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Xiong et al.

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(54) **REFRIGERANT LEAK DETECTION USING A SENSOR-READING CONTEXT ANALYSIS**

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F25B 49/00 (2006.01)
F28F 27/00 (2006.01)

(52) **U.S. Cl.**

CPC ***F25B 49/005*** (2013.01); ***F24F 11/36*** (2018.01); ***F28F 27/00*** (2013.01); *F25B 2500/222* (2013.01); *F28F 2265/16* (2013.01)

(58) **Field of Classification Search**

CPC F24F 11/36; F25B 49/005; F25B 250/222
See application file for complete search history.

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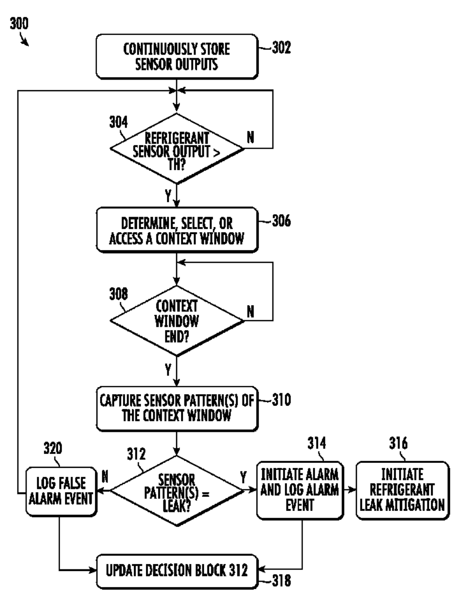
(57) **ABSTRACT**

A detection assembly operable to detect a refrigerant leak event includes a sensor network and a controller. The sensor network is operable to generate sensor outputs including triggering-sensor (TS) outputs and triggering-sensor context (TSC) outputs. The controller is operable to perform a sensor-reading context analysis on the sensor outputs. The sensor-reading context analysis includes accessing a set of the sensor outputs that occurred within a context time window, along with determining that a pattern of the set of sensor outputs represents the refrigerant leak event.

