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(54) **PREDICTIVE MAINTENANCE**

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G06F 16/245 (2006.01)

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CPC ***G06Q 10/20*** (2013.01); ***G06F 16/245*** (2019.01)

(57) **ABSTRACT**

Vehicular maintenance is predicted using real time telematics data and historical maintenance data. Different statistical models are used, and an intersecting set of results is generated. Environmental weather may also be used to further refine predictions.

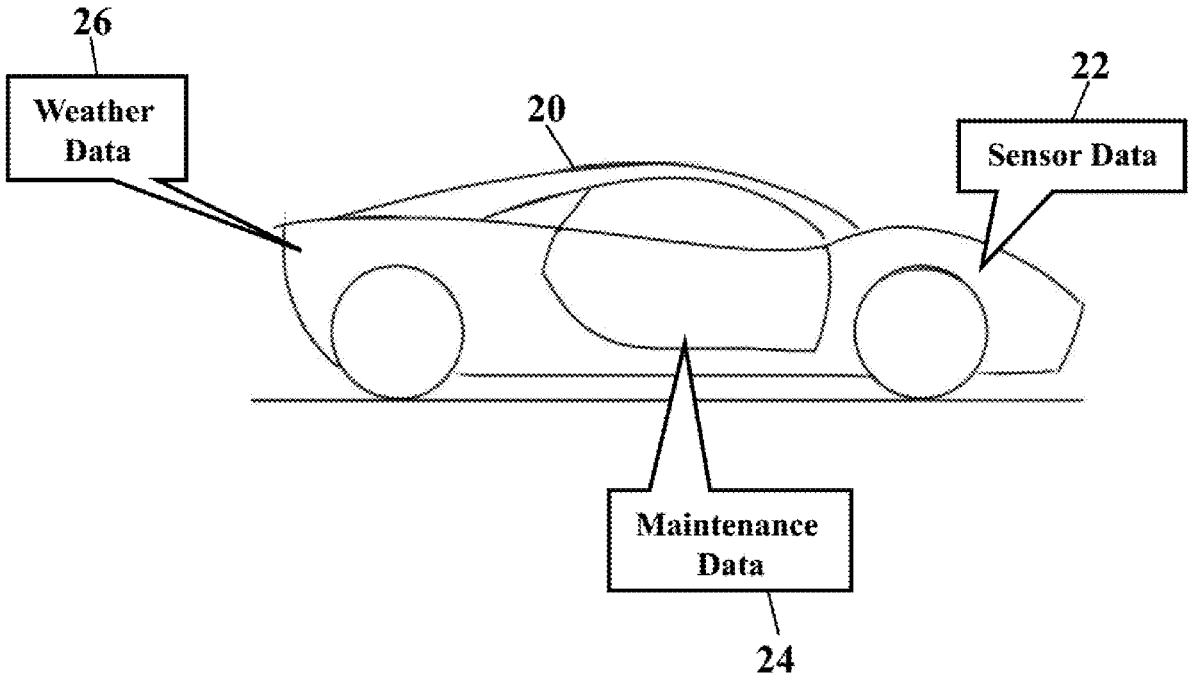


FIG. 1

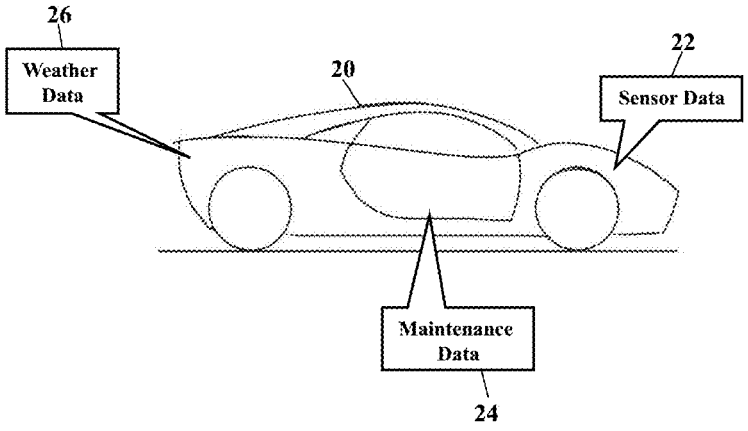


FIG. 2

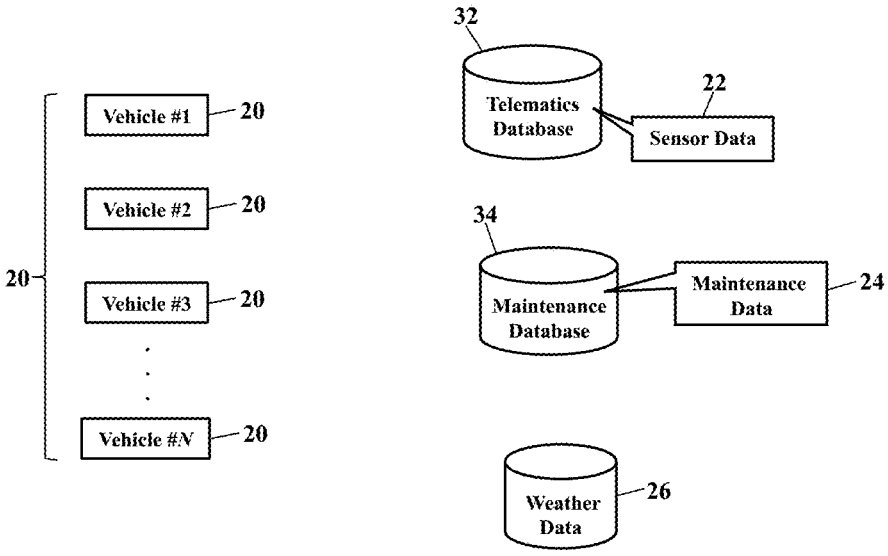

Vehicle #1
20
Vehicle #2
20
Vehicle #3
20
Vehicle #N
20
20
32
Telematics Database
22
Sensor Data
34
Maintenance Database
Maintenance Data
24
Weather Data
26

FIG. 3

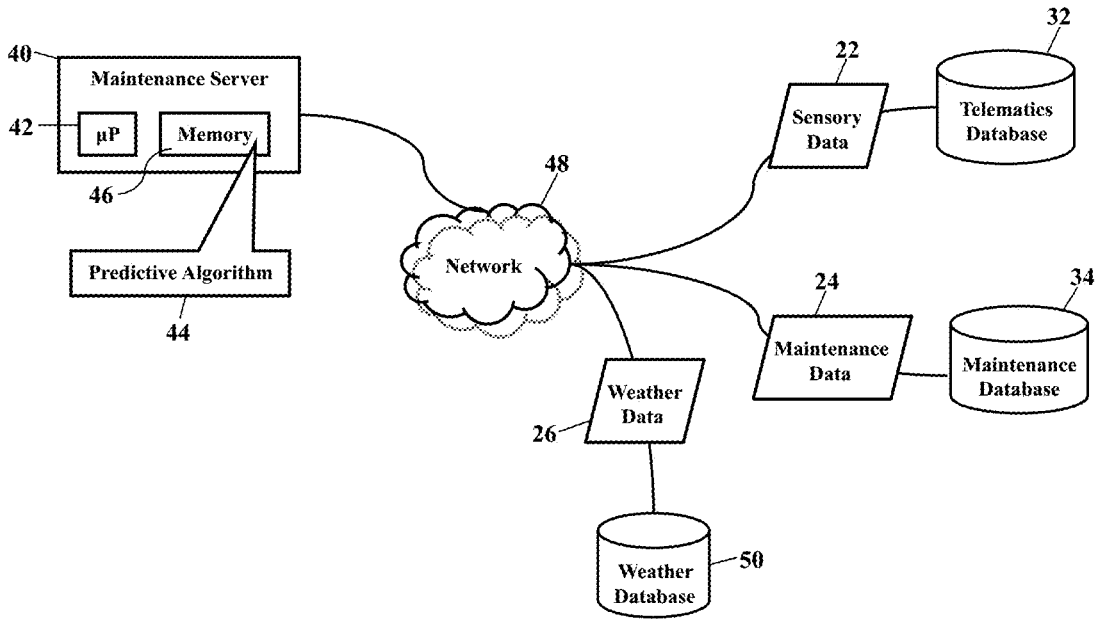

40
Maintenance Server
42
µP
Memory
46
Predictive Algorithm
44
48
Network
22
Sensory Data
32
Telematics Database
24
Maintenance Data
34
Maintenance Database
Weather Data
26
Weather Database
50

