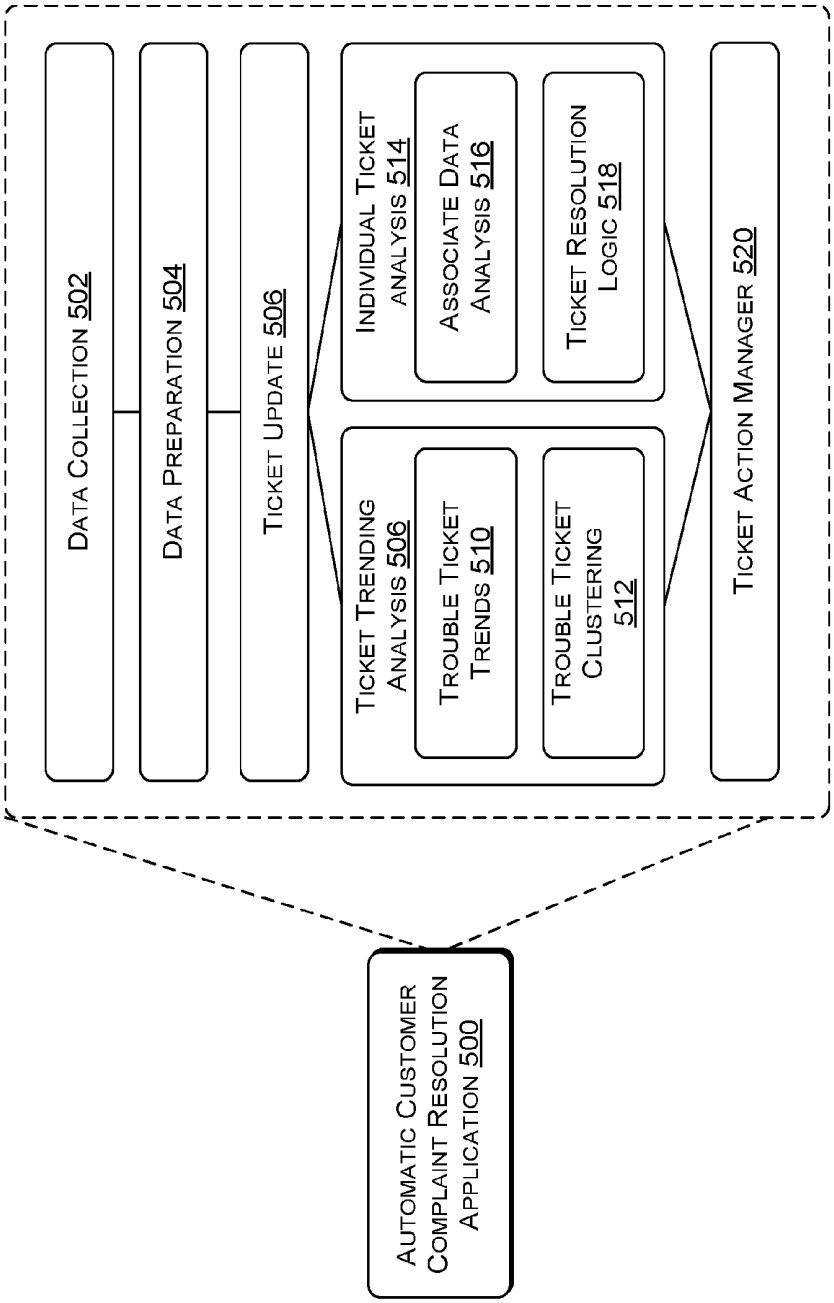

Automatic Customer Complaint Resolution Application 500
Data Collection 502
Data Preparation 504
Ticket Update 506
Ticket Trending Analysis 506
Trouble Ticket Trends 510
Trouble Ticket Clustering 512
Individual Ticket Analysis 514
Associate Data Analysis 516
Ticket Resolution Logic 518
Ticket Action Manager 520

FIG. 5

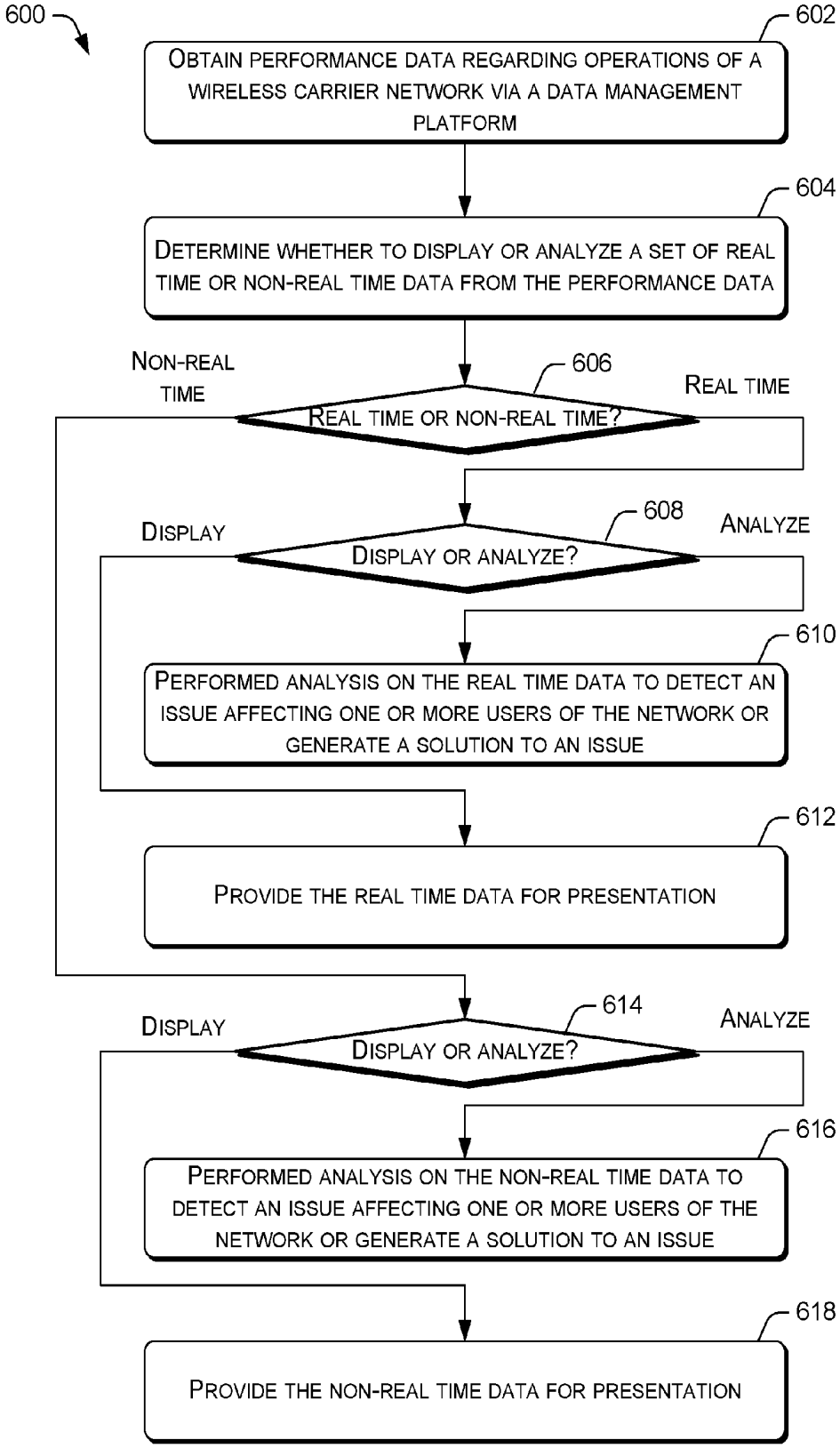

600
602
OBTAIN PERFORMANCE DATA REGARDING OPERATIONS OF A WIRELESS CARRIER NETWORK VIA A DATA MANAGEMENT PLATFORM
604
DETERMINE WHETHER TO DISPLAY OR ANALYZE A SET OF REAL TIME OR NON-REAL TIME DATA FROM THE PERFORMANCE DATA
NON-REAL TIME
606
REAL TIME
REAL TIME OR NON-REAL TIME?
608
DISPLAY
ANALYZE
DISPLAY OR ANALYZE?
610
PERFORMED ANALYSIS ON THE REAL TIME DATA TO DETECT AN ISSUE AFFECTING ONE OR MORE USERS OF THE NETWORK OR GENERATE A SOLUTION TO AN ISSUE
612
PROVIDE THE REAL TIME DATA FOR PRESENTATION
614
DISPLAY
ANALYZE
DISPLAY OR ANALYZE?
616
PERFORMED ANALYSIS ON THE NON-REAL TIME DATA TO DETECT AN ISSUE AFFECTING ONE OR MORE USERS OF THE NETWORK OR GENERATE A SOLUTION TO AN ISSUE
618
PROVIDE THE NON-REAL TIME DATA FOR PRESENTATION

FIG. 6

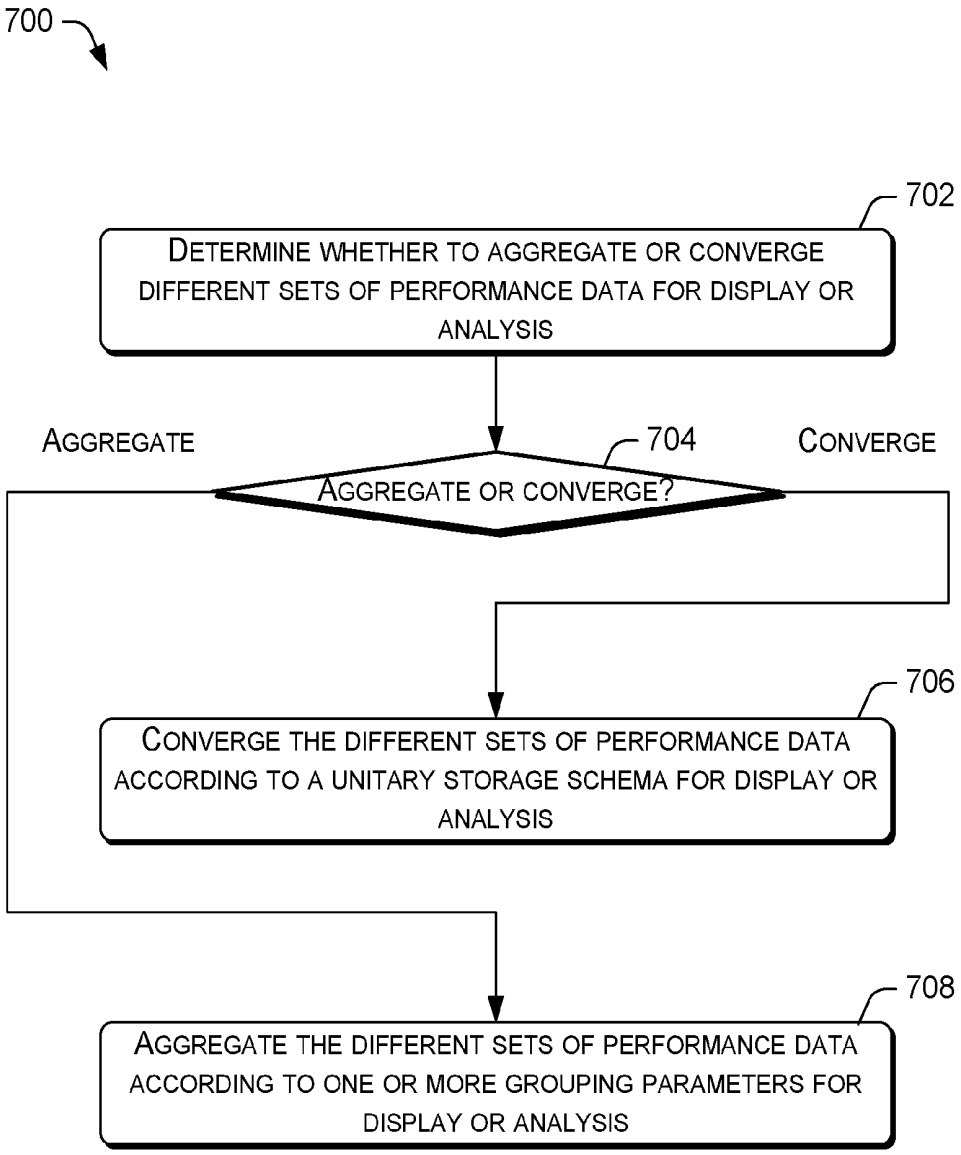

700
702
DETERMINE WHETHER TO AGGREGATE OR CONVERGE DIFFERENT SETS OF PERFORMANCE DATA FOR DISPLAY OR ANALYSIS
AGGREGATE
704
CONVERGE
AGGREGATE OR CONVERGE?
706
CONVERGE THE DIFFERENT SETS OF PERFORMANCE DATA ACCORDING TO A UNITARY STORAGE SCHEMA FOR DISPLAY OR ANALYSIS
708
AGGREGATE THE DIFFERENT SETS OF PERFORMANCE DATA ACCORDING TO ONE OR MORE GROUPING PARAMETERS FOR DISPLAY OR ANALYSIS