20 Claims, 6 Drawing Sheets



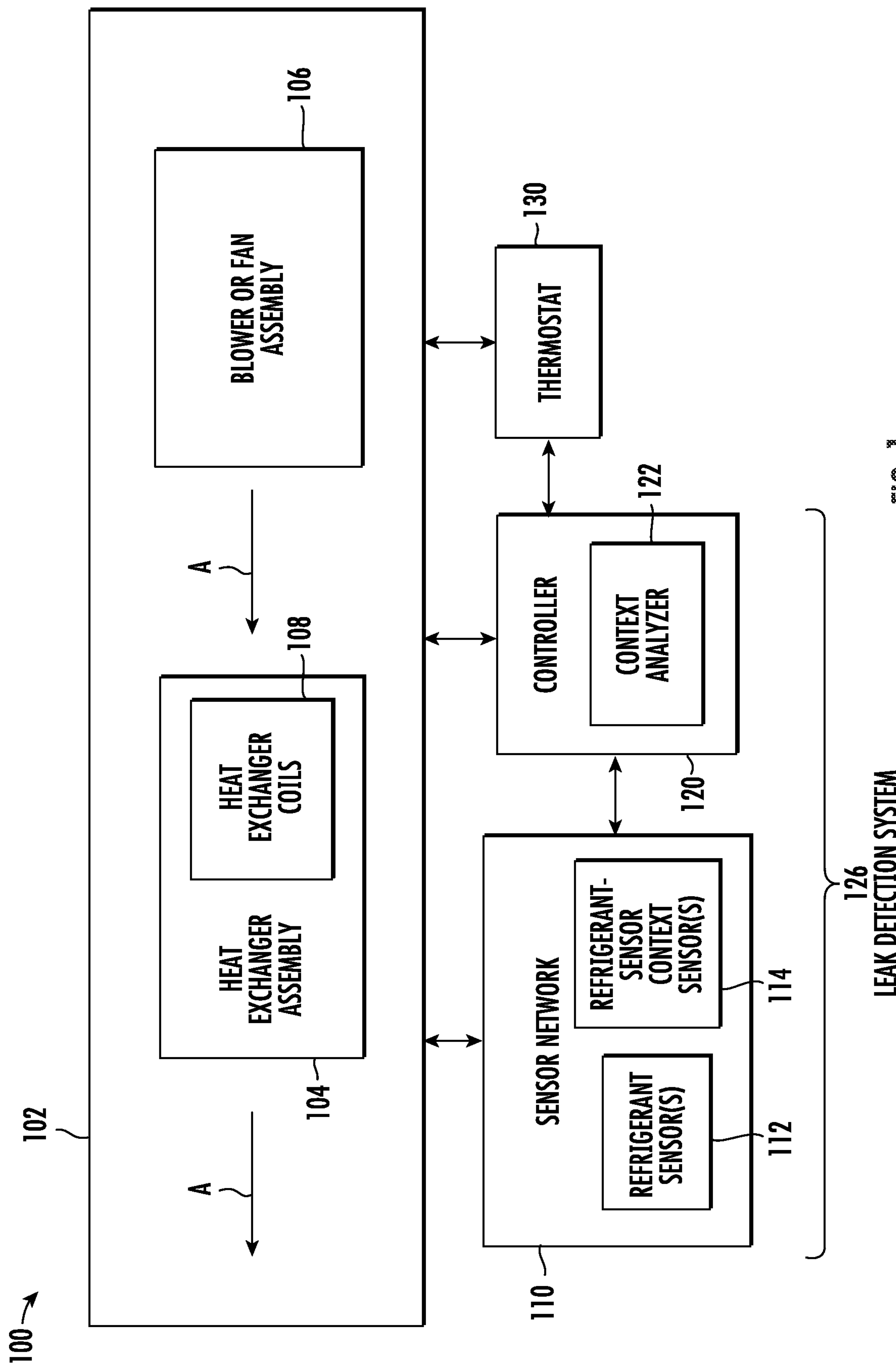

100
102
BLOWER OR FAN ASSEMBLY
106
A
A
HEAT EXCHANGER ASSEMBLY
HEAT EXCHANGER COILS
108
104
THERMOSTAT
130
CONTROLLER
CONTEXT ANALYZER
122
120
SENSOR NETWORK
REFRIGERANT-SENSOR CONTEXT SENSOR(S)
REFRIGERANT SENSOR(S)
114
112
110
126
LEAK DETECTION SYSTEM