FIG. 4

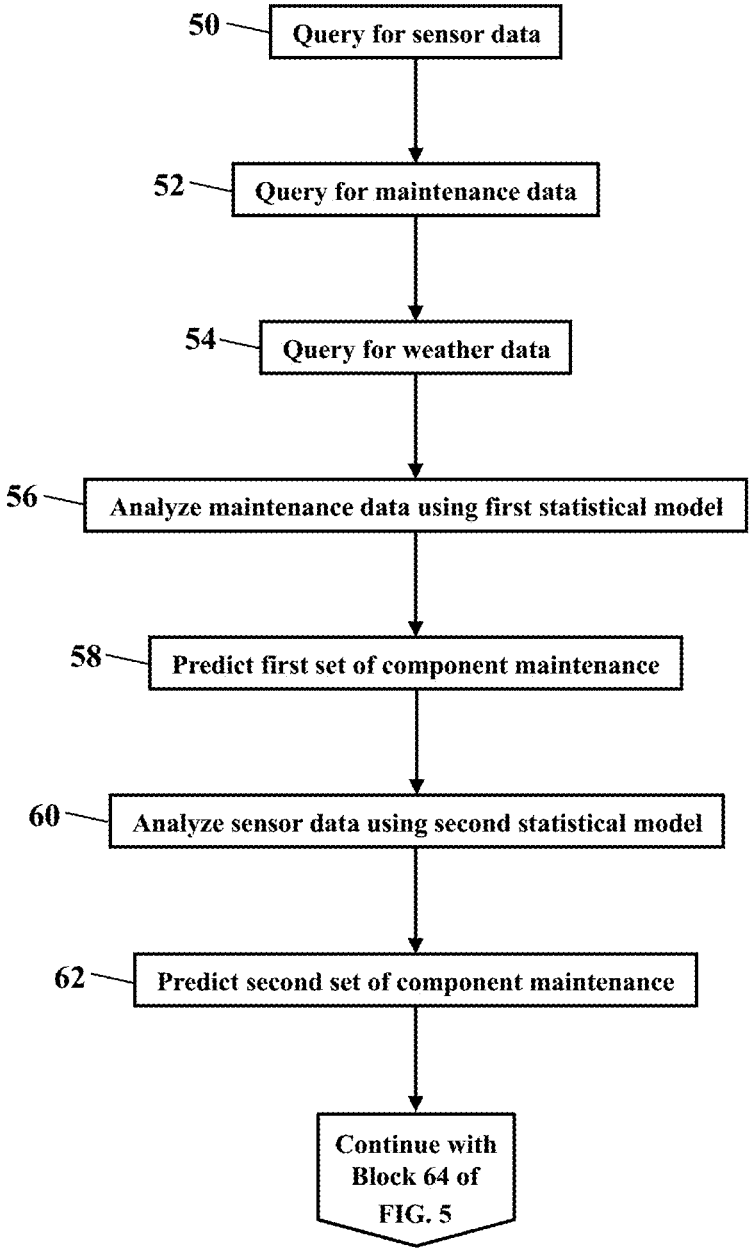

50
Query for sensor data
52
Query for maintenance data
54
Query for weather data
56
Analyze maintenance data using first statistical model
58
Predict first set of component maintenance
60
Analyze sensor data using second statistical model
62
Predict second set of component maintenance
Continue with Block 64 of FIG. 5

FIG. 5

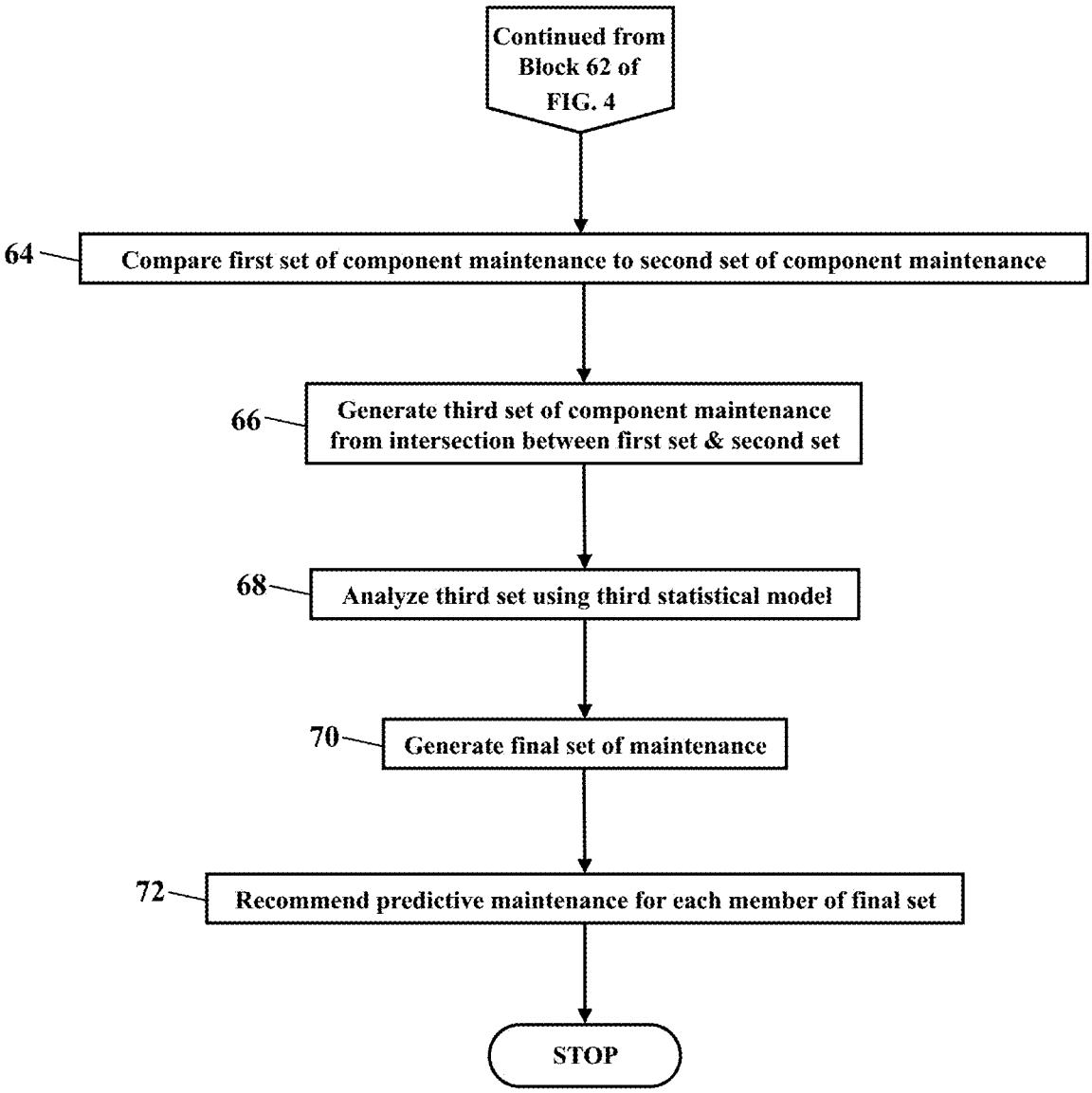

Continued from Block 62 of FIG. 4
64
Compare first set of component maintenance to second set of component maintenance
66
Generate third set of component maintenance from intersection between first set & second set
68
Analyze third set using third statistical model
70
Generate final set of maintenance
72
Recommend predictive maintenance for each member of final set
STOP