FIG. 7

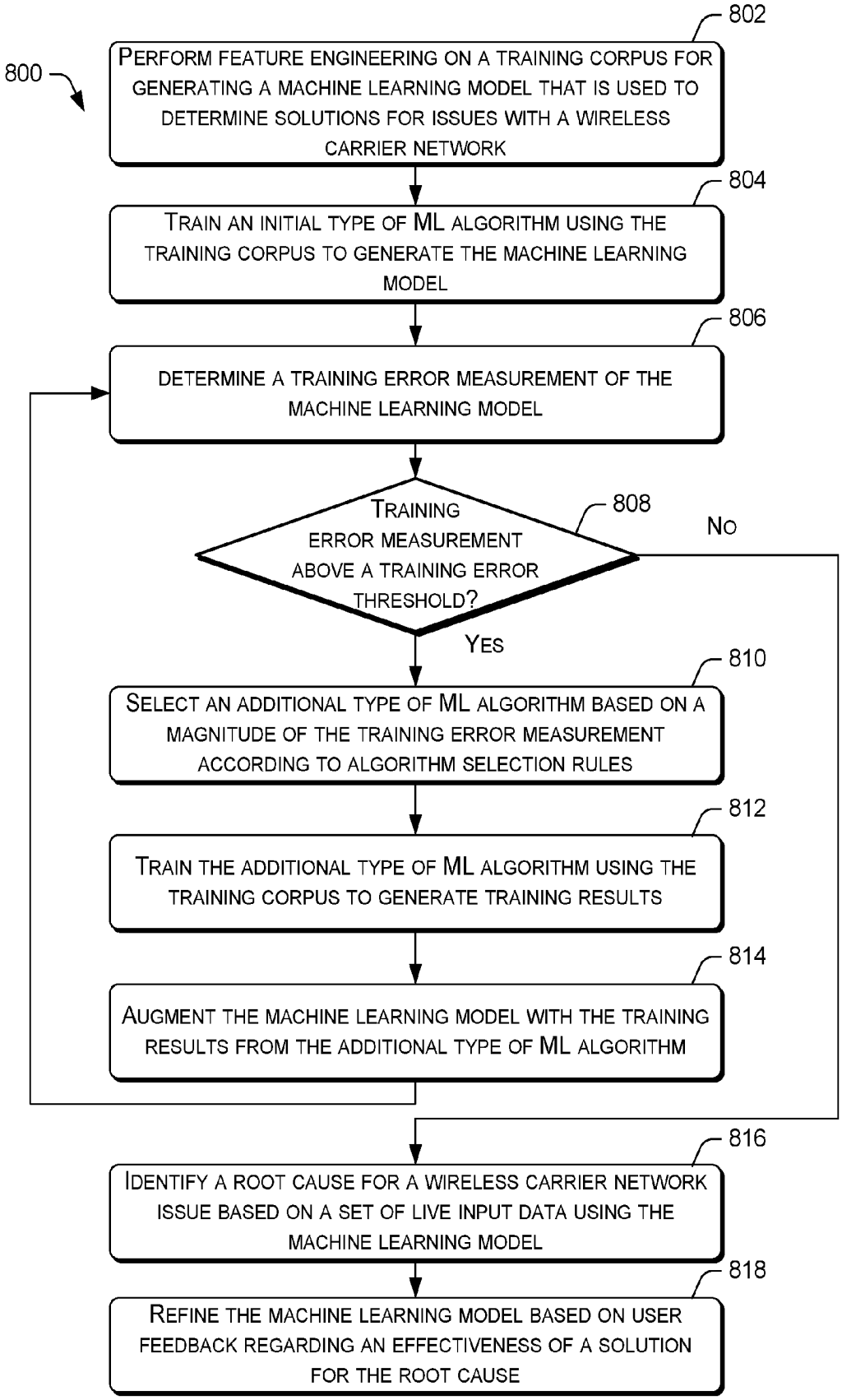

800
802
PERFORM FEATURE ENGINEERING ON A TRAINING CORPUS FOR GENERATING A MACHINE LEARNING MODEL THAT IS USED TO DETERMINE SOLUTIONS FOR ISSUES WITH A WIRELESS CARRIER NETWORK
804
TRAIN AN INITIAL TYPE OF ML ALGORITHM USING THE TRAINING CORPUS TO GENERATE THE MACHINE LEARNING MODEL
806
DETERMINE A TRAINING ERROR MEASUREMENT OF THE MACHINE LEARNING MODEL
808
TRAINING ERROR MEASUREMENT ABOVE A TRAINING ERROR THRESHOLD?
NO
YES
810
SELECT AN ADDITIONAL TYPE OF ML ALGORITHM BASED ON A MAGNITUDE OF THE TRAINING ERROR MEASUREMENT ACCORDING TO ALGORITHM SELECTION RULES
812
TRAIN THE ADDITIONAL TYPE OF ML ALGORITHM USING THE TRAINING CORPUS TO GENERATE TRAINING RESULTS
814
AUGMENT THE MACHINE LEARNING MODEL WITH THE TRAINING RESULTS FROM THE ADDITIONAL TYPE OF ML ALGORITHM
816
IDENTIFY A ROOT CAUSE FOR A WIRELESS CARRIER NETWORK ISSUE BASED ON A SET OF LIVE INPUT DATA USING THE MACHINE LEARNING MODEL
818
REFINE THE MACHINE LEARNING MODEL BASED ON USER FEEDBACK REGARDING AN EFFECTIVENESS OF A SOLUTION FOR THE ROOT CAUSE

FIG. 8

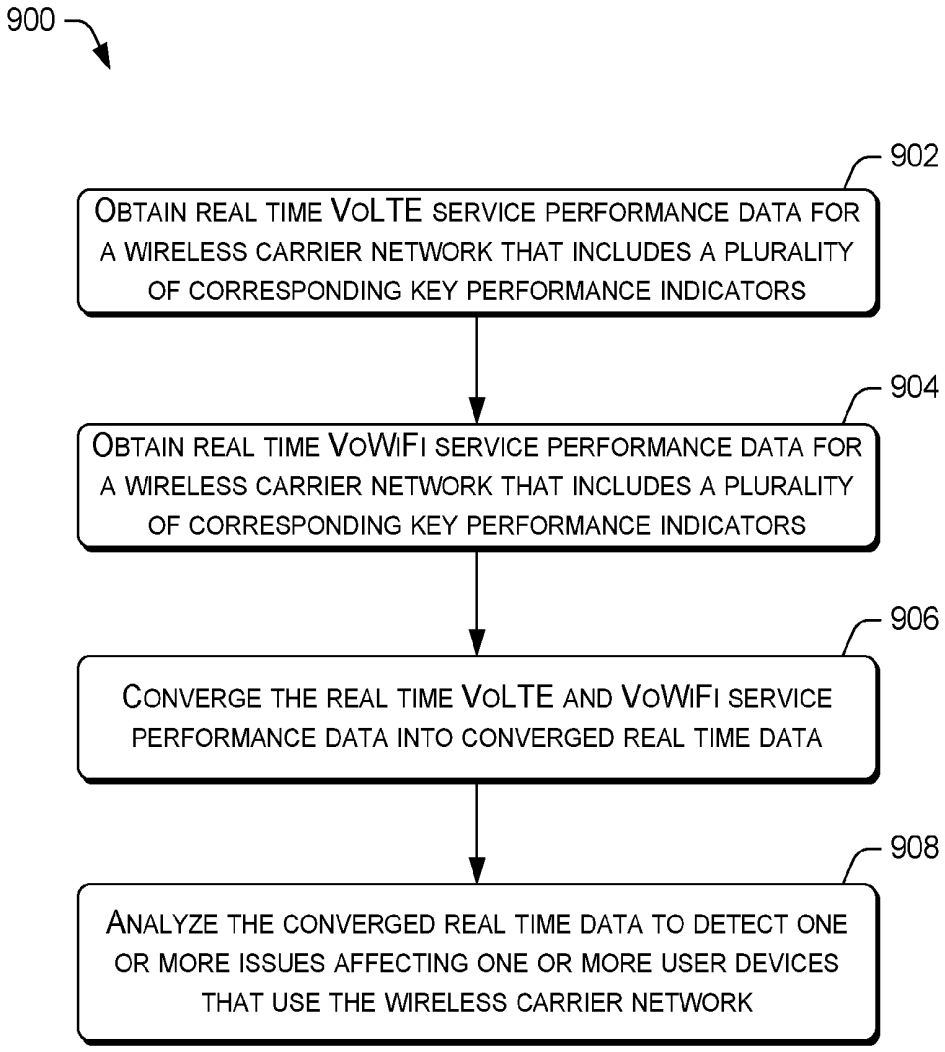

900
902
OBTAIN REAL TIME VOLTE SERVICE PERFORMANCE DATA FOR A WIRELESS CARRIER NETWORK THAT INCLUDES A PLURALITY OF CORRESPONDING KEY PERFORMANCE INDICATORS
904
OBTAIN REAL TIME VOWIFI SERVICE PERFORMANCE DATA FOR A WIRELESS CARRIER NETWORK THAT INCLUDES A PLURALITY OF CORRESPONDING KEY PERFORMANCE INDICATORS
906
CONVERGE THE REAL TIME VOLTE AND VOWIFI SERVICE PERFORMANCE DATA INTO CONVERGED REAL TIME DATA
908
ANALYZE THE CONVERGED REAL TIME DATA TO DETECT ONE OR MORE ISSUES AFFECTING ONE OR MORE USER DEVICES THAT USE THE WIRELESS CARRIER NETWORK

FIG. 9

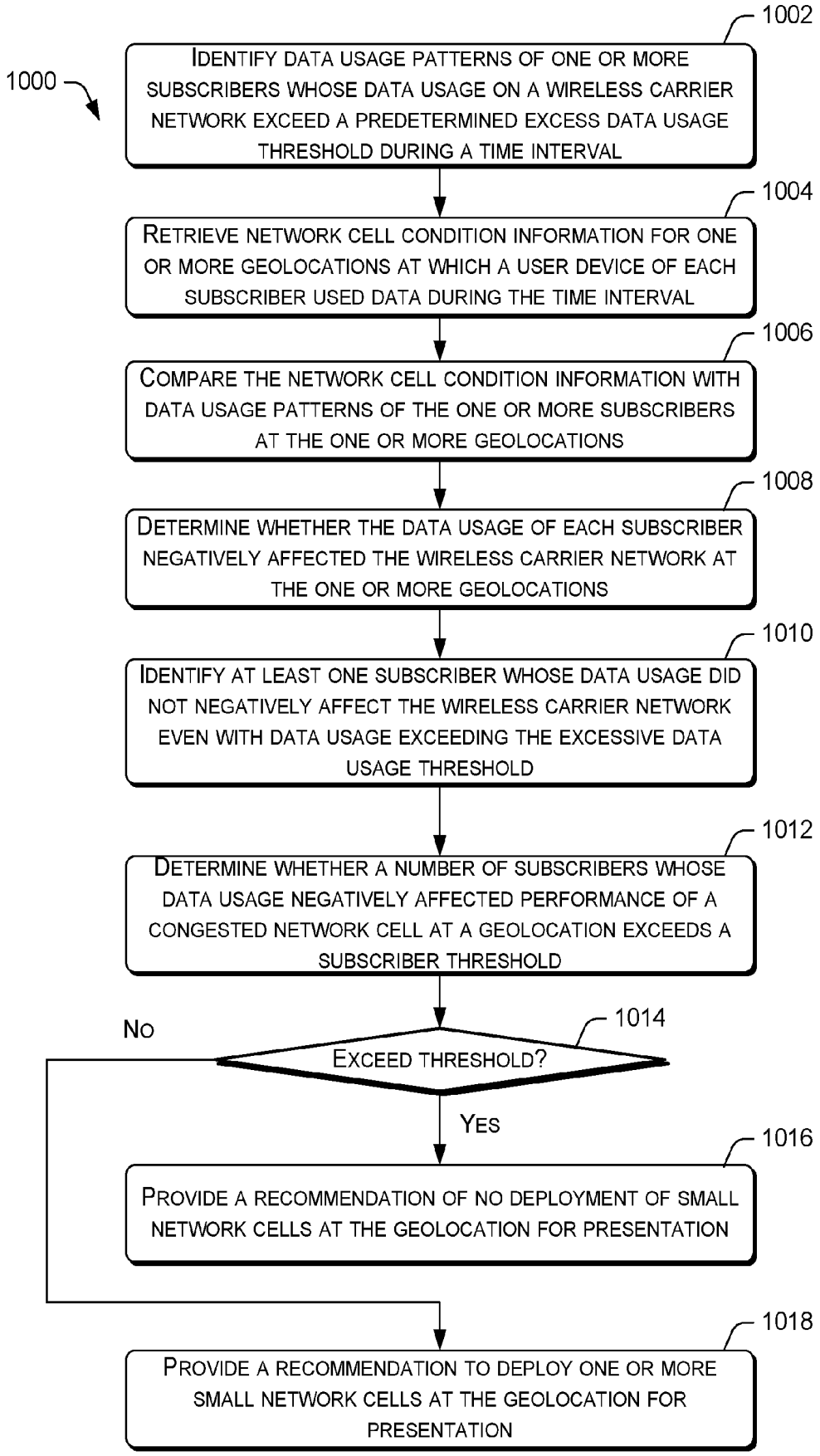

1000
1002
IDENTIFY DATA USAGE PATTERNS OF ONE OR MORE SUBSCRIBERS WHOSE DATA USAGE ON A WIRELESS CARRIER NETWORK EXCEED A PREDETERMINED EXCESS DATA USAGE THRESHOLD DURING A TIME INTERVAL
1004
RETRIEVE NETWORK CELL CONDITION INFORMATION FOR ONE OR MORE GEOLOCATIONS AT WHICH A USER DEVICE OF EACH SUBSCRIBER USED DATA DURING THE TIME INTERVAL
1006
COMPARE THE NETWORK CELL CONDITION INFORMATION WITH DATA USAGE PATTERNS OF THE ONE OR MORE SUBSCRIBERS AT THE ONE OR MORE GEOLOCATIONS
1008
DETERMINE WHETHER THE DATA USAGE OF EACH SUBSCRIBER NEGATIVELY AFFECTED THE WIRELESS CARRIER NETWORK AT THE ONE OR MORE GEOLOCATIONS
1010
IDENTIFY AT LEAST ONE SUBSCRIBER WHOSE DATA USAGE DID NOT NEGATIVELY AFFECT THE WIRELESS CARRIER NETWORK EVEN WITH DATA USAGE EXCEEDING THE EXCESSIVE DATA USAGE THRESHOLD
1012
DETERMINE WHETHER A NUMBER OF SUBSCRIBERS WHOSE DATA USAGE NEGATIVELY AFFECTED PERFORMANCE OF A CONGESTED NETWORK CELL AT A GEOLOCATION EXCEEDS A SUBSCRIBER THRESHOLD
1014
EXCEED THRESHOLD?
NO
YES
1016
PROVIDE A RECOMMENDATION OF NO DEPLOYMENT OF SMALL NETWORK CELLS AT THE GEOLOCATION FOR PRESENTATION
1018
PROVIDE A RECOMMENDATION TO DEPLOY ONE OR MORE SMALL NETWORK CELLS AT THE GEOLOCATION FOR PRESENTATION