FIG. 1

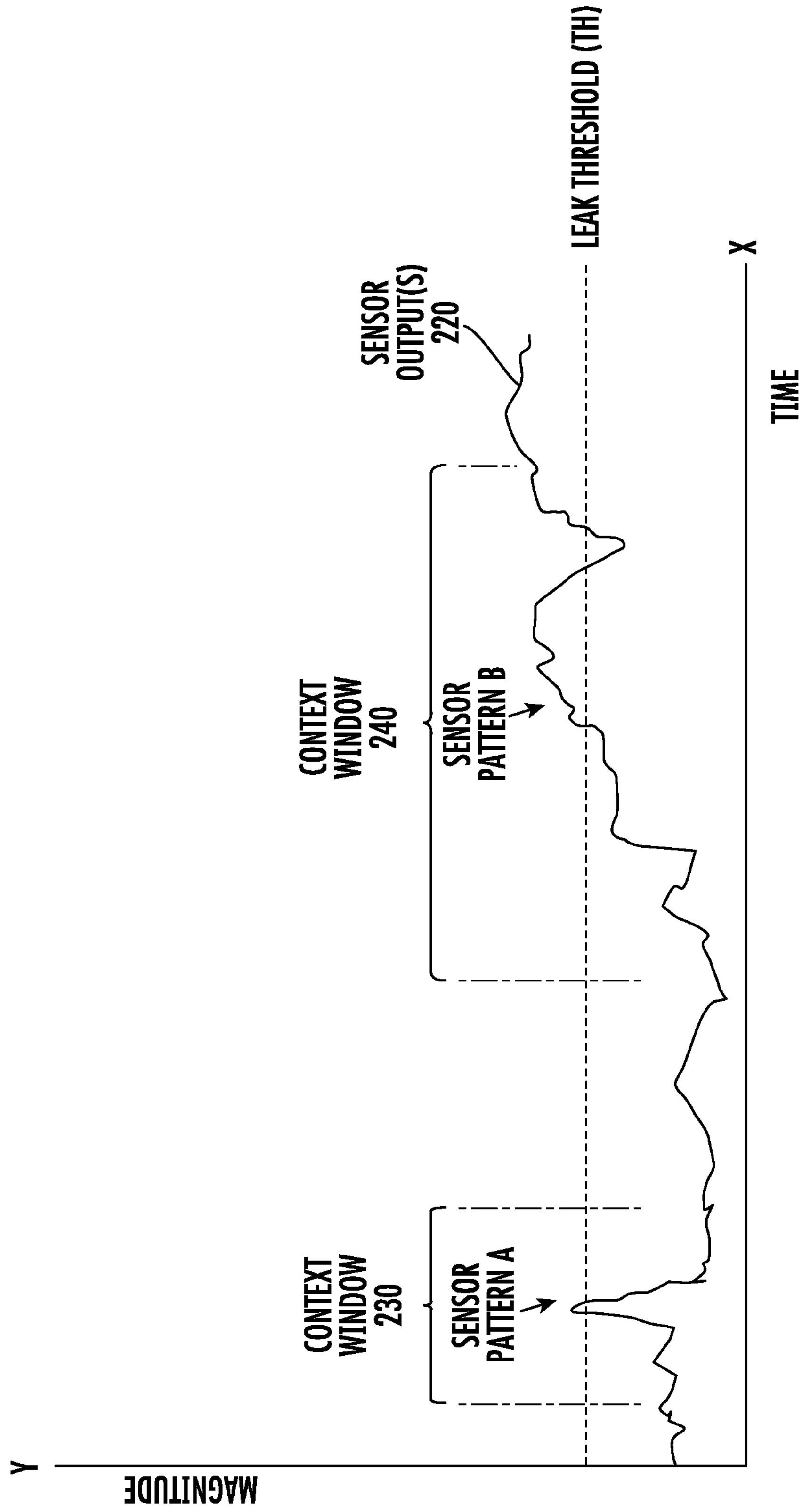

LEAK THRESHOLD (TH)
SENSOR OUTPUT(S) 220
X
TIME
CONTEXT WINDOW 240
SENSOR PATTERN B
CONTEXT WINDOW 230
SENSOR PATTERN A
Y
MAGNITUDE