FIG. 6

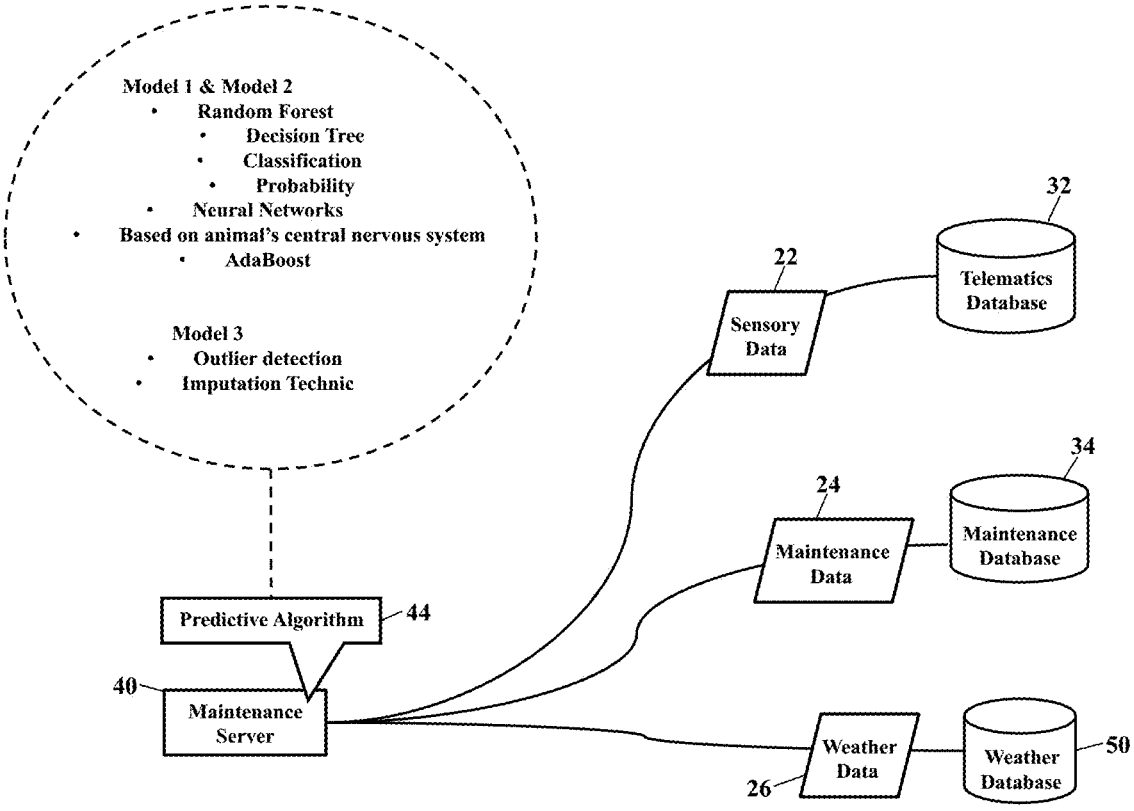
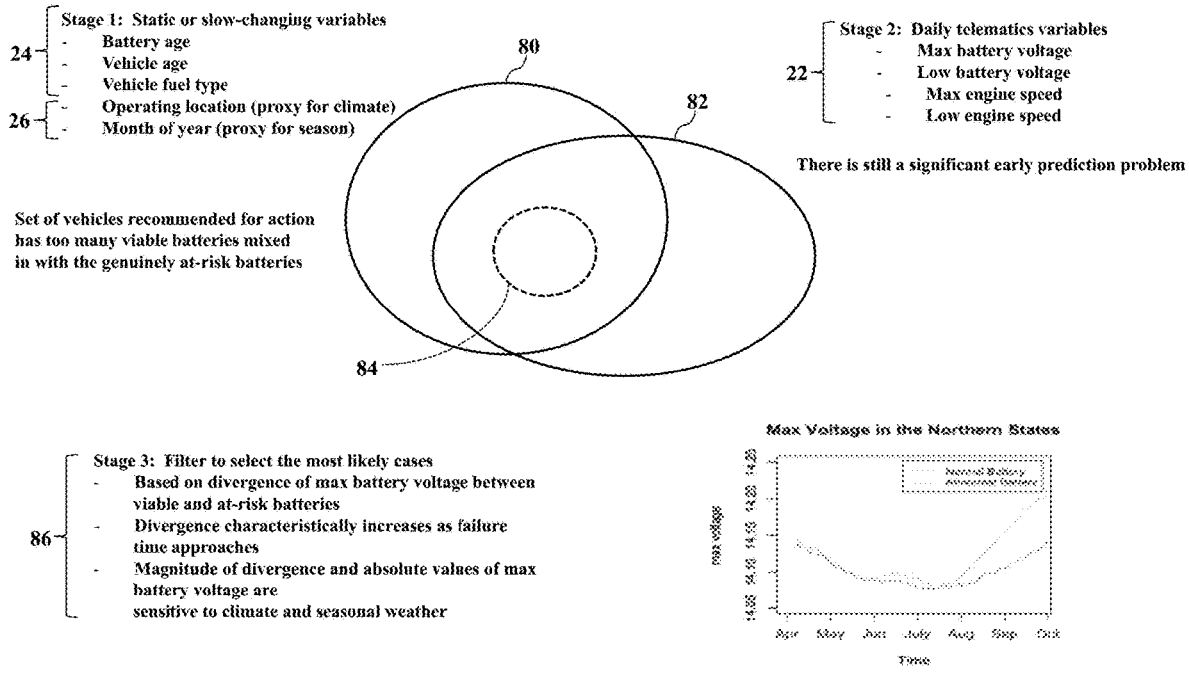

Model 1 & Model 2
• Random Forest
• Decision Tree
• Classification
• Probability
• Neural Networks
• Based on animal's central nervous system
• AdaBoost
Model 3
• Outlier detection
• Imputation Technic
Predictive Algorithm
44
40
Maintenance Server
22
Sensory Data
32
Telematics Database
24
Maintenance Data
34
Maintenance Database
Weather Data
26
Weather Database
50

FIG. 7


Stage 1: Static or slow-changing variables
- Battery age
- Vehicle age
- Vehicle fuel type
- Operating location (proxy for climate)
- Month of year (proxy for season)
24
26
80
82
84
Stage 2: Daily telematics variables
- Max battery voltage
- Low battery voltage
- Max engine speed
- Low engine speed
22
There is still a significant early prediction problem
Set of vehicles recommended for action has too many viable batteries mixed in with the genuinely at-risk batteries
Stage 3: Filter to select the most likely cases
- Based on divergence of max battery voltage between viable and at-risk batteries
- Divergence characteristically increases as failure time approaches
- Magnitude of divergence and absolute values of max battery voltage are sensitive to climate and seasonal weather
86
Max Voltage in the Northern States
Apr
May
Jun
July
Aug
Sep
Oct
Time

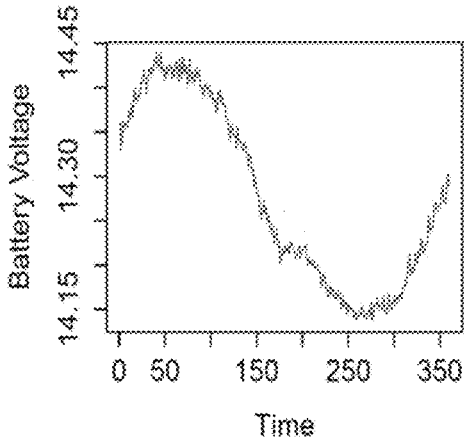


FIG. 8

FIG. 9

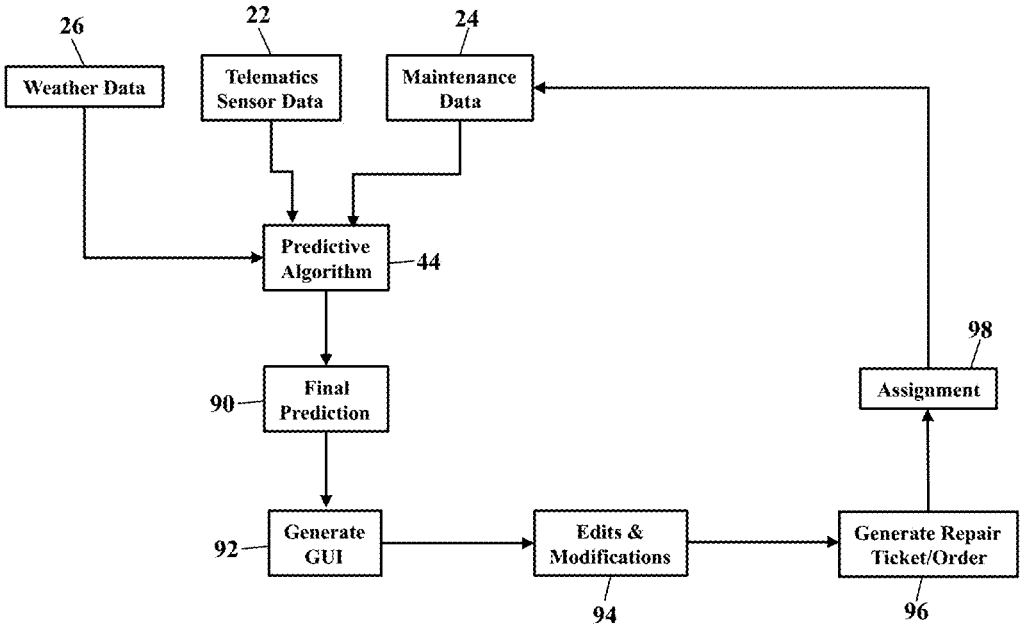

26
22
24
Weather Data
Telematics Sensor Data
Maintenance Data
Predictive Algorithm
44
98
Assignment
90
Final Prediction
92
Generate GUI
Edits & Modifications
94
Generate Repair Ticket/Order
96