FIG. 10

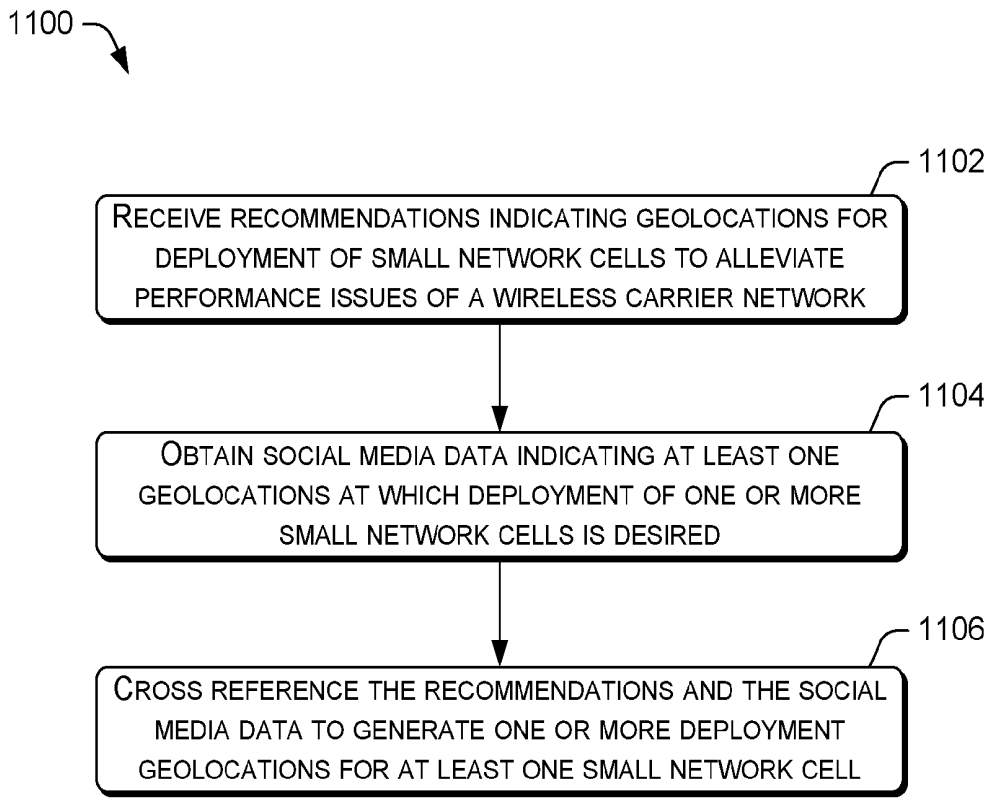

1100
1102
RECEIVE RECOMMENDATIONS INDICATING GEOLOCATIONS FOR DEPLOYMENT OF SMALL NETWORK CELLS TO ALLEVIATE PERFORMANCE ISSUES OF A WIRELESS CARRIER NETWORK
1104
OBTAIN SOCIAL MEDIA DATA INDICATING AT LEAST ONE GEOLOCATIONS AT WHICH DEPLOYMENT OF ONE OR MORE SMALL NETWORK CELLS IS DESIRED
1106
CROSS REFERENCE THE RECOMMENDATIONS AND THE SOCIAL MEDIA DATA TO GENERATE ONE OR MORE DEPLOYMENT GEOLOCATIONS FOR AT LEAST ONE SMALL NETWORK CELL

FIG. 11

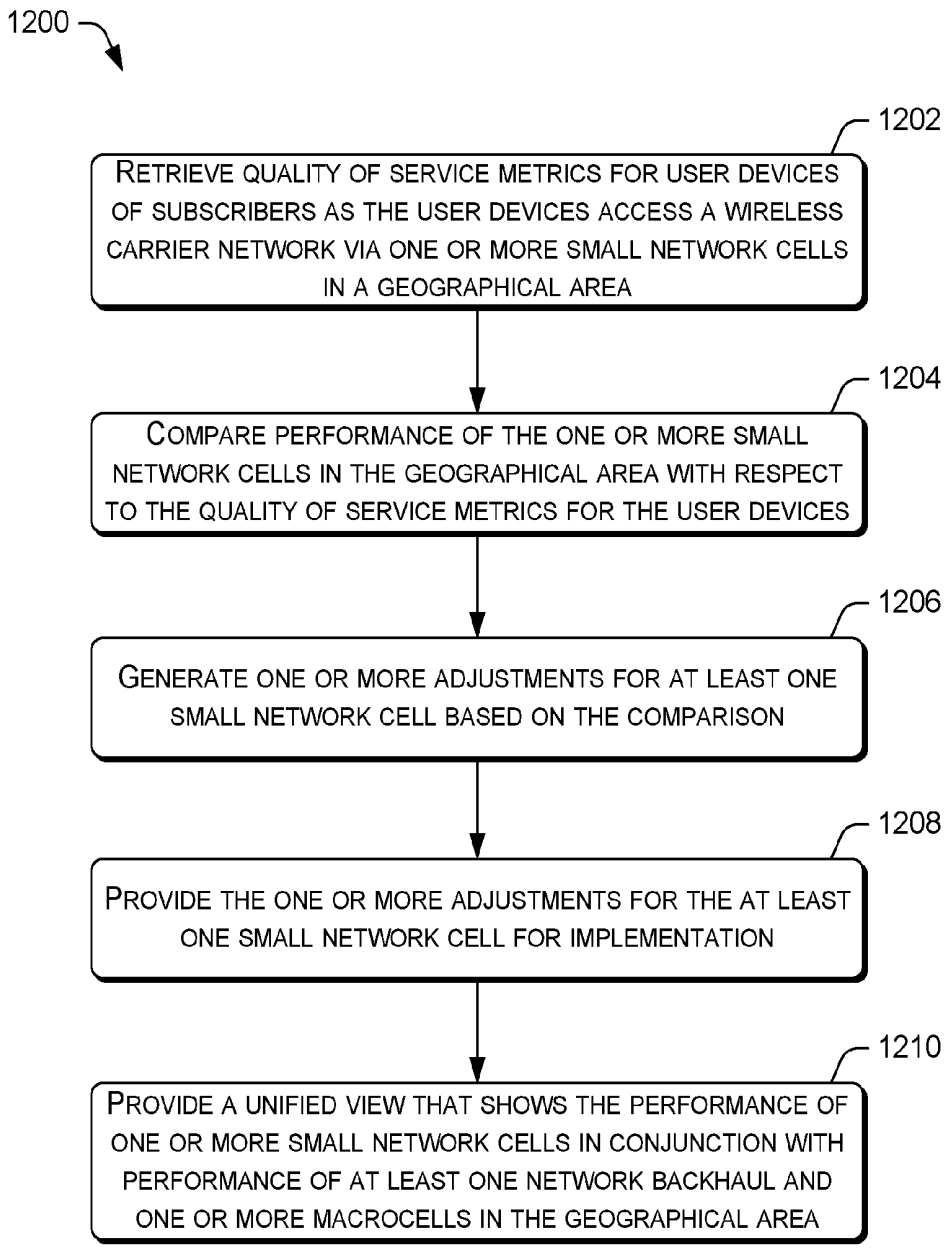

1200
1202
RETRIEVE QUALITY OF SERVICE METRICS FOR USER DEVICES OF SUBSCRIBERS AS THE USER DEVICES ACCESS A WIRELESS CARRIER NETWORK VIA ONE OR MORE SMALL NETWORK CELLS IN A GEOGRAPHICAL AREA
1204
COMPARE PERFORMANCE OF THE ONE OR MORE SMALL NETWORK CELLS IN THE GEOGRAPHICAL AREA WITH RESPECT TO THE QUALITY OF SERVICE METRICS FOR THE USER DEVICES
1206
GENERATE ONE OR MORE ADJUSTMENTS FOR AT LEAST ONE SMALL NETWORK CELL BASED ON THE COMPARISON
1208
PROVIDE THE ONE OR MORE ADJUSTMENTS FOR THE AT LEAST ONE SMALL NETWORK CELL FOR IMPLEMENTATION
1210
PROVIDE A UNIFIED VIEW THAT SHOWS THE PERFORMANCE OF ONE OR MORE SMALL NETWORK CELLS IN CONJUNCTION WITH PERFORMANCE OF AT LEAST ONE NETWORK BACKHAUL AND ONE OR MORE MACROCELLS IN THE GEOGRAPHICAL AREA

FIG. 12

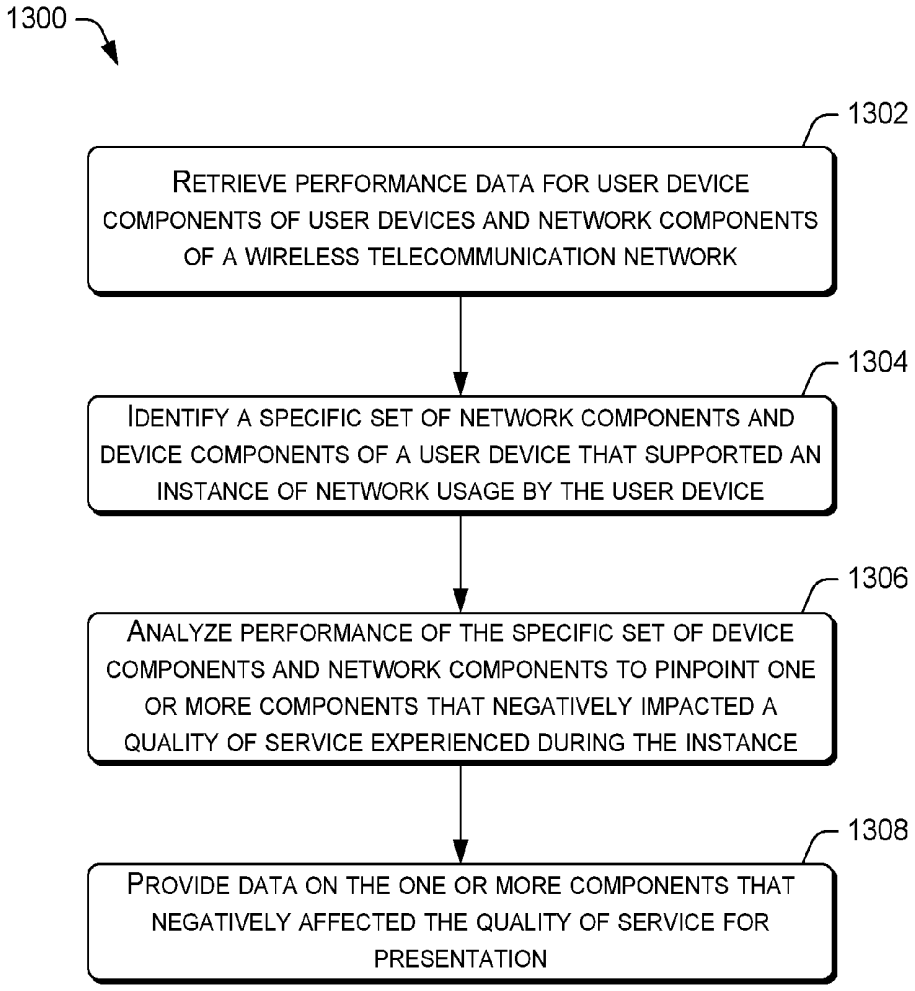

1300
1302
RETRIEVE PERFORMANCE DATA FOR USER DEVICE COMPONENTS OF USER DEVICES AND NETWORK COMPONENTS OF A WIRELESS TELECOMMUNICATION NETWORK
1304
IDENTIFY A SPECIFIC SET OF NETWORK COMPONENTS AND DEVICE COMPONENTS OF A USER DEVICE THAT SUPPORTED AN INSTANCE OF NETWORK USAGE BY THE USER DEVICE
1306
ANALYZE PERFORMANCE OF THE SPECIFIC SET OF DEVICE COMPONENTS AND NETWORK COMPONENTS TO PINPOINT ONE OR MORE COMPONENTS THAT NEGATIVELY IMPACTED A QUALITY OF SERVICE EXPERIENCED DURING THE INSTANCE
1308
PROVIDE DATA ON THE ONE OR MORE COMPONENTS THAT NEGATIVELY AFFECTED THE QUALITY OF SERVICE FOR PRESENTATION

FIG. 13

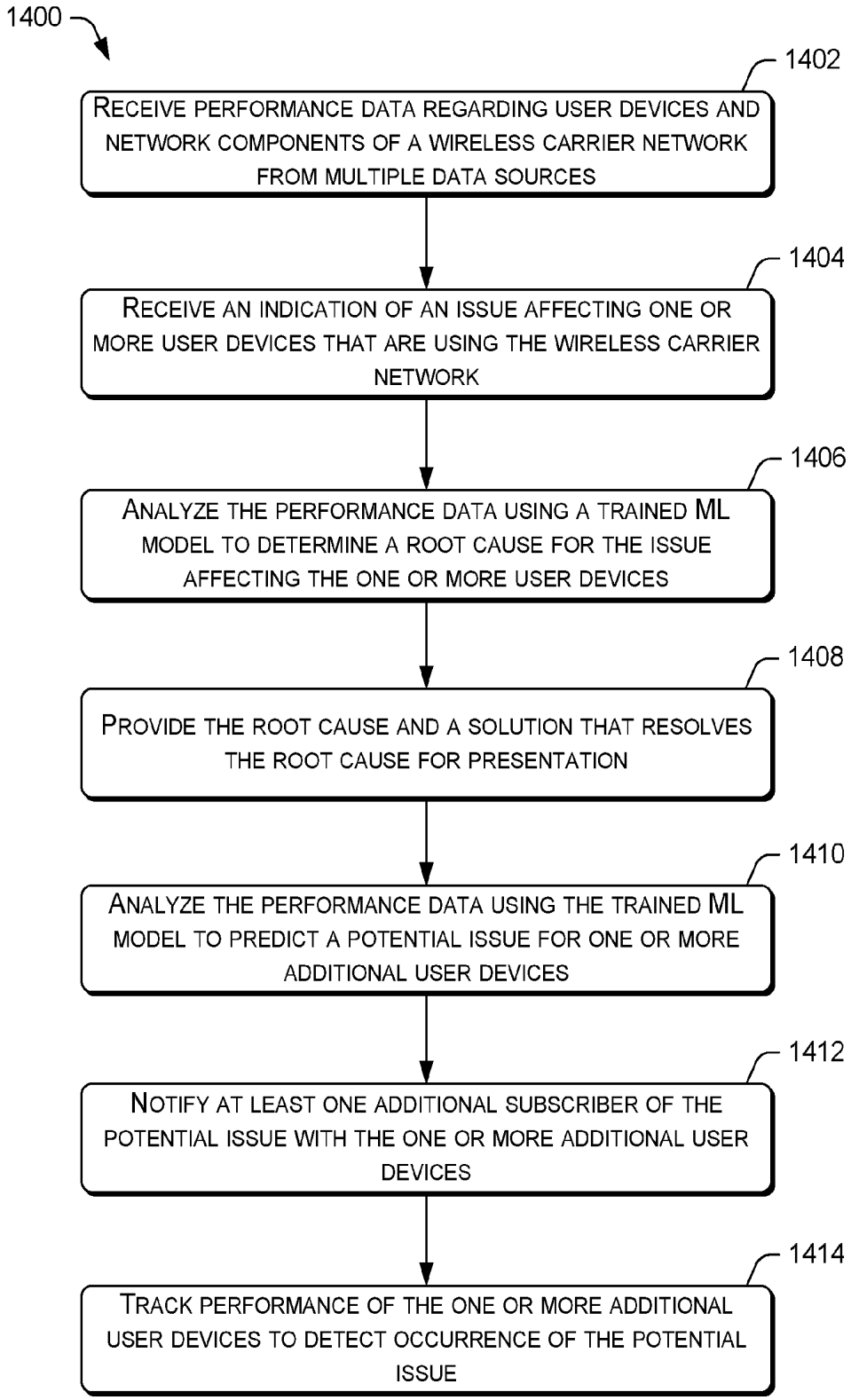

1400
1402
RECEIVE PERFORMANCE DATA REGARDING USER DEVICES AND NETWORK COMPONENTS OF A WIRELESS CARRIER NETWORK FROM MULTIPLE DATA SOURCES
1404
RECEIVE AN INDICATION OF AN ISSUE AFFECTING ONE OR MORE USER DEVICES THAT ARE USING THE WIRELESS CARRIER NETWORK
1406
ANALYZE THE PERFORMANCE DATA USING A TRAINED ML MODEL TO DETERMINE A ROOT CAUSE FOR THE ISSUE AFFECTING THE ONE OR MORE USER DEVICES
1408
PROVIDE THE ROOT CAUSE AND A SOLUTION THAT RESOLVES THE ROOT CAUSE FOR PRESENTATION
1410
ANALYZE THE PERFORMANCE DATA USING THE TRAINED ML MODEL TO PREDICT A POTENTIAL ISSUE FOR ONE OR MORE ADDITIONAL USER DEVICES
1412
NOTIFY AT LEAST ONE ADDITIONAL SUBSCRIBER OF THE POTENTIAL ISSUE WITH THE ONE OR MORE ADDITIONAL USER DEVICES
1414
TRACK PERFORMANCE OF THE ONE OR MORE ADDITIONAL USER DEVICES TO DETECT OCCURRENCE OF THE POTENTIAL ISSUE