FIG. 2

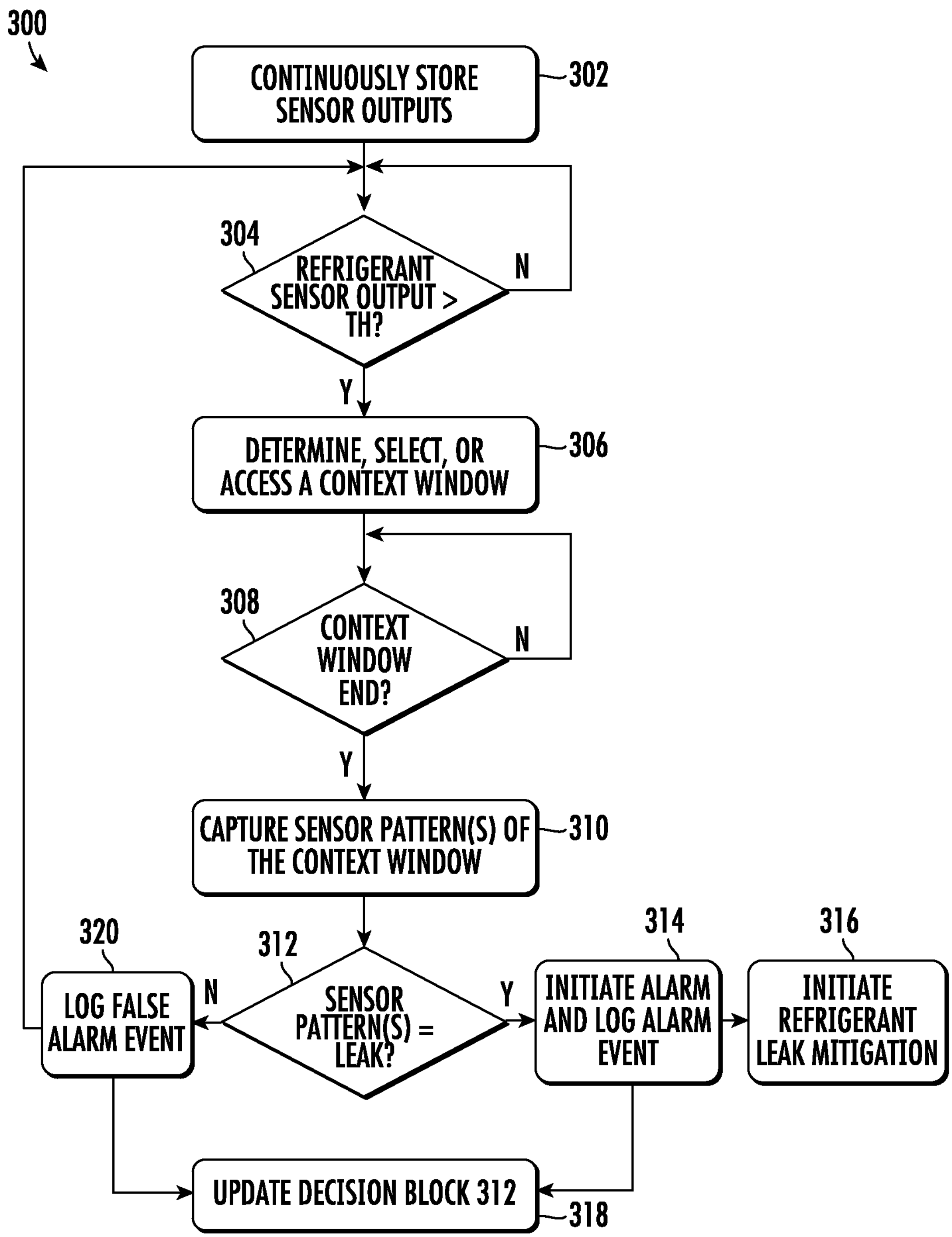

300
CONTINUOUSLY STORE SENSOR OUTPUTS
302
304
REFRIGERANT SENSOR OUTPUT > TH?
N
Y
DETERMINE, SELECT, OR ACCESS A CONTEXT WINDOW
306
308
CONTEXT WINDOW END?
N
Y
CAPTURE SENSOR PATTERN(S) OF THE CONTEXT WINDOW
310
320
312
314
316
LOG FALSE ALARM EVENT
N
SENSOR PATTERN(S) = LEAK?
Y
INITIATE ALARM AND LOG ALARM EVENT
INITIATE REFRIGERANT LEAK MITIGATION
UPDATE DECISION BLOCK 312
318

FIG. 3

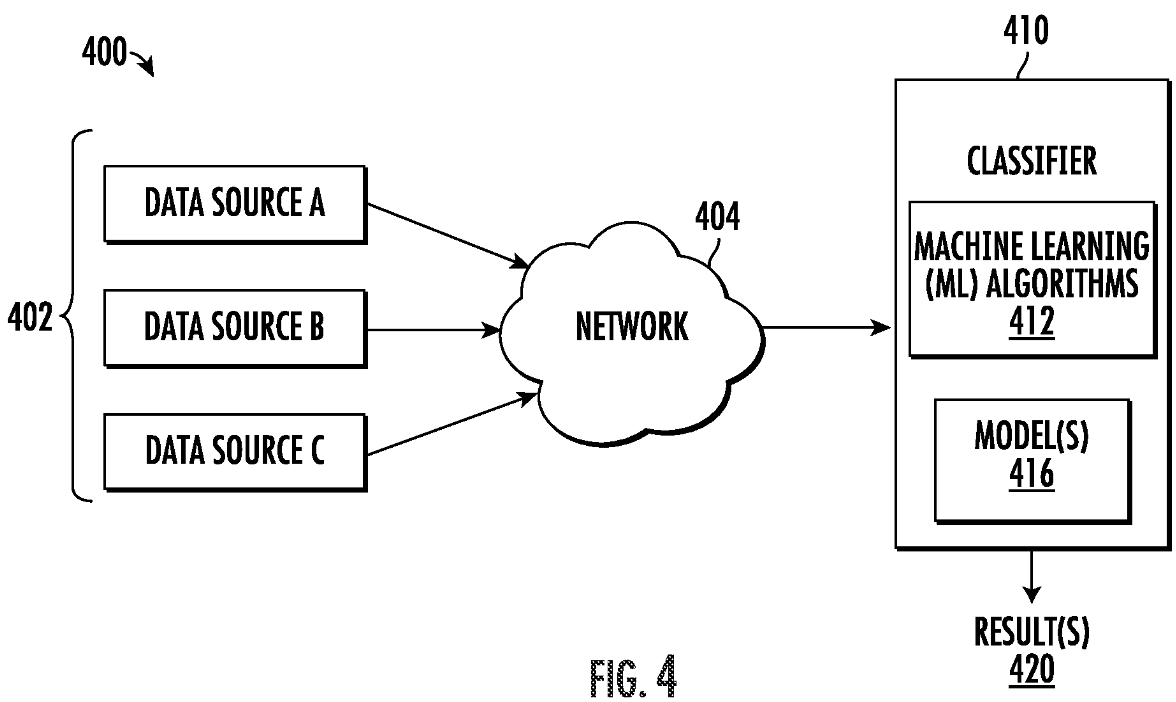

400
402
DATA SOURCE A
DATA SOURCE B
DATA SOURCE C
NETWORK
404
410
CLASSIFIER
MACHINE LEARNING (ML) ALGORITHMS 412
MODEL(S) 416
RESULT(S) 420