FIG. 10

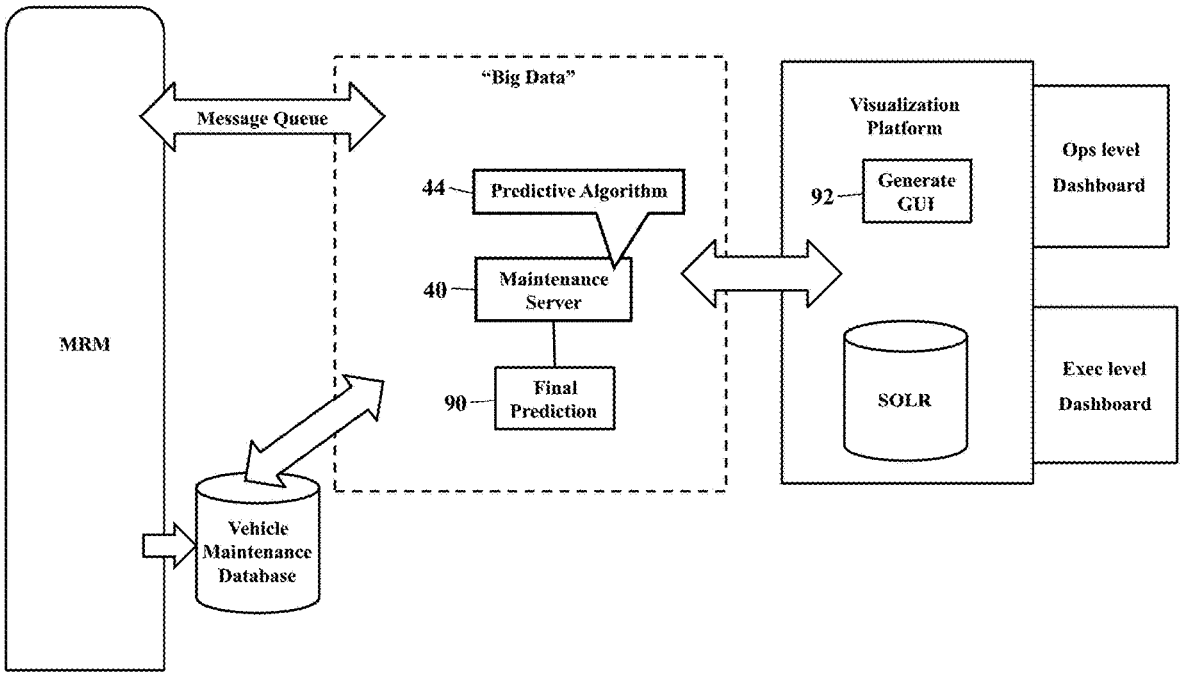

MRM
Message Queue
"Big Data"
44
Predictive Algorithm
40
Maintenance Server
90
Final Prediction
Vehicle Maintenance Database
Visualization Platform
92
Generate GUI
SOLR
Ops level Dashboard
Exec level Dashboard

FIG. 11

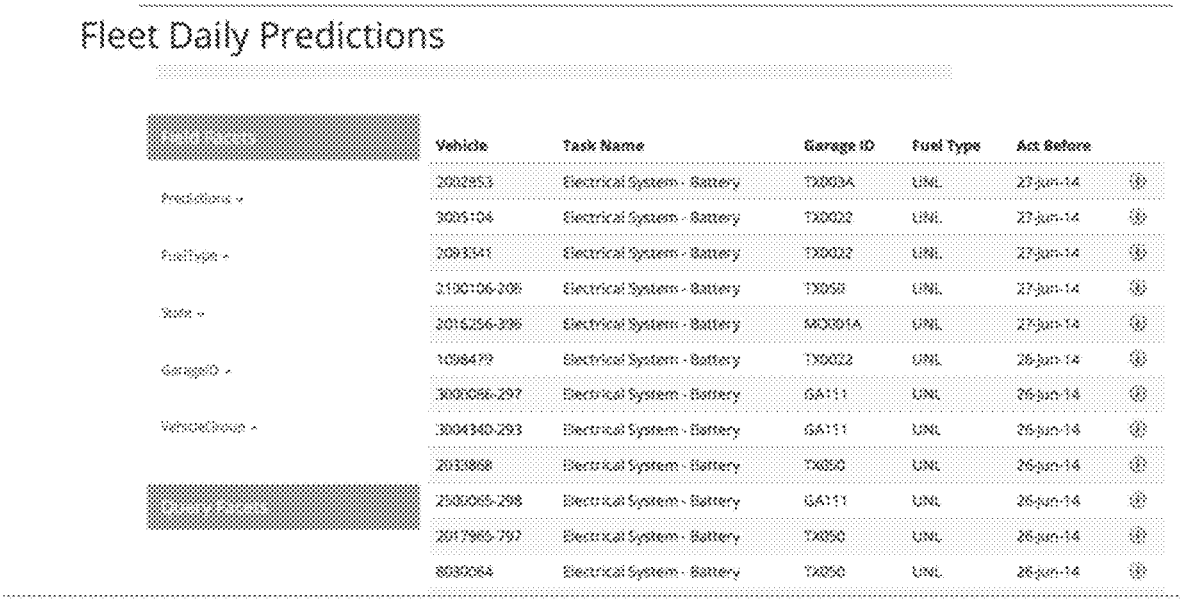

Fleet Daily Predictions
Vehicle
Task Name
Garage ID
Fuel Type
Act Before
Electrical System - Battery
UNL
27-Jun-14
26-Jun-14

FIG. 12

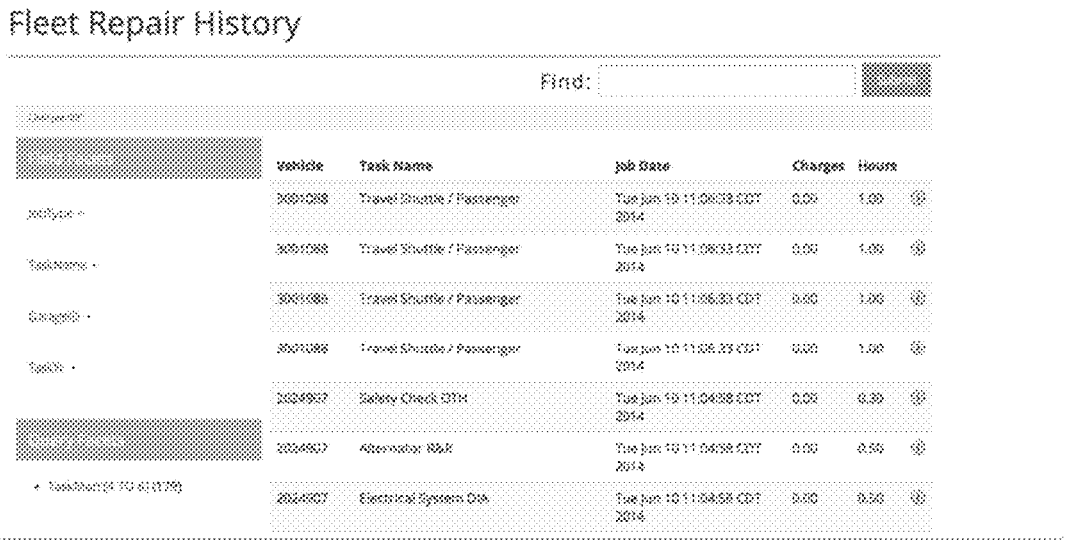

Fleet Repair History
Find:
Vehicle
Task Name
Job Date
Charges
Hours
Travel Shuttle / Passenger
Safety Check DTH
Alternator R&R
Electrical System Dia

FIG. 13

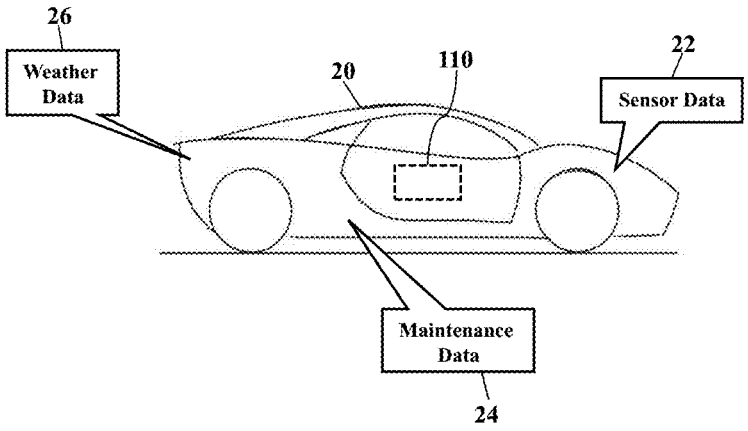


FIG. 14

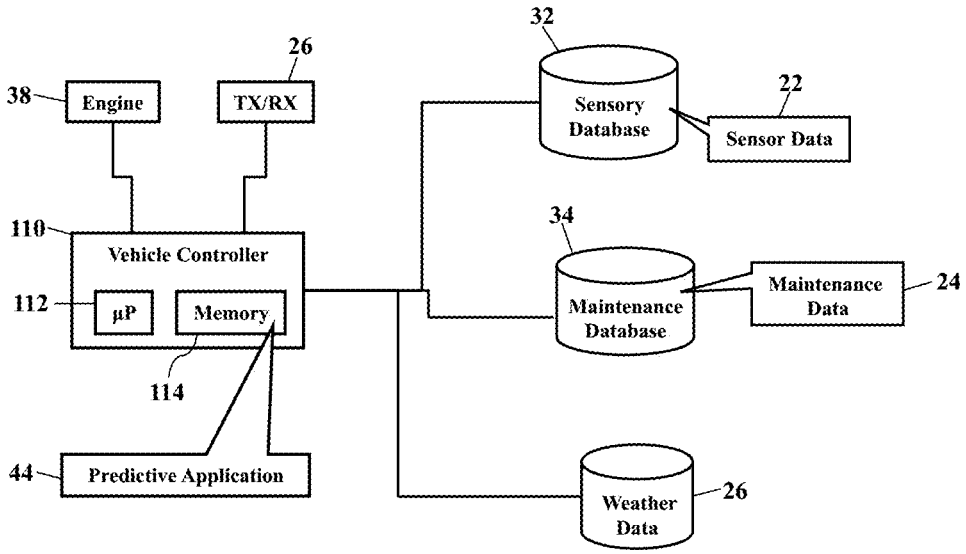

32
26
38
Engine
TX/RX
Sensory Database
22
Sensor Data
110
Vehicle Controller
34
112
µP
Memory
Maintenance Database
Maintenance Data
24
114
44
Predictive Application
Weather Data
26