FIG. 14

WIRELESS CARRIER NETWORK PERFORMANCE ANALYSIS AND TROUBLESHOOTING

CROSS REFERENCE TO RELATED PATENT APPLICATIONS

[0001] This application claims priority to U.S. Provisional Patent Application No. 62/193,002, filed on Jul. 15, 2015, entitled "Big Data Machine Learning Use Cases," which is hereby incorporated by reference in its entirety.

BACKGROUND

[0002] A wireless telecommunication carrier may face many challenges in finding and troubleshooting wireless communication device and carrier network issues that degrade the quality of service for their subscribers. These issues may lead to customer complaints, subscriber churn, and revenue loss for the wireless telecommunication carriers. While key performance indicators on network performance may provide some insight into the performance of the carrier network, such key performance indicators may not provide a complete picture. For example, such key performance indicators may not provide proper visibility on the real service experience of subscribers. Further, because key performance indicators are often aggregated on a network cell level, they may not provide insight with respect to non-network problems, such as subscriber or handset specific problems. Thus, key performance indicators on network performance generally do not provide an end-to-end view of the performance of all elements involved in a wireless telecommunication chain.

[0003] The lack of a comprehensive end-to-end view and proper troubleshooting tools may cause network engineers of the wireless telecommunication carrier to spend too much time performing manual analysis of customer complaints, even though the diagnosis and resolution of many complaints may be automated. For example, network engineers may spending an average of 30 minutes to resolve each subscriber trouble ticket, and the average turn around for the resolution of a subscriber trouble ticket may be as long as two days. Furthermore, as many as a quarter of the subscriber trouble tickets may go unresolved due to the lack of visibility to the underlying root cause at the time the issue actually occurred. The delay and the failure in resolving customer complaints regarding quality of service issues may result in a loss of revenue, customer base, and business reputation for the wireless telecommunication carrier.

BRIEF DESCRIPTION OF THE DRAWINGS

[0004] The detailed description is described with reference to the accompanying figures, in which the left-most digit(s) of a reference number identifies the figure in which the reference number first appears. The use of the same reference numbers in different figures indicates similar or identical items.

[0005] FIG. **1** illustrates an example architecture for performing comprehensive device and network data analysis of a wireless carrier network to resolve quality of service issues.

[0006] FIG. **2** is a block diagram showing various components of a data management platform and machine learning logic for performing the comprehensive device and network data analysis of a wireless carrier network to resolve quality of service issues.

[0007] FIG. **2** is a block diagram showing various components of a data management platform and machine learning logic for performing the comprehensive device and network data analysis of a wireless carrier network to resolve quality of service issues.

[0008] FIG. **3** is a block diagram of a machine learning pipeline for performing automatic customer complaint resolution for a wireless carrier network.

[0009] FIG. **4** is an illustrative user interface of an automatic customer complaint resolution application that provides a root cause and a resolution for a service issue.

[0010] FIG. **5** is a block diagram showing a work flow of the automatic customer complaint resolution application that provides a root cause and a resolution for a service issue.

[0011] FIG. **6** is a flow diagram of an example process for performing monitoring and machine learning-based analysis of device and network performance data to resolve quality of service issues.

[0012] FIG. **7** is a flow diagram of an example process for aggregating or converting multiple sets of data for display or analysis.

[0013] FIG. **8** is a flow diagram of an example process for training a machine learning model to generate a solution to a quality of service issue for a wireless carrier network.

[0014] FIG. **9** is a flow diagram of an example process for increasing VoLTE/VoWiFi service visibility to perform real-time detection and alerting of problems that affect the quality of service for a wireless carrier network.

[0015] FIG. **10** is a flow diagram of an example process for performing resource-aware subscriber monitoring to identify undesired excessive data usage by subscribers and ascertain capacity upgrade locations for the wireless carrier network.

[0016] FIG. **11** is a flow diagram of an example process for generating automatic suggestions of new geolocations for the installation of small network cells within the wireless carrier network.

[0017] FIG. **12** is a flow diagram of an example process for tracking the performance of network devices in relation to small network cells, macro cells, and backhauls of the wireless carrier network.

[0018] FIG. **13** is a flow diagram of an example process for generating an end-to-end look at the performance of device components of a user device and network components of a wireless carrier network in order to resolve a quality of service issue for a subscriber.

[0019] FIG. **14** is a flow diagram of an example process for using a trained machine learning model to automatically resolve trouble tickets for a wireless carrier network.

DETAILED DESCRIPTION

[0020] This disclosure is directed to techniques for using a data management platform in conjunction with analytic applications to perform comprehensive analysis of user device performance data and network performance data of a wireless carrier network to resolve quality of service issues for subscribers of the network. The user device performance data and the network performance data may be obtained from multiple data sources. In various embodiments, the multiple data sources may provide RAN Operation Support System (OSS) counters, Call Detail Records (CDRs), VoLTE call traces, Session Initiation Protocol (SIP) trace

data, Real-Time Transport Protocol (RTP) Control Protocol (RTCP) trace data, alarm data, alert data, trouble ticket data, social media data, operation data, key performance indicator (KPI) data, device performance data, as well as other data that are related to the operations of the wireless carrier network. Accordingly, the analytic applications may aggregate or converge the multiple sources of data to perform real time or non-real time comprehensive analysis that generates insight into the root causes of quality of service issues. The insight into the root causes of the quality of service issues may be further leveraged by the analytic applications to generate solutions for resolving the quality of service issues.

[0021] For example, an analytic application may perform resource-aware subscriber monitoring to determine whether excessive data usage by subscribers truly impacts the performance of the network at a particular geolocation. Based on such a determination, the analytic application may make a recommendation as to whether a capacity upgrade is to be implemented at the particular geolocation. In another example, an analytic application may generate an end-to-end look at the performance of device components of a user device and network components of the wireless carrier network in order to resolve a quality of service issue for a subscriber. In further embodiments, an automatic customer complaint resolution application may leverage a trained machine learning model to analyze the user device performance data and the network performance data to determine root causes for quality of service issues for subscribers.

[0022] The comprehensive analysis of user device performance data and network performance data of a wireless carrier network on a granular level may enable the discovery of root causes of quality of service issues that are invisible to conventional data analysis techniques. Accordingly, such analysis may pinpoint the root cause of a quality of service issue to a specific device or network component. Further, the use of a machine learning model during the analysis may enable the automatic resolution of customer complaints. Such automatic resolution may reduce issue resolution time while increase issue resolution rate. The techniques described herein may be implemented in a number of ways. Example implementations are provided below with reference to the following FIGS. **1-14**.

Example Architecture

[0023] FIG. **1** illustrates an example architecture for performing comprehensive device and network data analysis of a wireless carrier network to resolve quality of service issues. The architecture **100** may include a data management platform **102**, analytic applications **104**, and trained machine learning models **106**. The data management platform **102** and the analytic applications **104** may execute on computing nodes **108**. The computing nodes **108** may be distributed processing nodes that are scalable according to workload demand. In various embodiments, the computing nodes **108** may include general purpose computers, such as desktop computers, tablet computers, laptop computers, servers, and so forth. However, in other embodiments, the computing nodes **108** may be in the form of virtual machines, such as virtual engines (VE) and virtual private servers (VPS). The computing nodes **108** may store data in a distributed storage system, in which data may be stored for long periods of time and replicated to guarantee reliability. Accordingly, the computing nodes **108** may provide data and processing redundancy, in which data processing and data storage may be scaled in response to demand. Further, new computing nodes **108** may be added on the fly without affecting the operational integrity of the data management platform **102** and the analytic applications **104**.

[0024] The data management platform **102** may include a cloud layer that controls hardware resources, and a data management layer that manages data processing and storage. The cloud layer may provide software utilities for managing computing and storage resources. In various embodiments, the cloud layer may provide a generic user interface for handling multiple underlying storage services (e.g., local servers, Amazon AWS, Digital Ocean, etc.) that stores the call data collected by the data management platform **102**. The cloud layer may also provide an integrated view of multiple servers and clusters from various providers, such as Hortonworks, Cloudera, MapR, etc.). Additionally, the cloud layer may provide monitoring utilities to oversee utilization of resources and alerts for managing data storage or processing capacity. Accordingly, the cloud layer may facilitate the deployment, configuration, and activation of local and cloud servers, as well as facilitate the deployment, configuration, and activation of applications and/or services.

[0025] The data management layer may include software utilities and databases that facilitate the acquisition, processing, storage, reporting, and analysis of data from multiple data sources. In various embodiments, the data management layer may provide an application program interface (API) that decouples backend data management elements from data processing elements, such that the data may be distributed and stored in different data stores. For example, these data stores may include Hadoop distributed File System (HDFS), Apache Spark, Apache HBase, and/or so forth. The APIs of the data management layer may be used by custom analytic engines and/or other third party tools to access the data in the different data stores. The data management layer may further include multiple data adaptors that are able to obtain multiple types of data from multiple data sources. The data management platform **102** may access the multiple data sources via a network. The network may be a local area network (LAN), a larger network such as a wide area network (WAN), or a collection of networks, such as the Internet. The data management platform **102** may use multiple connectors in the form of applications, APIs, protocols, and services, to support connectivity with data sources and data stores, these connectors may include FTP/SFTP, HTTP/HTTPS, Java Message Service (JMS), Apache Kafka, Apache Flume, Apache Solr, Java Database Connectivity (JDBC), User Datagram Protocol (UDP), and/or so forth.

[0026] Accordingly, the data management platform **102** may provide the analytic applications **104** with data from a variety of data sources. The data sources may include an operation data source **110**, a trouble ticket data source **112**, an alarm data source **114**, social media data source **116**, and other data sources **118** that provide various types of performance data. The operation data source **110** may include a data collection that provides performance information about the wireless carrier network and the user devices that are using the wireless carrier network. In various embodiments, the performance information may include Radio Access Network (RAN) OSS counters, Call Detail Records (CDRs), VoLTE call traces, Session Initiation Protocol (SIP) trace data, Real-Time Transport Protocol (RTP) Control Protocol (RTCP) trace data, user device data traffic logs, user device

system event logs, user device bug reports, and/or other device and network component performance information. The data collection may further provide network topology data, network expansion/modification data, network coverage data, and planned maintenance data. The network topology data may include locations of network cells, network backhauls, core network components, and/o so forth. The network coverage data may include information on the signal coverage and communication bandwidth capabilities of the network cells, the performance specifications and operation statuses of backhaul, network cells, and core network components, and/or so forth. The network cells may include macrocells, picocell, femtocells, microcells, and/or so forth.

[0027] The performance information on user devices that are provided by the operation data source **110** may further include user device and account information. The device information may indicate technical capabilities, features, and operational statuses of user devices that are used by subscribers on the wireless carrier network. The user account information may include account details of multiple subscribers, such as account types, billing preferences, service plan subscriptions, payment histories, data consumption statistics, and/or so forth.

[0028] The trouble ticket data source **112** may include data on issues with the components or operations of the wireless carrier network. In some instances, network trouble tickets may be automatically generated by software agents that monitor the health and performance of the wireless carrier network. In other instances, subscriber trouble tickets may be manually inputted by customers and/or customer care representative to describe issues experienced by the customers. The trouble ticket data source **112** may further include data on the identities of the administrators, resolution reports for the issues, statistics for each type or category of issues reported, statistics on issue resolution rates, and/or so forth.

[0029] The alarm data source **114** may include alerts for the wireless carrier network that are generated based on predetermined alert rules by a status monitoring application of the network. An alert rule may specify that an alert is to be triggered when one or more conditions with respect to the operations of the network occurs. The conditions may be specific faults or issues that are detected with components of the network, deviation of actual performance indicators from predetermined threshold performance values, a number of user complaints regarding a network component, network node, or network service reaching or failing to reach a predetermined threshold, and/or so forth.

[0030] The social media data source **116** may include data collections provided by social networking portals. A social networking portal may be established by a wireless carrier network that is being evaluated by the analytic applications **104**. Another social networking portal may be a portal that is maintained by a third-party service provider for users to share social media postings. An additional social networking portal may be a web portal that is created and maintained by a particular user solely for the particular user to present social postings. The social networking portals may enable users to post and share information, reviews, and/or other comments regarding service providers, products, services, merchants, networks, and/or so forth. For example, the social networking portals may include blog web pages, message feed web pages, web forums, and/or electronic bulletin boards. A user may establish a personalized social networking portal so that other users may subscribe to the social postings of the user, leave comments for the user or other visitors to the personalized social networking portal, and/or perform other social networking activities.