FIG. 4

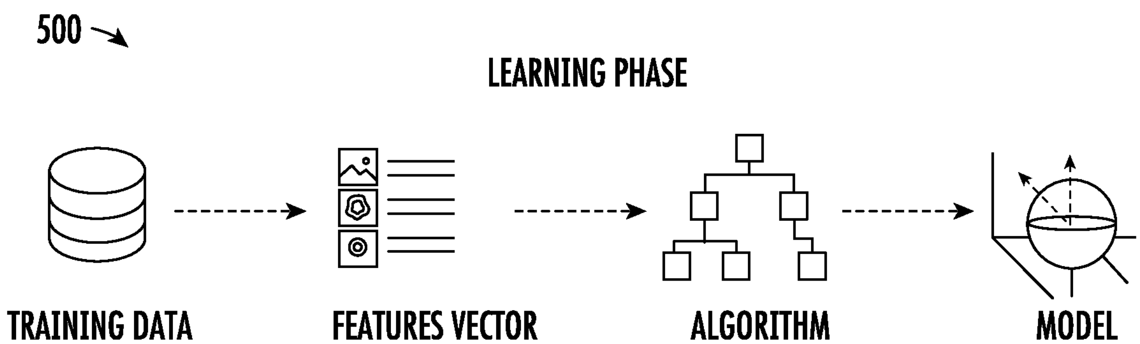

500
LEARNING PHASE
TRAINING DATA
FEATURES VECTOR
ALGORITHM
MODEL

FIG. 5

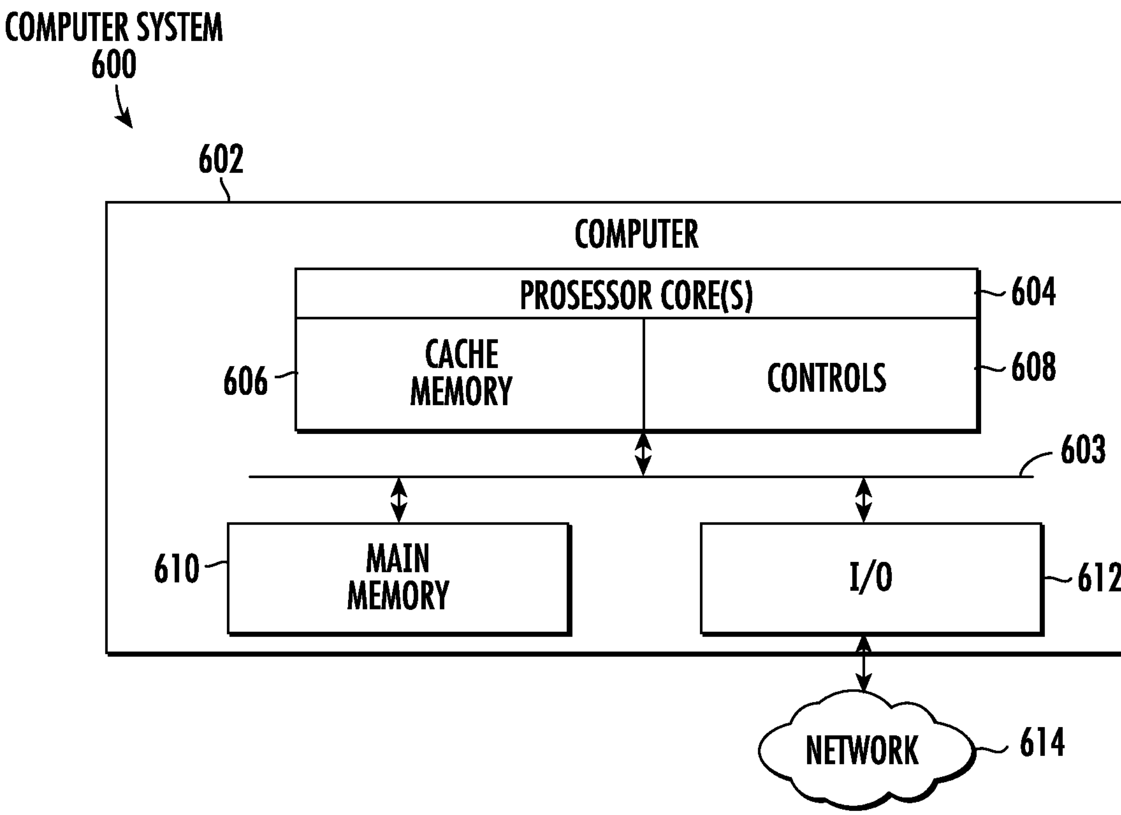

COMPUTER SYSTEM
600
602
COMPUTER
PROSESSOR CORE(S)
604
606
CACHE
MEMORY
CONTROLS
608
603
610
MAIN
MEMORY
I/O
612
NETWORK
614

FIG. 6

REFRIGERANT LEAK DETECTION USING A SENSOR-READING CONTEXT ANALYSIS

CROSS-REFERENCE TO RELATED APPLICATIONS

This application claims the benefit of U.S. Provisional Application No. 63/335,014 filed Apr. 26, 2022, the disclosure of which is incorporated herein by reference in its entirety.

BACKGROUND

Exemplary embodiments of the present disclosure relate to refrigerant detection assemblies for detecting leaks of moderate to low global warming potential (GWP) refrigerants, and more particularly, to refrigerant leak detection systems and methods operable to detect refrigerant leaks using a novel sensor-reading context analysis.

A wide variety of technologies exist for cooling applications, including but not limited to evaporative cooling, convective cooling, or solid state cooling such as electrothermic cooling. One of the most prevalent technologies in use for residential and commercial refrigeration and air conditioning is the vapor compression refrigerant heat transfer loop. Although existing refrigerants are effective coolants, the effect they can have on the environment has led to the institution of requirements that new refrigerants, which have moderate-to-low GWP values, be employed instead. Moderate-to-low GWP refrigerants A2L refrigerants) can be mildly flammable and thus their use in air conditioning systems can present risks that need to be addressed. In particular, to the extent that refrigerant leaks are possible in air conditioning systems, it is desirable to have a reliable and accurate leak detection system in place when moderate-to-low GWP refrigerants are in use in heating, ventilation, air conditioning and refrigeration (HVAC&R) products and other similar systems.

Refrigerant leaks can be detected using various types of refrigerant detection assemblies. Conventional refrigerant detection assemblies utilize threshold-based refrigerant leak detectors, such as a nondispersive infrared (NDIR) sensor or a metal-oxide-semiconductor-based (MOS-based) sensor, that compare sensor values with a single threshold to decide whether to trigger an alarm. However, such threshold-based detection schemes