FIG. 15

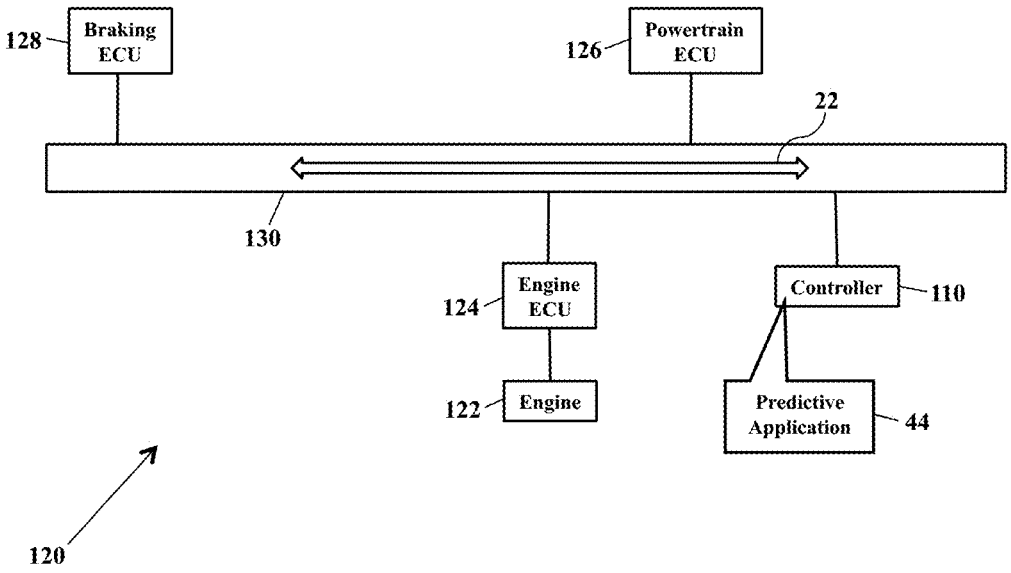

128
Braking ECU
126
Powertrain ECU
22
130
124
Engine ECU
Controller
110
122
Engine
Predictive Application
44
120

FIG. 16

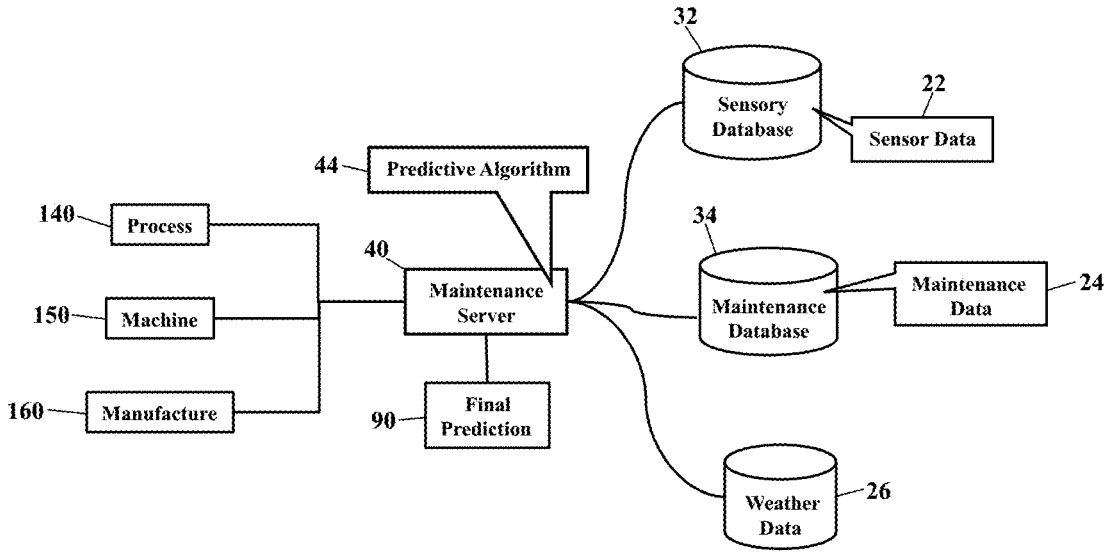

32
Sensory Database
22
Sensor Data
44
Predictive Algorithm
140
Process
40
Maintenance Server
34
Maintenance Database
Maintenance Data
24
150
Machine
160
Manufacture
90
Final Prediction
Weather Data
26

FIG. 17

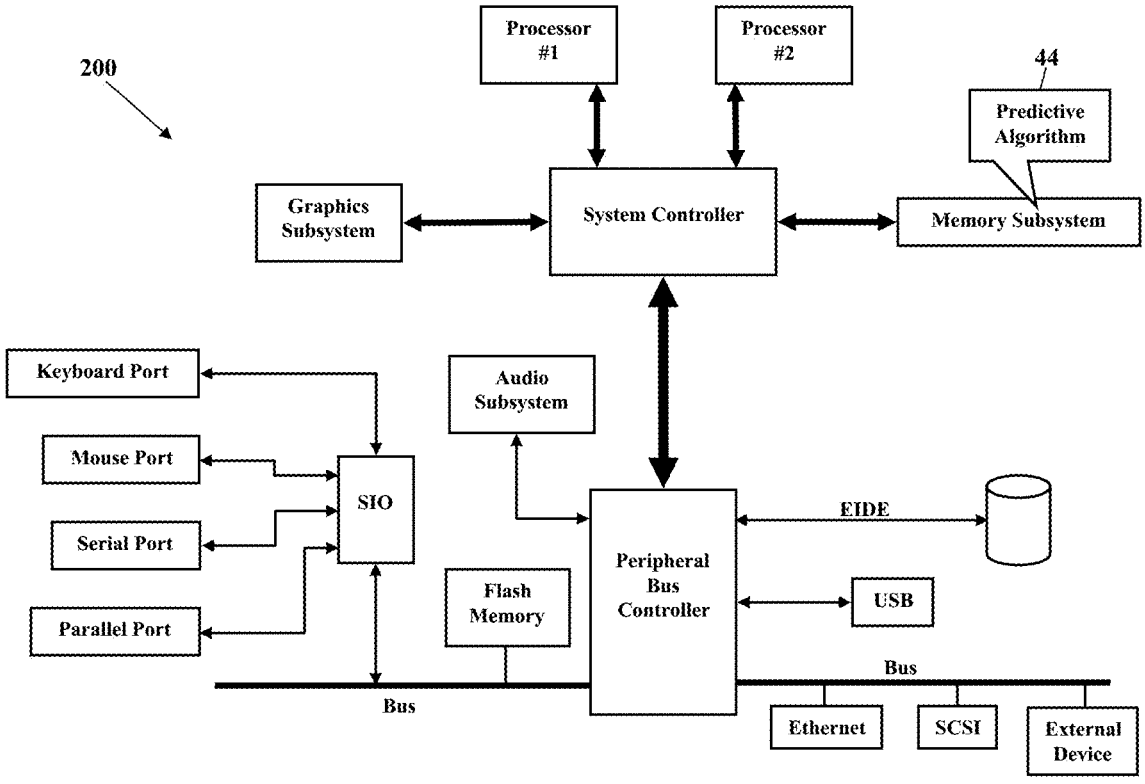
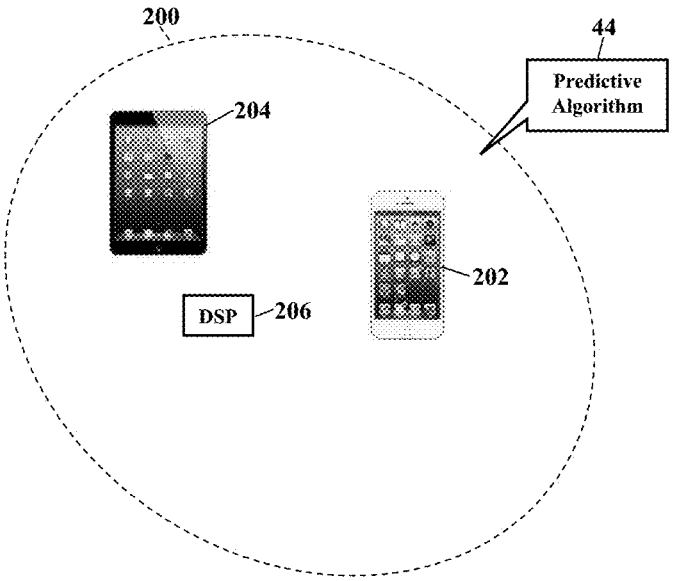

200
Processor #1
Processor #2
44
Predictive Algorithm
Graphics Subsystem
System Controller
Memory Subsystem
Keyboard Port
Audio Subsystem
Mouse Port
SIO
Serial Port
Peripheral Bus Controller
EIDE
Flash Memory
USB
Parallel Port
Bus
Bus
Ethernet
SCSI
External Device

FIG. 18



PREDICTIVE MAINTENANCE

RELATED APPLICATIONS

[0001] This patent application is a continuation of, and claims priority to each of, U.S. patent application Ser. No. 16/876,171, filed May 18, 2020, and entitled "PREDICTIVE MAINTENANCE", which is a continuation of U.S. patent application Ser. No. 16/115,644 (now U.S. Pat. No. 10,692,053), filed Aug. 29, 2018, and entitled "PREDICTIVE MAINTENANCE", which is a continuation of U.S. patent application Ser. No. 14/511,354 (now U.S. Pat. No. 10,096,004), filed Oct. 10, 2014, and entitled "PREDICTIVE MAINTENANCE", the entireties of which priority applications are incorporated by reference herein.