[0031] Once the data from the social media data collections are obtained via data adapters, a data mining algorithm of the data management platform **102** may extract words, terms, phrases, quotes, or ratings that are relevant to the operational conditions or performance status of the nodes, components, and/or services of the wireless carrier network. The data mining algorithm may use both machine learning and non-machine learning techniques such as decision tree learning, association rule learning, artificial neural networks, inductive logic, Support Vector Machines (SVMs), clustering, Bayesian networks, reinforcement learning, representation learning, similarity and metric learning, and sparse dictionary learning to extract the patterns. In one example, the data management platform **102** may discover a pattern of web blog posting that indicate users are dissatisfied with an aspect of a service provided by the wireless carrier network at a particular geographical location. In another example, the data management platform **102** may discover a pattern of message feed postings from multiple users that indicate a specific type of user device has a high error rate when used in conjunction with the wireless carrier network.

[0032] The additional data sources **118** may include other data sources that are controlled by the wireless carrier network or third-parties, such as data reports from the network monitoring tools. In various embodiments, the network monitoring tools may include diagnostic tools, optimization tools, configuration tools, and/or so forth. The data reports may include key performance indicators (KPIs). The KPIs may be generated based on KPI configuration files that designate specific KPIs to be generated. The KPIs may measure the performance of a specific device or network component. Alternatively, the KPIs may also provide high level aggregated performance measurements for multiple network or device components, for particular classes of network or device components, and/or so forth.

[0033] The analytic applications **104** may analyze the multiple sources of data obtained by the data management platform **102** to generate data reports **120** and troubleshoot solutions **122**. The data reports **120** may provide comprehensive or end-to-end analysis results that aids in the resolution of quality of service issues for the wireless carrier network. For example, the data reports **120** may provide capacity upgrade recommendations, pinpoint malfunctions in device components or network components, provide real-time detection and alerting of quality of service issues, provide suggestions of new geolocations for the installation of small network cells within the wireless carrier network, and/or so forth.

[0034] In some embodiments, the analytic applications may include an automatic customer complaint resolution application. The automatic customer complaint resolution application may leverage a trained machine learning model **106** to analyze the user device performance data and the network performance data to determine root causes for quality of service issues for subscribers. Thus, the automatic customer compliant resolution application may provide troubleshooting solutions **122** for the root causes. The trained machine learning model **106** may be created using feature engineering that ascertains the properties and relationships of the training corpus to distinguish between the

data classes. Further, the machine learning model **106** may incorporate a combination of multiple machine learning algorithms, such as a Bayesian algorithm, a decision tree algorithm, a (SVM) algorithm, to increase the accuracy of the root cause solutions generated by the model.

[0035] The analytic applications **104** may provide the data reports **120** and the troubleshooting solutions **122** for presentation by a dashboard application **124** on the user device **126**. The user device **126** may be coupled to the computing nodes **108** via a network. The dashboard application **124** may be enable a user to query and view the data reports **120** and the troubleshoot solutions **122**. In some embodiments, the dashboard application **124** may present a dashboard interface that displays the information by different criteria, such as by user, by network component, by geolocation, and/or so forth. Alternatively or concurrently, the dashboard interface may display the information via visual charts and graphs that allows the comparison and differentiation of performance data based on multiple viewing parameters.

Example Computing Device Components

[0036] FIG. **2** is a block diagram showing various components of a data management platform and a performance management engine that performs distributed multi-data source performance management. The data management platform **102** and the analytic applications **104** may be implemented by one or more computing nodes **108** of a distributed processing computing infrastructure. The number of computing nodes **108** may be scaled up and down by a distributed processing control algorithm based on the data processing demands of the data management platform **102** and/or the analytic applications **104**. For example, during peak performance data processing times, the number of computing nodes **108** that are executing performance data processing functionalities of the analytic applications **104** may be scaled up on the fly based on processing demand. However, once the processing demand drops, the number of computing nodes **108** that are executing the performance data processing functionalities may be reduced on the fly. Such scaling up and scaling down of the number of computing nodes **108** may be repeated over and over again based on processing demand.

[0037] The computing nodes **108** may include a communication interface **202**, one or more processors **204**, and memory **206**. The communication interface **202** may include wireless and/or wired communication components that enable the one or more computing nodes **108** to transmit data to and receive data from other networked devices. The computing nodes **108** may be accessed via hardware **208**. The hardware **208** may include additional user interface, data communication, or data storage hardware. For example, the user interfaces may include a data output device (e.g., visual display, audio speakers), and one or more data input devices. The data input devices may include, but are not limited to, combinations of one or more of keypads, keyboards, mouse devices, touch screens that accept gestures, microphones, voice or speech recognition devices, and any other suitable devices.

[0038] The memory **206** may be implemented using computer-readable media, such as computer storage media. Computer-readable media includes, at least, two types of computer-readable media, namely computer storage media and communications media. Computer storage media includes volatile and non-volatile, removable and non-removable media implemented in any method or technology for storage of information such as computer-readable instructions, data structures, program modules, or other data. Computer storage media includes, but is not limited to, RAM, ROM, EEPROM, flash memory or other memory technology, CD-ROM, digital versatile disks (DVD), high-definition multimedia/data storage disks, or other optical storage, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or any other non-transmission medium that can be used to store information for access by a computing device. In contrast, communication media may embody computer-readable instructions, data structures, program modules, or other data in a modulated data signal, such as a carrier wave, or other transmission mechanism.

[0039] The data management platform **102** may include a data collection module **212**, a data storage module **216**, and a data access module **218**. The modules may include routines, program instructions, objects, and/or data structures that perform particular tasks or implement particular abstract data types. The data collection module **212** may use data adaptors to retrieve data from the structured or unstructured databases of the data sources **110-118**. Since the structured databases provide data that are accessible via simple data retrieval algorithms, the data collection module **212** may use data-agnostic data adaptors to access the data sources without taking into consideration the underlying content of the data. Further, changes to the data content in each data source generally do not affect the functionality of the corresponding data-agnostic data adaptors. On the other hand, the data collection module **212** may use database-specific data adaptors to access structured databases.

[0040] The data collection module **212** may include a workflow scheduler that periodically checks for and retrieves newly available data from the multiple data sources. The workflow scheduler may handle the extraction and the handling of the data based on configurable policies. For example, a configurable policy may specify the source data location, frequency of data retrieval, handling procedures for late arrival data, data retention period, and data disposal following an expiration of the data retention period. The handling procedures for the late arrival data may specify a predetermined cutoff period during which any data arriving late may be incorporated with data that is retrieved on time for processing. Accordingly, the data collection module **212** may retrieve data with different generation latencies (e.g., one minute, 15 minutes, one hour, one day etc.), as well as data with different spatial aggregation (e.g., network cell data, network node data, radio network controller data, etc.) such that real time or non-real time data analysis may be performed.

[0041] In various embodiments, the data processing module **214** may implement adaptor-specific logics to decode the format of the performance data from the data sources **110-118**. Accordingly, the performance data may be fed into other modules for analysis and storage. In some embodiments, the data processing module **214** may aggregate data from multiple data sources for a particular time period into an aggregated data file of data sets according to one or more grouping parameters. The grouping parameters may include specific time periods (e.g., hourly, daily, etc.), network components, user device vendor, user device models, and/or so forth. In other embodiments, the grouping parameters may be used to aggregate the data into multiple datasets that

correspond to different levels of a network hierarchy. For example, the data may be aggregated into datasets that correspond to a subscriber level, a device level, a service area level, and a geographical market level. The geographical market level may further include a zip code sublevel, a municipality sublevel, or another location-based sublevel that may correspond to datasets for aggregation. Nevertheless, the aggregated data from the multiple data sources may be stored in the data sets according to their own storage schemas. In other embodiments, the data processing module **214** may converge the data from multiple data sources for a particular time period into a converged data file of data sets, in which the data are stored in the data sets according to a unitary storage schema.

[0042] The data storage module **216** may store data across multiple virtual data storage clusters with redundancy, so that the data may be optimized for quick access. The stored data may include the performance data from the data sources **110-118**, the aggregated and covered data files, data that are generated by the analytic applications **104**, and/or so forth. The data access module **218** may provide a data access API for accessing the data stored in the multiple virtual storage clusters. Accordingly, the API may be used by the analytic applications **104** as well as other third-party application to access the data that received and stored by the data management platform **102**.

[0043] The model training module **220** may trained machine learning models, such as the models **222(1)-222** (N), to analyze the performance data from the data sources **110-118** to determine root causes for quality of service issues for subscribers. In various embodiments, the model training module **220** may use a machine learning training pipeline to generate a machine learning model, in which the details of the machine learning training pipe are illustrated in FIG. **3**.

[0044] FIG. **3** is a block diagram of a machine learning pipeline **302** that is implemented by the model training module **220** to train a machine learning model for analyzing performance data to determine root causation. The machine learning pipeline **302** may include a training data input phase **304**, a feature engineering phase **306**, and a model generation phase **308**. In the training data input phase **304**, the model training module **220** may receive a training corpus comprised of one or more input datasets from the data management platform **102**. The training corpus may include training data that emulates data collected from the multiple data sources **110-118** and optionally a set of desired outputs for the training data. For example, the data that is received during the training data input phase **304** may include Operating Support System (OSS) counters, KPIs, network coverage details, device alarm data, network alarm data, device alert data, network alert data, CDRs, and/or so forth.

[0045] The model training module **220** may use the feature engineering phase **306** to pinpoint features in the training corpus. Accordingly, feature engineering may be used by the model training module **220** to figure out the significant properties and relationships of the input datasets that aid a model to distinguish between different classes of data. The model training module **220** may perform outlier detection analysis **310**, feature composition analysis **312**, and feature relevance analysis **314** during the feature engineering phase **306**. In the outlier detection analysis **310**, the model training module **220** may detect outlier features for exclusion from use in the generation of a machine learning model. In various implementations, the outlier detection analysis **310** may be performed using a clustering algorithm, such as a k-means algorithm, a Gaussian mixture algorithm, a bisecting k-means algorithm, a streaming k-means algorithm, or another outlier detection algorithm.

[0046] In the feature composition analysis **312**, the model training module **220** may transform at least some of the multiple features in the training corpus into a single feature. Accordingly, feature composition may decreased the number of input features while preserving the characteristics of the features. This decrease in the number of features may reduce the noise in the training corpus. As a result, the composition feature that is derived from the multiple features may improve the classification results for the datasets of the training corpus. In various implementations, the feature composition analysis **312** may be performed using various dimensionality reduction algorithm, such as a Singular Value Decomposition (SVD) algorithm, a Principal Component Analysis (PCA) algorithm, or another type of dimensionality reduction algorithm.

[0047] For example, the SVD algorithm may break a matrix of the training corpus into linearly independent components. These components may be a sets of values that approximate the underlying structure of the original dataset of values independently along each dimension. Due to the relatively small size of the components, many of these components may be ignored to generate an approximation of the training corpus that contains substantially fewer dimensions than the original. In another example, the PCA algorithm may use an orthogonal transformation to emphasize variations in the training corpus in order to bring out strong patterns in the data sets. The orthogonal transformation is defined in such a way that the first principal component has the largest possible variance, and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components.

[0048] In the feature relevance analysis **314**, the model training module **220** may identify redundant features in the training corpus to in order to eliminate such features from being used in the training of the machine learning model. An excessive number of features may cause a machine learning algorithm to over-fit a training corpus or slowdown the training process. In various implementations, the feature relevance analysis **314** may be performed using a dimensionality reduction algorithm (e.g., the PCA algorithm, a statistics algorithm, and/or so forth). The statistics algorithm may be a summary statistics algorithm, a correlation algorithm, a stratified sampling algorithm, and/or so forth.

[0049] The model training module **220** may perform the model generation phase **308** following the completion of the feature engineering phase **306**. During the model generation phase **308**, the model training module **220** may select an initial type of machine learning algorithm to training a machine learning model using a training corpus. For example, the model training module **220** may model the distribution of feature $(x|y=1)$ and $(x|y=0)$, in which $(x|y=1)$ is the distribution of features when there is a network coverage problem, $p(x|y=0)$ is the distribution of features when there is no network coverage problem, and $p(y)$ represents "prior probability". In such a scenario, the model training module **220** may make a prediction based on the models of $p(x|y=1)$ and $p(x|\ y=0)$ using Bayes' Rule, as follows:

$$p(y|x)=(p(x|y)p(y))/(p(x))=(p(x|y)p(y))/(p(x|y=1)+p(x|y=0)p(y=0)) \quad (1)$$

Thus, an assumption may be made that all x_i features are either binary (0 or 1), or continuous features that are partitioned into bins, i.e., discretize a continuous variable, and that each data point in the training corpus contains 20 binary features, that is:

$$x_1=[1,0,1,1,1,1 \ldots ,0] \quad (2)$$

in which the modeling of p(x|y) explicitly calls for an unachievable probability table for 2^{20} inputs. As a result, the model training module **220** may apply the Naïve Bayes assumption to model p (x|y), as follows:

$$p(x_i|y)=p(x_i|y,x_j) \quad (3)$$

[0050] The Naïve Bayes assumption states that if a given input vector x corresponds with a coverage problem i.e., y=1, and feature x_j appears in the input vector, the belief about the presence of the feature x_i in the input vector does not change. In other words, if the input vector represents a network coverage problem, the fact that the input vector indicates that there is "poor network coverage on 3G" will not affect the belief about the status of the feature "poor network coverage on 4G". In the real word this belief may not be true, because there may be a relationship between "poor network coverage on 4G" and "poor network coverage on 3G". However, the Naïve Bayes assumption is ruling out that possibility with the purpose of simplifying the estimation of p(x|y), as follows:

$$\begin{aligned} p(x_1, x_2, x_3, , , , x_{20} \mid y) &= p(x_1 \mid y)p(x_2 \mid y, x_1)p(x_3 \mid y, x_1, x_2) \ldots \\ &\quad p(x_{20} \mid y, x_1, x_2, x_3, , , x_{19}) \\ &= p(x_1 \mid y)p(x_2 \mid y)p(x_3 \mid y) \ldots p(x_{20} \mid y) \\ &= \prod_i^{20} p(x_i \mid y) \end{aligned} \quad (4)$$

Therefore,

$$p(y=1 \mid x) = \frac{p(x \mid y=1)p(y=1)}{p(x)} = \frac{\prod_i^{20} p(x_i \mid y=1)p(y=1)}{\prod_i^{20} p(x_i \mid y=1)p(y=1) + \prod_i^{20} p(x_i \mid y=0)p(y=0)} \quad (5)$$

[0051] Following the application of a selected machine learning algorithm to the training corpus, the model training module **220** may determine a training error measurement of the machine learning model. The training error measurement may indicate the accuracy of the machine learning model in generating a solution. Accordingly, if the training error measurement exceeds a training error threshold, the model training module **220** may use a rules engine **224** to select an additional type of machine learning algorithm based on a magnitude of the training error measurement. The training error threshold may be a stabilized error value that is greater than zero. In various embodiments, the rules engine **224** may contain algorithm selection rules that match specific ranges of training error measurement values to specific types of machine learning algorithms. The different types of machine learning algorithms may include a Bayesian algorithm, a decision tree algorithm, a SVM algorithm, an ensemble of trees algorithm (e.g., random forests and gradient-boosted trees), an isotonic regression algorithm, and/or so forth.

[0052] Following the selection of the additional type of machine learning algorithm, the model training module **220** may execute the additional type of machine learning algorithm on the training corpus to generate training results. In some instances, the model training module **220** may also supplement the training corpus with additional training datasets prior to the additional execution. The generated training results are then incorporated by the model training module **220** into the machine learning model. Subsequently, the model training module **220** may repeat the determination of the training error measurement for the machine learning model, and the selection of one or more types of additional machine learning algorithms to augment the machine learning model with additional training results until the training error measurement is at or below the training error threshold. Accordingly, the model training module **220** may use the machine learning algorithms **316(1)-316**(N) to generate a trained machine learning module **318**.

[0053] Returning to FIG. **2**, the analytic applications **104** may analyze the multiple sources of data obtained by the data management platform **102** to generate data reports **120** and troubleshoot solutions **122**. The analytic applications **104** may have built in application user interfaces that simplify the data querying and requesting process such that status data and troubleshooting solutions may be provided via the application user interfaces. The application user interfaces of the analytic applications **104** may be displayed by the dashboard application **124**. The analytic applications may process real time or non-real time data, in which data from multiple data sources may be aggregated or converged. The data reports **120** may provide real time or non-time views of device and network status data based on the performance data from the data sources **110-118**. Accordingly, a user may use the data reports **120** to continuously or periodically monitor the statuses pertaining to all aspects of the wireless carrier network. The aspects may include the statuses of wireless carrier network itself, the network components of the network, user devices that are using the wireless carrier network, and/or device components of the user devices.

[0054] In further embodiments, the analytic applications **104** may generate troubleshooting solutions using one or more of the trained machine learning models **226(1)-226**(N). The troubleshooting solutions may be generated based on the performance data from one or more of the data sources **110-118** provided by the data management platform **102**. For example, the trained machine learning models may be used to automatically analyze CDRs to identify root causes of quality of service issues with the wireless carrier network. In other examples, the trained machine learning modules may be used to improve network quality of service, increase network performance efficiency, analyze cell data to identify fraud, analyze patterns to predict subscriber, analyze subscriber usage patterns to identify geographical area for implementing new network services. For example, an analytic application may use a trained machine learning model to identify a root cause for an issue that is the subject of a subscriber trouble ticket, a subject of a network generated trouble ticket, or detected by an analytic application. In various embodiments, the analytic application may retrieve

a troubleshooting solution from a solutions database that resides on the computing nodes **108** based on a diagnosed root cause of an issue.

[0055] In some embodiments, an analytic application may provide an application user interface that enables a user to provide feedback on whether a trained machine learning model was effective in resolving a quality of service issue. In such embodiments, the subscriber or a customer service representative may use an application user interface provided by the analytic application to indicate whether the solution is effective in resolving the issue outlined in the trouble ticket. Thus, if the feedback is that the solution did not resolve the issue, the analytic application may refer the trouble ticket to a network engineer for resolution. Furthermore, the analytic application may provide an indication to the model training module **220** that the solution did not work. In turn, the model training module **220** may retrain a machine learning model. During retraining, the model training module **220** may receive an input from the engineer indicating a correct solution to an issue outlined in the trouble ticket. Accordingly, the input from the engineer may be added as a data point to the training corpus for retraining of the machine learning algorithms of the machine learning model. In some instances, the engineering may also provide additional input to the model training module **220** that indicates specific anomalous data (e.g., observations or assertions) to be removed from the training corpus. The removal of the specific anomalous data from the training corpus may prevent the machine learning model from generating ineffective solutions for performance data inputs.

[0056] Alternatively or concurrently, the model training module **220** may configure the rules engine **224** to modify the algorithm selection rules during retraining. The modifications to the algorithm selection rules may change a range of training error measurement values that correspond to a type machine of learning algorithm, cause specific ranges of training error measurement values to match to different types of machine learning algorithms, and/or so forth. In this way, the model training module **220** may generated a modified trained machine learning model based on the feedback.

[0057] A summary of different types of performance data and the output results that are generated by the permutations of features of analytic applications **104** are listed in below, in which the monitoring output type corresponds to the generation of data reports **120**, and analytics output type corresponds to the generation of troubleshooting solutions **122**:

TABLE

Comparison of Input and Output Data Types of the Analytic Applications

Type of Data Source	Temporality of Data	Output Type
Aggregated	Non-Real Time	Monitoring
Aggregated	Non-Real Time	Analytics
Aggregated	Real Time	Monitoring
Aggregated	Real Time	Analytics
Converged	Non-Real Time	Monitoring
Converged	Non-Real Time	Analytics
Converged	Real Time	Monitoring
Converged	Real Time	Analytics

Additional details regarding the operations of the analytic applications **104** are described below with respect to FIGS. **5** and **9-14**.

Example User Interface

[0058] FIG. **4** is an illustrative user interface **400** of an automatic customer complaint resolution application that provides a root cause and a resolution for a service issue. The user interface **400** may include an application menu section **402**, a ticket selection section **404**, and a ticket detail section **406**. The application menu section **402** may provide options that enables a user to view subscriber trouble tickets, network trouble tickets, alarm data, overall network performance data, as well as data regarding individual calls of subscribers. For example, a user may select network performance to show different visualizations of network performance. The different visualizations of network performance may be filtered by zip code, by a particular geographical area, by a particular network cell, by a particular user device, and/or so forth. However, as shown in FIG. **4**, a user has selected the subscriber trouble ticket option such that the user is able to view trouble tickets that are initiated by specific subscribers.

[0059] The selection of the subscriber trouble ticket option may cause the user interface **400** to display the ticket selection section **404**. The ticket selection section **404** may include options for the selecting subscriber trouble tickets that fall within a specific date range for display. For example, a user is able to select a specific date and a range of dates that immediately precede the specific date. In turn, the ticket selection section **404** may display subscriber tickets that fall within the specific date range. For example, as show in FIG. **4**, a subscriber trouble ticket for a coverage problem experience by the user device of a particular subscriber may be displayed in the ticket selection section **404**.

[0060] The selection of a subscriber trouble ticket that is displayed in the ticket selection section **404** may cause the ticket detail section **406** to display details for the ticket. For example, the ticket selection section **404** may show a nature of the service complaint, a description of the service issue, details for the user device that is associated with the service complaint, including device type information for the user device (e.g., device make, device model). In this case, the service complaint is frequent dropped calls regardless of user device location. Furthermore, the ticket detail section **406** may further display a root cause of the service issue as determined by the automatic customer complaint resolution application. For example, the ticket detail section **406** may show that the root cause is failures of call handover between network cells for the user device. Accordingly, the solution for solving the root cause may be the reconfiguration of the network cells to modify timing of handover initiation commands sent to the specific type of the user device. The modification may ensure that dropped calls due to network cell handovers may be diminished or eliminated.

[0061] Thus, as shown in FIG. **5**, the implementation of an automatic customer complaint resolution application **500** may initially involve data collection **502**. The data collected may include topology data, performance data, trouble ticket data, alerts, etc., for a specific time period and/or specific groups. For example, the trouble ticket data may be collected for a previous hour for specific groups of network nodes and/or user devices. In at least one embodiment, the

trouble ticket data may include lists of trouble tickets, compliant details associated with each ticket, network coverage information, site/node frequency band support information, and/or so forth. During data preparation **504**, the data may be prepared for analysis via aggregation, convergence, and/or other forms of data processing. In some embodiments, the automatic customer complaint resolution application may also perform ticket update **506**. During the ticket update **506**, the trouble tickets may be updated based on data from other sources. For example, customer trouble ticket data may be updated with corresponding CDR data or other performance data that are related to each customer trouble ticket.

[0062] Following the updating of the trouble tickets data, the automatic customer complaint resolution application **500** may perform data analysis. The data analysis may involve trouble ticket trend analysis **508** that provides trouble ticket trends **510** for specific areas, such as particular markets or particular zip codes. In some instances, the automatic customer complaint resolution application **500** may perform trouble ticket clustering **512** during the trouble ticket trend analysis. The trouble ticket clustering **512** may enable the automatic customer complaint resolution application **500** to provide clustered trouble ticket data scores for different regions, such as different neighborhoods. The data analysis may further involve individual ticket analysis **514** to resolve tickets. The individual ticket analysis **514** may include the analysis of associated data to **516** for individual trouble tickets. For example, the associated data may include user KPIs, network KPIs, alerts, network component health indicators, and/or so forth. Thus, by using a ticket resolution logic **518** that includes one or more trained machine learning models, the automatic customer complaint resolution application **500** may determine a root cause for resolving the trouble ticket. In various instances, the ticket resolution logic **518** may use predefined analytic rules, as well as parameters for prioritizing analysis of different types of collected data. In some embodiments, the automatic customer complaint resolution application **500** may include a ticket action manager **520** that implements a decision flow and defines the actions to be taken for every trouble ticket. Following the analysis, the ticket resolution logic **518** may generate resolution messages that provide details for resolving the trouble tickets. In some instances, the ticket resolution logic **518** may also generate a work log that documents the root causes and resolutions for the trouble tickets.

Example Processes

[0063] FIGS. **6-14** present illustrative processes **600-1400** for performing comprehensive device and network data analysis of a wireless carrier network to resolve quality of service issues. Each of the processes **600-1400** is illustrated as a collection of blocks in a logical flow chart, which represents a sequence of operations that can be implemented in hardware, software, or a combination thereof. In the context of software, the blocks represent computer-executable instructions that, when executed by one or more processors, perform the recited operations. Generally, computer-executable instructions may include routines, programs, objects, components, data structures, and the like that perform particular functions or implement particular abstract data types. The order in which the operations are described is not intended to be construed as a limitation, and any number of the described blocks can be combined in any order and/or in mirror to implement the process. For discussion purposes, the processes **600-1400** are described with reference to the architecture **100** of FIG. **1**.

[0064] FIG. **6** is a flow diagram of an example process **600** for performing monitoring and machine learning-based analysis of device and network performance data to resolve quality of service issues. At block **602**, the data management platform **102** may obtain performance data regarding operations of a wireless carrier network. The performance data may be include operation data obtained from the operational data source **110**, trouble ticket data from the trouble ticket data source **112**, alarm data from the alarm data source **114**, relevant social media data from the social media data source **116**, and additional data from the other data sources **118**. The performance data may be relevant to the one or more network components of the wireless carrier network or one or more device components of user devices that use the wireless carrier network.

[0065] At block **604**, an analytic application may determine whether to display or analyze a set of real time or non-real time data from the input data. In various embodiments, the display or analysis of the real time may enable the analytic application to facilitate performance monitoring. On the other hand, the display or analysis of the non-real time may enable the analytic application to facilitate the diagnosis and resolution of performance issues. The analytic application may make such a determination based on a query that is inputted into an application user interface that is provided by the application. Thus, at decision block **606**, if the analytic application determines that real time data is to be analyzed or displayed, the process **600** may proceed to decision block **608**.

[0066] At decision block **608**, the analytic application may determine whether the real time data is to be displayed or analyzed. The analytic application may make such a determination based on the performance data query that is inputted into the application user interface of the application. Thus, if the analytic application determines that the real time data is to be analyzed, the process **600** may proceed to block **610**. At block **610**, the analytic application may perform analysis of the real time data to detect an issue affecting one or more subscribers of the wireless carrier network or generate a solution to an issue. In some embodiments, the analytic application may perform the analysis using a machine learning model. The analytic application may provide the issue and/or the solution for display via the application user interface. However, returning to decision block **608**, if the analytic application determines that the real time data is to be displayed, the process **600** may proceed to block **612**. At block **612**, the analytic application may provide the real time data for presentation via the application user interface.

[0067] Returning to decision block **606**, if the analytic application determines that the non-real time data is to be analyzed or displayed, the process **600** may proceed to decision block **614**. At decision block **614**, the analytic application may determine whether the non-real time data is to be displayed or analyzed. The analytic application may make such a determination based on the performance data query that is inputted into the application user interface of the application. Thus, if the analytic application determines that the real time data is to be analyzed, the process **600** may proceed to block **616**.

[0068] At block **616**, the analytic application may perform analysis of the non-real time data to detect an issue affecting one or more subscribers of the wireless carrier network or generate a solution to an issue. In some embodiments, the analytic application may perform the analysis using a machine learning model. The analytic application may provide the issue and/or the solution for display via the application user interface. However, returning to decision block **614**, if the analytic application determines that the non-real time data is to be displayed, the process **600** may proceed to block **618**. At block **618**, the analytic application may provide the real time data for presentation via the application user interface.

[0069] FIG. **7** is a flow diagram of an example process **700** for aggregating or converting multiple sets of data for display or analysis. An analytic application may perform the process **700** prior to analyzing or displaying at least some of the performance data collected by the data management platform **102**. At block **702**, the analytic application may determine whether to aggregate or converge different sets of performance data for display or analysis. The analytic application may make such a determination based on the performance data query that is inputted into the application user interface of the application. Thus, at decision block **704**, if the analytic application determines that the different sets of performance data are to be converged, the process **700** may proceed to block **706**. At block **706**, the data management platform **102** may converge the different sets of performance data according to a unitary storage schema for display or analysis. The convergence of the different sets of performance data by the data management platform **102** may be performed based on a request from the analytic application. In alternative embodiments, the data management platform **102** may converge the different sets of performance data in advance based on a predicted or expected request for the converged data from the analytic application.

[0070] Returning to decision block **704**, if the analytic application determines that the different sets of performance data are to be aggregated, the process **700** may proceed to block **708**. At block **708**, the data management platform **102** may aggregate the different sets of performance data according to one or more grouping parameters for display or analysis. The aggregation of the different sets of performance data by the data management platform **102** may be performed based on a request from the analytic application. In alternative embodiments, the data management platform **102** may aggregate the different sets of performance data in advance based on a predicted or expected request for the aggregated data from the analytic application.