BACKGROUND

[0002] Predictive maintenance saves time and money. As equipment is used, maintenance is required. Being able to predict when that maintenance may be required allows operators to take preemptive action, which in turn reduces the rate of unanticipated breakdowns and their associated cost, delay, and equipment downtime.

BRIEF DESCRIPTION OF THE DRAWINGS

[0003] The features, aspects, and advantages of the exemplary embodiments are understood when the following Detailed Description is read with reference to the accompanying drawings, wherein:

[0004] FIGS. **1-2** are simplified schematics illustrating an environment in which exemplary embodiments may be implemented;

[0005] FIG. **3** is a more detailed block diagram illustrating the operating environment, according to exemplary embodiments;

[0006] FIGS. **4-5** are flowcharts illustrating a general process of predictive maintenance, according to exemplary embodiments;

[0007] FIG. **6** is a schematic illustrating the statistical models, according to exemplary embodiments;

[0008] FIG. **7** is another schematic illustrating vehicular maintenance, according to exemplary embodiments;

[0009] FIG. **8** is a graph illustrating weather considerations, according to exemplary embodiments;

[0010] FIG. **9** is a flow diagram illustrating predictive maintenance, according to exemplary embodiments

[0011] FIG. **10** is a schematic illustrating ingestion of input data, according to exemplary embodiments

[0012] FIGS. **11-12** are schematic illustrating reporting features, according to exemplary embodiments;

[0013] FIGS. **13-15** are schematics illustrating other exemplary operating environments; and

[0014] FIGS. **16-18** depict still more operating environments for additional aspects of the exemplary embodiments.

DETAILED DESCRIPTION

[0015] The exemplary embodiments will now be described more fully hereinafter with reference to the accompanying drawings. The exemplary embodiments may, however, be embodied in many different forms and should not be construed as limited to the embodiments set forth herein. These embodiments are provided so that this disclosure will be thorough and complete and will fully convey the exemplary embodiments to those of ordinary skill in the art. Moreover, all statements herein reciting embodiments, as well as specific examples thereof, are intended to encompass both structural and functional equivalents thereof. Additionally, it is intended that such equivalents include both currently known equivalents as well as equivalents developed in the future (i.e., any elements developed that perform the same function, regardless of structure).

[0016] Thus, for example, it will be appreciated by those of ordinary skill in the art that the diagrams, schematics, illustrations, and the like represent conceptual views or processes illustrating the exemplary embodiments. The functions of the various elements shown in the figures may be provided through the use of dedicated hardware as well as hardware capable of executing associated software. Those of ordinary skill in the art further understand that the exemplary hardware, software, processes, methods, and/or operating systems described herein are for illustrative purposes and, thus, are not intended to be limited to any particular named manufacturer.

[0017] As used herein, the singular forms "a," "an," and "the" are intended to include the plural forms as well, unless expressly stated otherwise. It will be further understood that the terms "includes," "comprises," "including," and/or "comprising," when used in this specification, specify the presence of stated features, integers, steps, operations, elements, and/or components, but do not preclude the presence or addition of one or more other features, integers, steps, operations, elements, components, and/or groups thereof. It will be understood that when an element is referred to as being "connected" or "coupled" to another element, it can be directly connected or coupled to the other element or intervening elements may be present. Furthermore, "connected" or "coupled" as used herein may include wirelessly connected or coupled. As used herein, the term "and/or" includes any and all combinations of one or more of the associated listed items.

[0018] It will also be understood that, although the terms first, second, etc. may be used herein to describe various elements, these elements should not be limited by these terms. These terms are only used to distinguish one element from another. For example, a first device could be termed a second device, and, similarly, a second device could be termed a first device without departing from the teachings of the disclosure.

[0019] FIGS. **1-2** are simplified schematics illustrating an environment in which exemplary embodiments may be implemented. FIG. **1** illustrates a vehicle **20** used for transportation of people and cargo. As the vehicle **20** operates, wear and tear takes a toll on the vehicle's components. As the reader likely understands, the brakes, tires, engine, and other components wear and/or degrade as usage and miles accumulate. A conventional maintenance program would require inspection and replacement of various components at particular mileages.

[0020] Exemplary embodiments take a smarter approach. Exemplary embodiments predict when maintenance should be performed, based on actual data about the vehicle **20**. For example, exemplary embodiments wirelessly obtain sensor data **22** from the vehicle's on-board sensors. As the reader again likely understands, the vehicle **20** has many controllers and sensors that monitor the performance of the engine, transmission, brakes, suspension, and other systems. Any of this sensor data **22** is wirelessly uploaded from the vehicle **20** to a central server, thus providing generally real-time,

on-road reporting of outputs, diagnostic codes, and other information. Exemplary embodiments analyze the sensor data **22** to predict when the maintenance should be performed. Exemplary embodiments also obtain historical maintenance data **24** of the vehicle **20**. As the vehicle **20** accumulates miles, service records are stored that log and detail the historical maintenance performed on the vehicle **20**. Moreover, exemplary embodiments also obtain weather data **26**. As the reader again understands, the environmental weather conditions (such as temperature, humidity, and precipitation) may affect wear and tear of the vehicle's components. Northern salty roads, for example, promote wear and corrosion of braking components, thus requiring more frequent repair than southern climates. Exemplary embodiments collect the sensor data **22**, the historical maintenance data **24**, and the weather data **26** to predict what maintenance should be performed, and when that maintenance should be performed. The maintenance may thus be performed just in time, thus anticipating a service need and recommending preemptive action.

[0021] FIG. **2** illustrates service populations. Here exemplary embodiments may also consult computer databases containing data for one or more populations **30** of vehicles. As many different vehicles share common or similar components, information from fleets or populations of different vehicles may further refine the predictive maintenance. For example, a telematics database **32** may store the sensor data **22** from many vehicles. As vehicles across a fleet or manufacturer gain usage, each vehicle may transmit its sensor data **22** for logging in the telematics database **32**. The telematics database **32** may thus store telematics on-board diagnostic data (e.g., OBD codes) for many different vehicles. Likewise, a maintenance database **34** may store the maintenance data **24** for many different vehicles. As the population **30** of vehicles accumulates service miles, the maintenance database **34** may log maintenance records, problem reports, customer issues, and any other historical data regarding each vehicle **20**. The weather data **26** may further augment predictions of maintenance due to environmental conditions. All this data may thus be used to further predict when maintenance should be performed on any individual vehicle **20** or the entire population **30** of vehicles. That is, patterns in populations may be used to anticipate a service need of any vehicle **20**. Exemplary embodiments thus empower fleet operators, vehicle manufactures, and even government regulators to predict vehicular maintenance, thus enhancing both profits and safety.

[0022] FIG. **3** is a more detailed block diagram illustrating the operating environment, according to exemplary embodiments. FIG. **3** illustrates a maintenance server **40** that predicts maintenance to be performed on cars, trucks, planes, trains, or any other vehicle. Indeed, the maintenance server **40** may predict maintenance for any machine or process, as later paragraphs will explain. The maintenance server **40** has a processor **42** (e.g., "μP"), application specific integrated circuit (ASIC), or other component that executes a predictive algorithm **44** stored in a memory **46**. The predictive algorithm **44** instructs the processor **42** to perform operations, such as retrieving the sensor data **22** from the telematics database **32** using a communications network **48**. The predictive algorithm **44** also instructs the processor **42** to retrieve the maintenance data **24** from the maintenance database **34** and to retrieve the weather data **26** from a weather database **50**. The predictive algorithm **44** causes the processor **42** to analyze the sensor data **22**, the maintenance data **24**, and the weather data **26** and to predict component service and/or failures. That is, whatever data is provided, the predictive algorithm **44** uses the data to predict failures, based on the data.