[0071] FIG. **8** is a flow diagram of an example process **800** for training a machine learning model to generate a solution to a quality of service issue for a wireless carrier network. At block **802**, the model training module **220** may perform feature engineering on a training corpus for generating a machine learning model. The machine learning model is used to determine solutions for issues with a wireless carrier network that affects one or more user devices. In various embodiments, the feature engineering may include performing outlier detection analysis, feature composition analysis, and/or feature relevance analysis to reduce noise in the training corpus and reduced the amount of data that is processed during the training of machine learning models.

[0072] At block **804**, the model training module **220** may train an initial type of machine learning algorithm using the training corpus to generate the machine learning model. In various embodiments, the initial type of machine learning algorithm may be a Bayesian algorithm, a decision tree algorithm, a SVM algorithm, an ensemble of trees algorithm (e.g., random forests and gradient-boosted trees), or an isotonic regression algorithm.

[0073] At block **806**, the model training module **220** may determine a training error measurement of the machine learning model. The training error measurement may indicate the accuracy of the machine learning model in generating a solution in comparison to an expected baseline accuracy. Thus, at decision block **808**, if the model training module **220** determines that the training error measurement is above a training error threshold, the process **800** may proceed to block **810**. At block **810**, the model training module **220** may select an additional type of machine learning algorithm to be trained based on a magnitude of the training error measure in accordance with algorithm selection rules. In various embodiments, the algorithm selection rules may be used by a rules engine of the model training module **220** to match a specific ranges of training error measurement value to a specific type of machine learning algorithm.

[0074] At block **812**, the model training module **220** may train the additional type of machine learning algorithm using the training corpus to generate training results. The additional type of machine learning algorithm may differ from the initial type of machine learning algorithm. For example, if the initial type of machine learning algorithm is a Bayesian algorithm, then the additional type of machine learning algorithm may be a decision tree algorithm.

[0075] At block **814**, the model training module **220** may augment the machine learning model with the training results from the additional type of machine learning algorithm. Subsequently, the process **800** may loop back to block **806** so that another training error measurement of the machine learning model may be determined. Returning to decision block **808**, if the model training module **220** determines that the training error measurement is at or below the training error threshold, the process **800** may proceed directly to block **816** as the generation of a trained machine learning model is deemed to be complete.

[0076] At block **816**, an analytic application may identify a root cause for an issue affects one or more subscribers of a wireless carrier network based on a set of live performance data using the machine learning model. The analytic application may further generate a solution for the root cause using a solutions database. In various embodiments, the live performance data may be real time or non-real time data pertaining to one or more network components of the wireless carrier network and/or one or more device components of the user devices that are using the wireless carrier network. The live performance data may include aggregated or converged data sets that are obtained from the data sources **110-118**. The live performance data may be selected for analysis by a user via an application user interface of the analytics application. In turn, the analytic application may provide the solution that is generated using the machine learning model via the application user interface.

[0077] At block **818**, the model training module **220** may refine the machine learning model based on user feedback regarding an effective of the solution. In various embodiments, the feedback in the form an indication of whether the solution solved or did not solve the issue may be received by

the analytic application via an application user interface. In turn, the analytic application may pass an indication that the solution was ineffective to the model training module **220**. In response to the indication, the model training module **220** may retrain the machine learning model. During retraining, the feedback may be added as one or more data points to the training corpus for training the machine learning algorithms of the machine learning model. The feedback may further indicate specific anomalous data (e.g., observations or assertions) to be removed from the training corpus. Alternatively or concurrently, the refinement may include the modification of the algorithm selection rules. The modifications to the algorithm selection rules may change a range of training error measurement values that correspond to a type machine of learning algorithm, cause specific ranges of training error measurement values to match to different types of machine learning algorithms, and/or so forth.

[0078] FIG. **9** is a flow diagram of an example process **900** for increasing VoLTE/VoWiFi service visibility to perform real-time detection and alerting of problems that affect the quality of service for a wireless carrier network. At block **902**, the data management platform **102** may obtain real-time voice over LTE (VoLTE) performance data for a wireless carrier network that includes a plurality of corresponding KPIs. The plurality of KPIs may measure the performance of network components of the wireless carrier network and/or performance of device components of user devices that use the wireless carrier network. In various embodiments, the KPIs may be high level KPIs that capture service performance, such as call establishment delays, mean opinion scores (MOS) of call audio quality, one-way audio problems, and network cell handover problems.

[0079] At block **904**, the data management platform **102** may obtain real time voice over WiFi (VoWiFi) service performance data for a wireless carrier network that includes a plurality of corresponding KPIs. The plurality of KPIs may measure the performance of network components of the wireless carrier network and/or performance of device components of user devices that use the wireless carrier network. In various embodiments, the KPIs may be high level KPIs that capture service performance, such as call establishment delays, MOS of call audio quality, one-way audio problems, difficulties with transitions between VoWiFi and VoLTE, and/or so forth.

[0080] At block **906**, the data management platform **102** may converge the real time VoLTE and VoWiFi service performance data into converged real time data. The convergence may transform the datasets of the real time VoLTE and VoWiFi data storage according to a unitary storage schema. The data management platform **102** may perform such transformation for an analytic application that is to analyze the converged real time data.

[0081] At block **908**, the analytic application may analyze the converged real time data to detect one or more issues affecting one or more user devices that use the wireless carrier network. The issues may be a large scale problem that may otherwise go undetected without the use of the trained machine learning model. For example, an issue may be a widespread problem with a specific type of user devices or a specific type of agent application on user devices. In various embodiments, the analytic application detect any issue with a specific type of device component or network component when the values of one or more KPIs that measure device or network component performances differ from their respective predetermined acceptable values or predetermined acceptable value ranges.

[0082] FIG. **10** is a flow diagram of an example process **1000** for performing resource-aware subscriber monitoring to identify undesired excessive data usage by subscribers and ascertain capacity upgrade locations for the wireless carrier network. At block **1002**, an analytic application may identify data usage patterns of one or more subscribers whose data usage on a wireless carrier network exceed a predetermined excess data usage threshold during a time interval. For example, the excess data usage threshold may be 50 gigabytes per month, and a user may have used 60 gigabytes in a month. The analytic application may identify these subscribers by reviewing the data usage patterns of multiple subscribers of the wireless carrier network as collected by the data management platform **102**. In various embodiment, the data usage pattern of a subscriber may indicate the geolocations at which the subscriber is consuming the data, the amount of data used in a time period (e.g., one day, one week, one month, etc.), the peak and off peak data usage times in a daily cycle, the type of data consumption (e.g., media streaming, web browsing, gaming, etc.) that the subscriber engages in, and/or so forth.

[0083] At block **1004**, the analytic application may retrieve network cell condition information for one or more geolocations at which the user device of each subscriber used data during a time interval from a data store of the computing nodes **108**. In various embodiments, the network cell condition information for a geolocation may include the amount of network bandwidth available at different times in a daily cycle, the signal spectrums of the network cell that are utilized at different times, the signal coverage area of the network cell, the distances between the network cell and other network cells, and/or so forth. The network cell conditions may be obtained by the data management platform **102**.

[0084] At block **1006**, an analytic application may compare the network cell condition information with data usage patterns of the one or more subscribers at the one or more geolocations. The comparison may indicate correlations between data usage by the one or more subscribers and available bandwidth of network cells at the different geolocations. At block **1008**, the analytic application may determine whether data usage of each subscriber negatively affected the wireless carrier network at the one or more geolocations. For example, data usage by some of the subscribers who engaged in excess data usage negatively affected network bandwidth availability at a network cell because the usage occurred at peak times. However, data usage by other subscribers with excess usage may have occurred at non-peak times and therefore did not negatively affect network bandwidth availability at the network cell. In another example, the excess data usage by a subscriber may not negatively affect the bandwidth availability of a network cell of a geolocation due to a high concentration of other network cells proximate to the geolocation.

[0085] At block **1010**, the analytic application may identify at least one subscriber whose data usage did not negatively affect the wireless carrier network even with data usage exceeding the excessive data usage threshold. At block **1012**, the analytic application may determine whether a number of subscribers whose data usage negatively affected the performance of a congested network cell at a geolocation exceeds a subscriber threshold. In various

embodiments, a network cell may be determined to be congested if the available bandwidth of the network cell drops below an availability threshold, if the number of call failures due to lack of response from the network cell exceeds a call failure threshold, and/or if the number of failed call handovers exceeds a predetermined handover failure threshold.

[0086] Accordingly, at decision block **1014**, if the analytic application determines that the number of subscribers whose data usage negatively affected performance of the congested network cell at the geolocation exceeds the threshold ("yes" at decision block **1014**), the process **1000** may proceed to block **1016**. At block **1016**, the analytic application may provide a recommendation of no deployment of small network cells at the geolocation. This is because the congestion at the network cell is due to excess data usage by subscribers rather than a true lack of network capacity at the geolocation. Instead, the subscribers with the excess data usage may receive notices to reduce their data usage or they may be banned from using the wireless carrier network. The analytic application may provide the recommendation for viewing via an application user interface.

[0087] However, if the analytic application determines that the number of subscribers whose data usage negatively affected performance of the congested network cell at the geolocation does not exceed the threshold ("no" at decision block **1014**), the process **1000** may proceed to block **1018**. At block **1018**, the analytic application may provide a recommendation to deploy one or more small network cells at the geolocation. This is because the congestion at the network cell is considered to be due to a true lack of network capacity at the geolocation and not excess data usage by subscribers. The analytic application may provide the recommendation for viewing via an application user interface.

[0088] FIG. **11** is a flow diagram of an example process **1100** for generating automatic suggestions of new geolocations for the installation of small network cells within the wireless carrier network. At block **1102**, the analytic application may receive recommendations of geolocations for the deployment of small network cells to alleviate performance issues of a wireless carrier network. In various embodiments, the recommendation may be generated by the analytic application or another analytic application based on performance data from the operation data source **110**, the trouble ticket data source **112**, and/or the alarm data source **114**. For example, the recommendation may be generated based on OSS counters and data received from user devices regarding quality of service (i.e., call drops, one-way audio problems, etc.) at various geolocations. The small network cells may include microcells, femtocell, picocells, and/or so forth.

[0089] At block **1104**, the analytic application may obtain social media data indicating at least one geolocation at which the deployment of one or more small network cells is desired. In various embodiments, the social media data may include social postings on blog web pages, message feed web pages, web forums, and/or electronic bulletin boards. The social postings may highlight network problems with the wireless carrier network as experienced by different subscribers at various geolocations.

[0090] At block **1106**, the analytic application may cross reference the recommendations and the social media data to generate one or more deployment geolocation for at least one small network cell. For example, a deployment geolocation may be a location that appears both in the recommendation and a predetermined number of social postings. In another example, a deployment geolocation may be a location that appears both in the recommendation and social postings from a predetermined number of social media users. In an additional example, a deployment geolocation may be a location that appears in the recommendation and a predetermined number of social postings of a predetermined number of social media users. The analytic application may provide the at least one geolocation for viewing via an application user interface.

[0091] FIG. **12** is a flow diagram of an example process **1200** for tracking the performance of network devices in relation to small network cells, macro cells, and backhauls of the wireless carrier network. At block **1202**, an analytic application may retrieve quality of service metrics for user devices of subscribers as the user devices access a wireless carrier network via one or more small network cells in a geographical area. In various embodiments, the quality of service metrics may include call establishment delays, MOS of call audio quality, records of one-way audio problems, records of call drops, and/or so forth.

[0092] At block **1204**, the analytic application may compare the performance of one or more small network cells in the geographical area with respect to the quality of service metrics for the user devices. In various embodiments, a small network cell may be a microcell, a femtocell, or a picocell. The performance of a small network cell may include an available bandwidth of the network cell, a signal coverage area of the cell, a data throughput of the network cell, average up time of the network cell, and/or so forth during a time interval.

[0093] At block **1206**, the analytic application may generate one or more adjustments for at least one small network cell based on the comparison. The adjustments may include moving the small network cell to a different location, reorient an antenna of the small network cell in a different direction to reshape a cell coverage area, modifying the data throughput of the communication between the small network cell and a macrocell, updating the device software of the small network cell, and/or so forth. Accordingly, the adjustments may improve the quality of service provided to the subscribers.

[0094] At block **1208**, the analytic application may provide the one or more adjustments for the at least one small network cell for implementation. In various embodiments, the one or more adjustments may be presented by the analytic application to a user via an application user interface. In turn, the user may reconfigure the one or more small network cells based on the presented information.

[0095] At block **1210**, the analytic application may provide a unified view that shows the performance of one or more small network cells in conjunction with performance of at least one network backhaul and one or more macrocells in the geographical area. The unified view may display a comprehensive look at the performance of the wireless carrier network in the geographical area, such that a user may examine the integration of the network components in the area. The analytic application may provide the unified view via an application user interface.

[0096] FIG. **13** is a flow diagram of an example process **1300** for generating an end-to-end look at the performance of device components of a user device and network components of a wireless carrier network in order to resolve a

quality of service issue for a subscriber. At block **1302**, an analytic application may retrieve performance data for user device components of user devices and network components of a wireless carrier network from a data store on the computing nodes **108**. The performance data may be obtained by the data management platform **102** from multiple data sources, such as the data sources **110-118**. The user device components may include device applications (e.g. a telephony application), device hardware (e.g., a radio transceiver), and/or so forth. The network components of the wireless carrier network may include network cells, RAN elements, backhauls, core network elements (e.g., gateway servers, Policy and Charging Rule Functions (PCRFs), IP multimedia subsystem (IMS) core, etc.), and Internet servers (e.g., application servers, multimedia servers, etc.)).

[0097] At block **1304**, the analytic application may identify a specific set of network components and device components of a user device that supported an instance of network usage by the user device. The instance of network usage may be a VoIP call, a VoWiFi call, a Video over LTE call, a streaming of multimedia, or another type of data communication that is initiated or received by the user device. The analytic application may identify the components in response to a complaint report initiated by a user regarding the instance of network usage.

[0098] At block **1306**, the analytic application may analyze the performance of the specific set of device components and network components to input one or more components that negatively impacted a quality of service experienced by the user during the instance. For example, a component may be determine to have negatively impacted the quality of service when a performance metric of the component is below a predetermined performance threshold. In another example, the component may be determine to have negatively impacted the quality of service when the component is a bottleneck that is responsible for the biggest delay experienced by the user during the usage instance. In an additional example, the component may be determine to have negatively impacted the quality of service when the component experienced a rate of error that is higher than a maximum error threshold.