[0023] FIGS. **4-5** are flowcharts illustrating the general process of the predictive algorithm **44**, according to exemplary embodiments. The telematics database **32** is queried for the sensor data **22** (Block **50**). The maintenance database **34** is queried for the maintenance data **24** (Block **52**). The weather database **50** is queried for the weather data **26** (Block **54**). The maintenance data **24** is analyzed using a first statistical model (Block **56**) to predict a first set of component maintenance (Block **58**). That is, in simple words, exemplary embodiments make a first prediction of the components that may require maintenance, based on the maintenance data **24** in the maintenance database **34**. The sensor data **22** is then analyzed using a second statistical model (Block **60**) to predict a second set of component maintenance (Block **62**). Again, in simple words, exemplary embodiments make a second prediction of the components that may require maintenance, based on the sensor data **22** in the telematics database **32**. Exemplary embodiments have thus utilized two different datasets (e.g., the maintenance data **24** in the maintenance database **34** and the sensor data **22** in the telematics database **32**) to predict two different sets of components that may require maintenance.

[0024] The flowchart continues with FIG. **5**. After the two different datasets are generated, the first set of component maintenance is compared to the second set of component maintenance (Block **64**). Matching results indicate both datasets predict the same maintenance in the same components. That is, a third set of component maintenance is generated from an intersection (Block **66**) between the first set of component maintenance (predicted from the maintenance data **24** in the maintenance database **34**) and the second set of component maintenance (predicted from the sensor data **22** in the telematics database **32**). Once the intersecting third set of component maintenance is generated, exemplary embodiments analyze the intersecting third set of component maintenance using a third statistical model (Block **68**) to generate a final set of maintenance (Block **70**). Predictive maintenance may thus be recommended for each component member of the final set of maintenance (Block **72**). Exemplary embodiments, then, may use any combination of three (3) statistical models to predict what components need maintenance. Indeed, if two (2) of the models make the same component prediction, the third statistical model may further refine the final prediction.

[0025] FIG. **6** is a schematic illustrating the statistical models, according to exemplary embodiments. FIG. **6** illustrates just some of the statistical algorithms that exemplary embodiments may use. While exemplary embodiments may use any statistical model, this disclosure will be primarily explained using the RANDOM FOREST® algorithm, based on its accuracy and simplicity. As the RANDOM FOREST® algorithm is well known, no detailed explanation of the algorithm is needed. Exemplary embodiments, then, may use the RANDOM FOREST® algorithm to analyze the maintenance data **24** in the maintenance database **34**. The RANDOM FOREST® algorithm may also be used to analyze the sensor data **22** in the telematics database **32**. Once the intersecting results are determined, exemplary embodiments may then use any statistical model to detect or observe

anomalies in the intersecting/matching results. For example, exemplary embodiments may use any outlier detection model to make the final prediction of maintenance.

[0026] FIG. **7** is another schematic illustrating vehicular maintenance, according to exemplary embodiments. Here the exemplary maintenance data **24** may be an age of a battery, the age of the corresponding vehicle, and/or a type of fuel used by the vehicle. The weather data **26** is represented by the governmental state of usage or registration (a proxy for climate) and a calendar date and time (a proxy for season). This static maintenance data **24** and the weather data **26** is analyzed using the RANDOM FOREST® algorithm to generate the first set **80** of component maintenance. The exemplary sensor data **22** (real time or near real time battery voltage and engine RPM speed) is also analyzed using the RANDOM FOREST® algorithm to generate a second set **82** of component maintenance. The third set **84** of component maintenance is generated from the intersecting matches between first set **80** of component maintenance and the second set **82** of component maintenance. The outlier detection model **86** is then used to make the final prediction of maintenance. Using these exemplary datasets, then, exemplary embodiments may predict a failure of the battery in the corresponding vehicle.

[0027] FIG. **8** is a graph illustrating weather considerations, according to exemplary embodiments. As this disclosure previously mentioned, environmental weather conditions may greatly impact the service life of a vehicle component. Because the weather data (illustrated as reference numeral **26** in FIGS. **1-3** & **6**) may also be an input to the predictive algorithm **44**, the weather data **26** may further refine any prediction of maintenance. FIG. **8**, for example, illustrates the impact of the weather data **26** on the predicted life of the battery in the corresponding vehicle. Volatility in humidity data (e.g., average, minimum and/or maximum), temperature data (e.g., average, minimum and/or maximum), and/or precipitation data may thus affect the life of battery. FIG. **8** thus illustrates seasonal variance in battery voltage with time. Service lifetime of the battery is thus impacted by service ambient conditions.

[0028] FIG. **9** is a flow diagram illustrating predictive maintenance, according to exemplary embodiments. The telematics sensor data **22** is fed as a daily input to the predictive algorithm **44**. The maintenance data **24** and the weather data **26** may also be provided as a daily input. The predictive algorithm **44** runs the statistical models (as above explained) to generate the statistical outliers as the final prediction of maintenance (Block **90**). Once the statistical outliers are generated, exemplary embodiments process the data in the final prediction of maintenance and generate a graphical user interface (or "GUI") (Block **92**). The graphical user interface is thus generated for display on a display device (not shown for simplicity). For example, the graphical user interface may be processed and/or generated as a web page for download to a client device using any web browser application. The graphical user interface may thus be provided from a server to a client device, thus allowing the final prediction of maintenance to be processed for visual presentation. A user of the client device may thus visually inspect the predictive maintenance recommended by the predictive algorithm **44** and make any desired modifications or edits (Block **94**). Because maintenance is predicted, a repair ticket or work order is generated (Block **96**) and assigned for repair (Block **98**). The corresponding maintenance is then logged as feedback to the maintenance data **24**.

[0029] The final prediction **90** is a refinement. The core concept of the third stage, final prediction **90** is to use outlier detection techniques to refine the prediction results from the first two classification stages. Results from first two models could result in early prediction issue. Early prediction issue causes a battery to be predicted as going to fail, too early. Early prediction problem causes wastage of battery life. The third stage model uses outlier detection technic to overcome early prediction problem. Exemplary embodiments used the maintenance data **24**, battery voltage obtained from OBDII sensor data **22**, and the weather data **26** to observe that batteries which are in good condition tend to show a different voltage pattern over time compared to the batteries which are about to die. These two distinctive patterns were used to produce the final prediction **90** of bad batteries, which are about to fail in the coming weeks.

[0030] FIG. **10** is a schematic illustrating ingestion of input data, according to exemplary embodiments. Here the sensor data **22** may be provided by a mobile resource management (or "MRM") data feed, which is vehicular information obtained from any known vendor. The sensor data **22** is consumed in a "Big Data" environment by the maintenance server **50** using a message queue, which is known. The mobile resource management data feed also sends a summarized view of the sensor data **22** to a fleet operation's database (e.g., "Vehicle Maintenance Database"). The fleet operation's database also provides the maintenance data **24** of the fleet vehicles. The predictive algorithm **44** processes these inputs to generate the final prediction of maintenance (Block **90**). Any visualization software may then be used to generate the graphical user interface (Block **92**) (such as the known SOLR® enterprise platform). Different summary views may then be provided, depending on the audience (e.g., operations or executives).

[0031] FIGS. **11-12** are schematic illustrating reporting features, according to exemplary embodiments. FIG. **11**, for example, illustrates a daily maintenance report that may be generated, based on the predictions. As exemplary embodiments may receive daily data feeds, each day may result in new or updated predictions as daily service miles are accumulated. Indeed, some fleet vehicles may accumulate hundreds of miles per day, so predictive maintenance is a daily requirement. Exemplary embodiments may thus generate a daily report identifying the vehicles to be maintained and the repair to be performed. Moreover, the report may also include a target date of the predicted repair for scheduling purposes. FIG. **11**, for example, illustrates a daily report notifying of potential battery failures in certain fleet vehicles, based on the sensor data **22**, the maintenance data **24**, and the weather data **26** (as above explained). Fleet operations are thus given two (2) weeks to complete the repair before imminent failure is predicted. The daily report illustrated in FIG. **11** is generated by the known SOLR® software tool. FIG. **12** illustrates a history report that details maintenance repairs completed on a daily basis. The history report, of course, may have different calendar frames, such as a weekly or monthly review of repair efforts.

[0032] FIGS. **13-14** are schematics illustrating other exemplary operating environments. Here the vehicle **20** may predict its own maintenance, based on input data. As the sensors in the vehicle **20** already collect its sensor data **22**, the vehicle itself may predict when repairs are needed. The

vehicle **20**, for example, may have a controller **110** that collects the sensor data **22**. The controller **110** may also query for the maintenance data **24**, whether locally or remotely retrieved. Moreover, as modern vehicles have wireless communications capabilities, the controller **110** may retrieve the weather data **26**. As FIG. **14** illustrates, the controller **110** may thus analyze all this data and predict when its components require repair. The controller **110** may have a processor **112** (e.g., "μP"), application specific integrated circuit (ASIC), or other component that executes any or all of the predictive algorithm **44** stored in a memory **114**. The predictive algorithm **44** instructs the processor **42** to perform operations, such as retrieving the sensor data **22**, the maintenance data **24**, and/or the weather data **26**. The predictive algorithm **44** causes the controller **110** to predict component service and/or failures, as this disclosure explains.