[0099] At block **1308**, the analytic application may provide data on the one or more components that negatively affected the quality of service for presentation. The presentation of such data may enable a user to initiate remediation measures to correct the problem with the one or more components. In various embodiments, the analytic application may provide the data on the one or more components via an application user interface.

[0100] FIG. **14** is a flow diagram of an example process **1400** for using a trained machine learning model to automatically resolve trouble tickets for a wireless carrier network. At block **1402**, the data management platform **102** may receive performance data regarding user devices and network components of a wireless carrier network from multiple sources. The performance data may include data that are collected from the data sources **110-118**. For example, the performance data may include operation data, trouble ticket data, alarm data, social media data, and/or so forth. The performance data may measure the performance of one or more network components of the wireless carrier network and/or one or more device components of user devices that use the network. In various embodiments, the performance data may be visualized according to specific subscribers, specific geolocations, specific geographical areas, specific network cells, and/or so forth.

[0101] At block **1404**, an analytic application may receive an indication of an issue affecting one or more user devices that are using the wireless carrier network. In various embodiments, the indication may be a trouble ticket that is initiated by a subscriber or automatically initiated by a network monitoring application. The issue may impact that quality of service that is received by the subscribers of the one or more user devices as the subscribers make voice calls, multimedia calls, upload data, and/or download data using the wireless carrier network.

[0102] At block **1406**, the analytic application may analyze the performance data using a trained machine learning model to determine a root cause for the issue affecting the one or more user devices. In various embodiments, the performance data that is analyzed may be real time or non-real time data for a particular time interval. Further, the performance data may include aggregated or converged data. The trained machine learning model may employ multiple machine learning algorithms to analyze the performance data. For example, in some instances, the analytic application may track the geolocations of a subscriber as the subscriber roams between the geolocations during a particular time interval. Subsequently, the analytic application may analyze the performance data that are related to these geolocations using the trained machine learning model to ascertain the root cause. In other instances, the analytic application may analyze the performance of various network cells to generate a list of one or more top offender cells that contribute to the issue.

[0103] At block **1408**, the analytic application may provide the root cause and a solution that resolves the root cause for presentation. In various embodiments, the analytic application may retrieve the solution from a solutions database. The analytic application may provide information on the root cause and the solution for viewing via an application user interface. The information on the root cause and/or the solution to the root cause may be visualized with reference to specific subscribers, specific user devices, specific geolocations, specific geographical areas, specific network cells, and/or so forth.

[0104] At block **1410**, the analytic application may analyze the performance data using the trained machine learning model to predict a potential issue for one or more additional user devices that use the wireless carrier network. For example, the analysis of the performance data may indicate that a potential issue existing for a specific type of user devices due to hardware or software component similarity of the specific type to user devices that are found to be experiencing a particular issue. In another example, the analysis of the performance data may indicate that a common problem (e.g., a software security vulnerability) experienced by a specific group of user devices is likely to lead to another issue (e.g., unresponsive user device) if the common problem is not fixed in a timely fashion.

[0105] At block **1412**, the analytic application may notify at least one additional subscriber of the potential issue with one or more additional user devices. In some embodiments, the analytic application may perform the notification by displaying an alert on an application user interface to a user that is a network engineer, such that the network engineering may notify the subscribers. In other embodiments, the analytic application may automatically send alert messages

directly to the subscribers using the contact information of the subscribers. The alert message may include information that enables the subscribers to take preventative measures to stop the potential issue from occurring.

[0106] At block **1414**, the analytic application may track the performance of the one or more additional user devices to detect occurrence of the potential issue on at least one additional user device. If the analytic application detects that the potential issue actually occurred, the analytic application may directly take remediation action or cause another application component of the wireless carrier network to take remediation action. The remediation action may include sending another alert message to a subscriber that is using an additional user device, informing a network engineer to contact the subscriber in order to resolve the issue, automatically terminating service to the additional user device until the issue is resolved, automatically pushing a software update to the additional user device to fix the issue, and/or so forth.

[0107] The comprehensive analysis of user device performance data and network performance data of a wireless carrier network on a granular level may enable the discovery of root causes of quality of service issues that are invisible to conventional data analysis techniques. Accordingly, such analysis may pinpoint the root cause of a quality of service issue to a specific device or network component. Further, the use of a machine learning model during the analysis may enable the automatic resolution of customer complaints. Such automatic resolution may reduce issue resolution time while increase issue resolution rate.

CONCLUSION

[0108] Although the subject matter has been described in language specific to structural features and/or methodological acts, it is to be understood that the subject matter defined in the appended claims is not necessarily limited to the specific features or acts described. Rather, the specific features and acts are disclosed as exemplary forms of implementing the claims.

What is claimed is:

1. One or more non-transitory computer-readable media storing computer-executable instructions that upon execution cause one or more processors to perform acts comprising:

obtaining performance data for one or more network components of a wireless carrier network and one or more device components of user devices that use the wireless carrier network;

processing the performance data by at least one of aggregating multiple datasets of the performance data into aggregated performance data according to one or more grouping parameters or converge a plurality of datasets of the performance data into converged performance data according to a unitary storage schema;

performing analysis on at least one of the aggregated performance data or the converged performance data to detect an issue affecting one or more users of the wireless carrier network or to generate a solution to the issue, the aggregate performance data and the converged performance data including non-real time data or real time data; and

providing at least one of the issue or the solution to the issue for presentation.

2. The one or more non-transitory computer-readable media of claim **1**, wherein the acts further comprise providing at least a portion of the aggregated performance data or the converged performance data for presentation.

3. The one or more non-transitory computer-readable media of claim **1**, wherein the performance data includes one or more of network component performance data, user device performance data, social media data, alarm data, trouble ticket data, or key performance indicator data generated by a network monitoring tool.

4. The one or more non-transitory computer-readable media of claim **1**, wherein the one or more grouping parameters include a specific time period, a specific entity component, a specific user device vendor, a specific user device model, or different levels of an entity hierarchy that includes a subscriber level, a device level, a service area level, and a geographical market level, wherein the geographical market level further includes a zip code sublevel, a municipality sublevel, or an additional location-based level.

5. The one or more non-transitory computer-readable media of claim **1**, wherein the performing includes performing the analysis using a trained machine learning model that employs multiple types of machine learning algorithms to analyze the aggregated performance data or the converged performance data.

6. The one or more non-transitory computer-readable media of claim **1**, wherein the issue is reported for analysis via a subscriber or a network monitoring application generated trouble ticket.

7. The one or more non-transitory computer-readable media of claim **1**, wherein the obtaining includes obtaining real time Voice over LTE (VoLTE) service performance data and real time Voice over WiFi (VoWiFi) service performance data for the wireless carrier network, each of the VoLTE service performance data and the VoWiFi service performance data including corresponding key performance indicators (KPIs), wherein the processing includes converging the VoLTE service performance data and the VoWiFi service performance data into converged real time data, and wherein the performing includes analyzing the converged real time data to detect one or more issues affecting one or more user devices that use the wireless carrier network.

8. The one or more non-transitory computer-readable media of claim **1**, wherein the performing the analysis includes:

identifying data usage patterns of one or more users whose data usage on the wireless carrier network exceed a predetermined excess data usage threshold during a time interval;

retrieving network cell condition information for one or more geolocations at which a user device of each user of the one or more users used data during the time interval;

comparing the network cell condition information with the data usage patterns of the one or more users at the one or more geolocations;

determining whether a number of users whose data usage negatively affected performance of a congested network cell at a geolocation exceeds a threshold;

providing a recommendation of no deployment of small network cells at the geolocation for presentation in response to a determination that the number of users exceeded the threshold; and

providing a recommendation to deploy one or more small network cells at the geolocation for presentation, the one or more small network cells including a microcell, a femtocell, or a picocell.

9. The one or more non-transitory computer-readable media of claim **8**, further comprising identifying at least one user whose data usage did not negatively affect the wireless carrier network even when the data usage of the user exceeded the predetermined excessive data usage threshold.

10. The one or more non-transitory computer-readable media of claim **1**, wherein the performing the analysis includes:

receiving recommendations indicating geolocations for deployment of small network cells to alleviate performance issues of the wireless carrier network, the small network cells including a microcell, a femtocell, or a picocell;

obtaining social media data indicating at least one geolocation at which deployment of one or more small network cells is desired; and

cross referencing the recommendations and the social media data to generate one or more deployment geolocations for at least one small network cell.

11. The one or more non-transitory computer-readable media of claim **1**, wherein the performing the analysis includes:

retrieving receiving quality of service metrics for the user devices as the user devices access the wireless carrier network via one or more small network cells in a geographical area, the one or more small network cells including a microcell, a femtocell, or a picocell;

comparing performance of the one or more small network cells in the geographical area with respect to the quality of services for the user devices;

generating one or more adjustments for at least one small network cell based comparison of the performance of the one or more small network cells and quality of service for the user devices; and

providing the one or more adjustments for the at least one small network cell for implementation, the one or more adjustments including moving a small network cell to a different location, reorient an antenna of the small network cell in a different direction to reshape a cell coverage area, modifying a data throughput of communication between the small network cell and a macrocell, or updating device software of the small network cell.

12. The one or more non-transitory computer-readable media of claim **11**, wherein the performing the analysis further includes providing a unified view that shows the performance of the one or more small network cells in conjunction with performance one at least one network backhaul and one or more macrocells in the geographical area.

13. The one or more non-transitory computer-readable media of claim **1**, wherein the performing the analysis includes:

retrieving the performance data for one or more network components of a wireless carrier network and one or more device components of user devices that use the wireless carrier network;

identifying a specific set of network components and device components of a user device that supported an instance of network usage of the wireless carrier network by the user device;

analyzing performance of the specific set of device components and network components to pinpoint one or more components that negatively impacted a quality of service experienced by a user of the user device during the instance; and

providing data on the or more components that negatively affected quality of service for presentation.

14. A computer-implemented method, comprising:

obtaining, via a data management platform executing on one or more computing nodes, performance data for one or more network components of a wireless carrier network or one or more device components of user devices that use the wireless carrier network, the performance data including one or more of network component performance data, user device performance data, social media data, alarm data, trouble ticket data, or key performance indicator data generated by a network monitoring tool;

processing, via the data management platform executing on one or more computing nodes, the performance data by at least one of aggregating multiple datasets of the performance data into aggregated performance data according to one or more grouping parameters or converge a plurality of datasets of the performance data into converged performance data according to a unitary storage schema;

performing, via an analytic application executing on the one or more computing nodes, analysis on at least one of the aggregated performance data or the converged performance data to detect an issue affecting one or more users of the wireless carrier network or to generate a solution to the issue, the aggregate performance data and the converged performance data including non-real time data or real time data; and

providing, via the analytic application executing on the one or more computing nodes, at least one of the issue or the solution to the issue for presentation.

15. The computer-implemented method of claim **14**, wherein the obtaining includes obtaining real time Voice over LTE (VoLTE) service performance data and real time Voice over WiFi (VoWiFi) service performance data for the wireless carrier network, each of the VoLTE service performance data and the VoWiFi service performance data including corresponding key performance indicators (KPIs), wherein the processing includes converging the VoLTE service performance data and the VoWiFi service performance data into converged real time data, and wherein the performing includes analyzing the converged real time data to detect one or more issues affecting one or more user devices that use the wireless carrier network.

16. The computer-implemented method of claim **14**, wherein the performing the analysis includes:

identifying data usage patterns of one or more users whose data usage on the wireless carrier network exceed a predetermined data usage threshold during a time interval;

retrieving network cell condition information for one or more geolocations at which a user device of each user of the one or more users used data during the time interval;

comparing the network cell condition information with the data usage patterns of the one or more users at the one or more geolocations;

determining whether a number of users whose data usage negatively affected performance of a congested network cell at a geolocation exceeds a threshold;

providing a recommendation of no deployment of small network cells at the geolocation for presentation in response to a determination that the number of users exceeded the threshold; and

providing a recommendation to deploy one or more small network cells at the geolocation for presentation, the one or more small network cells including a microcell, a femtocell, or a picocell.

17. The computer-implemented method of claim **14**, wherein the performing the analysis includes:

receiving recommendations indicating geolocations for deployment of small network cells to alleviate performance issues of the wireless carrier network, the small network cells including a microcell, a femtocell, or a picocell;

obtaining social media data indicating at least one geolocation at which deployment of one or more small network cells is desired; and

cross referencing the recommendations and the social media data to generate one or more deployment geolocations for at least one small network cell.

18. The computer-implemented method of claim **14**, wherein the performing the analysis includes:

retrieving receiving quality of service metrics for user devices as the user devices access the wireless carrier network via one or more small network cells in a geographical area, the one or more small network cells including a microcell, a femtocell, or a picocell;

comparing performance of the one or more small network cells in the geographical area with respect to the quality of services for the user devices;

generating one or more adjustments for at least one small network cell based comparison of the performance of the one or more small network cells and quality of service for the user devices;

providing the one or more adjustments for the at least one small network cell for implementation, the one or more adjustments including moving a small network cell to a different location, reorient an antenna of the small network cell in a different direction to reshape a cell coverage area, modifying a data throughput of communication between the small network cell and a macrocell, or updating device software of the small network cell; and

providing a unified view that shows the performance of the one or more small network cells in conjunction with performance one at least one network backhaul and one or more macrocells in the geographical area.

19. The computer-implemented method of claim **14**, wherein the performing the analysis includes:

retrieving the performance data for one or more network components of a wireless carrier network or one or more device components of user devices that use the wireless carrier network;

identifying a specific set of network components and device components of a user device that supported an instance of network usage of the wireless carrier network by the user device;

analyzing performance of the specific set of device components and network components to pinpoint one or more components that negatively impacted a quality of service experienced by a user of the user device during the instance; and

providing data on the or more components that negatively affected quality of service for presentation.

20. A system, comprising:

one or more processors; and

memory including a plurality of computer-executable components that are executable by the one or more processors to perform a plurality of actions, the plurality of actions comprising:

obtaining performance data for one or more network components of a wireless carrier network and one or more device components of user devices that use the wireless carrier network, the performance data including one or more of network component performance data, user device performance data, social media data, alarm data, trouble ticket data, or key performance indicator data generated by a network monitoring tool;

processing the performance data by at least one of aggregating multiple datasets of the performance data into aggregated performance data according to one or more grouping parameters or converge a plurality of datasets of the performance data into converged performance data according to a unitary storage schema;

performing analysis on at least one of the aggregated performance data or the converged performance data using a trained machine learning model to detect an issue affecting one or more users of the wireless carrier network or to generate a solution to the issue, the aggregate performance data and the converged performance data including non-real time data or real time data; and

providing at least one of the issue or the solution to the issue for presentation.

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