[0033] FIG. **15** is a block diagram illustrating a controller area network (or "CAN") **120**, according to exemplary embodiments. As the reader may understand, the vehicle **20** may have many electronic systems controlling many components and systems. For example, the engine **122** may have an engine controller **124** (or electronic control unit or "ECU"). The transmission may have a powertrain electronic control unit **126**. The braking system may have a brake electronic control unit **128**. There may be many more electronic control units throughout the vehicle **20**. The controller area network **120** thus allows all the various electronic control units to communicate with each other. A CAN bus **130**, for example, allows the various electronic control units to send and receive messages that are addressed to one or more of the electronic control units. The controller **110** may connect to or interface with the CAB bus **130**, thus allowing the controller **110** to monitor or read any sensor data **22** sent into or along the CAN bus **130**.

[0034] Exemplary embodiments thus use data analysis to predict maintenance. Exemplary embodiments may overlay the telematics sensor data **22** with the maintenance data **24**, thus allowing correlations between sensor readings, the environmental weather data **26**, and actual equipment failures. Statistical models may thus predict failures using machine-learning algorithms. Model-derived rules may guide forward-going decisions on when to perform the maintenance. Preventive maintenance can be wasteful, especially if performed too soon. Reactive maintenance, however, is costly when performed too late. Exemplary embodiments, instead, predict maintenance based on historical vehicle data generated from vehicle activity. Users and maintenance coordinators may thus determine the most effective cost expenditure models to improve customer experience.

[0035] FIG. **16** is a schematic illustrating yet another exemplary operating environment. As this disclosure above mentioned, exemplary embodiments may be applied to any process **140**, any machine **150**, and any manufacture **160**. That is, the maintenance server **40** may obtain the sensor data **22**, the maintenance data **24**, and the weather data **26** for any use whatsoever. The predictive algorithm **44** may then be executed to make the final prediction **90**, as this disclosure explains.

[0036] FIG. **17** is a schematic illustrating still more exemplary embodiments. FIG. **17** is a more detailed diagram illustrating a processor-controlled device **200**. As earlier paragraphs explained, the predictive algorithm **44** may operate in any processor-controlled device. FIG. **17**, then, illustrates the predictive algorithm **44** stored in a memory subsystem of the processor-controlled device **200**. One or more processors communicate with the memory subsystem and execute either, some, or all applications. Because the processor-controlled device **200** is well known to those of ordinary skill in the art, no further explanation is needed.

[0037] FIG. **18** depicts other possible operating environments for additional aspects of the exemplary embodiments. FIG. **18** illustrates the predictive algorithm **44** operating within various other processor-controlled devices **200**. FIG. **18**, for example, illustrates that the predictive algorithm **44** may entirely or partially operate within a mobile communications device, such as a smartphone **202** and a tablet computer **204**. As processing and memory capabilities increase in mobile communications devices, mobile devices may execute some or all of the predictive algorithm **44**. Indeed, any computer system, communications device, or processor-controlled device utilizing a processor and/or a digital signal processor (DP/DSP) **206** may execute some or all of the predictive algorithm **44**. The device **200** may also include watches, radios, clocks, printers, gateways, mobile/implantable medical devices, and other apparatuses and systems. Because the architecture and operating principles of the various devices **200** are well known, the hardware and software componentry of the various devices **200** are not further shown and described.

[0038] Exemplary embodiments may be applied regardless of networking environment. Exemplary embodiments may be easily adapted to any devices having cellular, WI-FI®, and/or BLUETOOTH® capability. Exemplary embodiments may be applied to devices utilizing any portion of the electromagnetic spectrum and any signaling standard (such as the IEEE 802 family of standards, GSM/CDMA/TDMA or any cellular standard, and/or the ISM band). Exemplary embodiments, however, may be applied to any processor-controlled device operating in the radio-frequency domain and/or the Internet Protocol (IP) domain. Exemplary embodiments may be applied to any processor-controlled device utilizing a distributed computing network, such as the Internet (sometimes alternatively known as the "World Wide Web"), an intranet, the local-area network **100** (LAN), and/or a wide-area network (WAN). Exemplary embodiments may be applied to any processor-controlled device utilizing power line technologies, in which signals are communicated via electrical wiring. Indeed, exemplary embodiments may be applied regardless of physical componentry, physical configuration, or communications standard(s).

[0039] Exemplary embodiments may utilize any processing component, configuration, or system. The processor explained herein could be multiple processors, which could include distributed processors or parallel processors in a single machine or multiple machines. The processor can be used in supporting a virtual processing environment. The processor could include a state machine, application specific integrated circuit (ASIC), programmable gate array (PGA) including a Field PGA, or state machine. When any of the processors execute instructions to perform "operations", this could include the processor performing the operations directly and/or facilitating, directing, or cooperating with another device or component to perform the operations.

[0040] Exemplary embodiments may be physically embodied on or in a computer-readable storage medium.

This computer-readable medium, for example, may include CD-ROM, DVD, tape, cassette, floppy disk, optical disk, memory card, memory drive, and large-capacity disks. This computer-readable medium, or media, could be distributed to end-subscribers, licensees, and assignees. A computer program product comprises processor-executable instructions for predictive maintenance, as the above paragraphs explained.

[0041] While the exemplary embodiments have been described with respect to various features, aspects, and embodiments, those skilled and unskilled in the art will recognize the exemplary embodiments are not so limited. Other variations, modifications, and alternative embodiments may be made without departing from the spirit and scope of the exemplary embodiments.

1. A method, comprising:

obtaining, by a vehicle controller comprising a processor, at least two different datasets associated with a vehicle from a group of datasets comprising a sensor dataset, a maintenance dataset, and a weather dataset;

predicting, by the vehicle controller, using respective different machine learning models for the at least two different datasets, respective groups of components of the vehicle for maintenance; and

predicting, by the vehicle controller, using an additional machine learning model on an intersecting set of components of the respective groups of components, a final component of the intersecting set of components of the vehicle for maintenance.

2. The method of claim **1**, wherein the additional machine learning model is different from the respective different machine learning models.

3. The method of claim **1**, further comprising wirelessly sending, by the vehicle controller, the prediction of the final component of the vehicle for maintenance to a remote server.

4. The method of claim **1**, further comprising generating, by the vehicle controller, a webpage by the vehicle controller, the webpage describing the prediction of the final component of the vehicle for maintenance.

5. The method of claim **1**, further comprising generating, by the vehicle controller, a graphical user interface for a display of the prediction of the final component of the vehicle for maintenance.

6. The method of claim **1**, further comprising recommending, by the vehicle controller, a service appointment associated with the prediction of the final component of the vehicle for maintenance.

7. The method of claim **1**, wherein at least one of the respective different machine learning models comprises a random forest process.

8. A system, comprising:

a processor; and

a memory, coupled to the processor, that stores executable instructions, that when executed by the processor, facilitate performance of operations, comprising:

retrieving different datasets associated with a vehicle from a group of datasets comprising a sensor dataset, a maintenance dataset, and a weather dataset;

determining, based on respective outputs from applying respective different machine learning models to the at least two different datasets, respective components of the vehicle for maintenance; and

generating, based on an output of applying an additional machine learning model to an intersecting set of components of the respective components, a prediction for at least one final component of the vehicle that implicates maintenance.

9. The system of claim **8**, wherein the respective different machine learning models do not comprise the additional machine learning model.

10. The system of claim **8**, wherein the operations further comprise generating network-accessible content describing the prediction for the at least one final component of the vehicle.

11. The system of claim **10**, wherein the operations further comprise publishing the network-accessible content describing the prediction for the at least one final component of the vehicle.

12. The system of claim **8**, wherein the operations further comprise causing a user interface to be rendered describing the prediction for the at least one final component of the vehicle.

13. The system of claim **12**, wherein causing the user interface to be rendered comprises causing at least one of a video, an image or audio describing the prediction to be rendered in the vehicle.

14. The system of claim **8**, wherein at least one of the respective different machine learning models is configured to generate an output that at least in part applies a random forest process.

15. The system of claim **8**, wherein the operations further comprise recommending a specified service appointment associated with the maintenance of the at least one final component of the vehicle.

16. A non-transitory computer-readable medium having instructions stored thereon that, when executed by a processor, facilitate performance of operations, comprising:

retrieving different datasets associated with a vehicle from at least two of a sensor dataset, a maintenance dataset, and a weather dataset;

identifying, using respective first machine learning models on the different datasets, respective intermediate sets of components of the vehicle for which maintenance is potentially to be performed, wherein the respective first machine learning models are different from one another; and

generating, using a second machine learning model on an intersecting set of components comprising an intersection of the respective intermediate sets of components, a prediction for a final set of components of the vehicle for which maintenance is to be performed.

17. The non-transitory computer-readable medium of claim **16**, wherein the second machine learning model is different from the respective first machine learning models.

18. The non-transitory computer-readable medium of claim **16**, wherein the operations further comprise displaying a user interface describing the prediction via a display device that is part of the vehicle.

19. The non-transitory computer-readable medium of claim **16**, wherein using of the respective first machine learning models comprises using at least one of the respective first machine learning models that applies a random forest classifier.

20. The non-transitory computer-readable medium of claim **16**, wherein the operations further comprise recommending a time and a place for the final set of components of the vehicle to be maintained according to the prediction.

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