have the drawback of false alarms (i.e., generating a leak alarm when no leak has actually occurred) at a rate that is higher than acceptable for most applications. Frequent false alarms lead to downtime and require visits from technicians, thereby compromising the trustworthiness of the overall refrigerant detection system and, more specifically, the trustworthiness of the refrigerant detection sensors used in the detection system.

BRIEF DESCRIPTION

According to an embodiment, a detection assembly operable to detect a refrigerant leak event includes a sensor network and a controller. The sensor network is operable to generate sensor outputs including triggering-sensor (TS) outputs and triggering-sensor context (TSC) outputs. The controller is operable to perform a sensor-reading context analysis on the sensor outputs. The sensor-reading context analysis includes accessing a set of the sensor outputs that occurred within a context time window, along with determining that a pattern of the set of sensor outputs represents the refrigerant leak event.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the controller includes a classifier operable to execute a machine learning algorithm trained to perform the sensor-reading context analysis as a classification task.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the machine learning algorithm has been trained using a training dataset including experimental data that results from experimental tests applied to the detection assembly, along with in-use data that results from in-use operations of the detection assembly.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, accessing the set of the sensor outputs that occurred within the context time window is based at least in part on a determination that at least one of the TS outputs represents a triggering event.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the triggering event includes the at least one of the TS outputs exceeding a threshold.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the at least one of the TS outputs includes a parameter of a refrigerant flowing through a closed loop refrigeration circuit.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the parameter includes a concentration.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the sensor network includes a triggering sensor operable to generate the TS outputs, along with a first type of context sensor operable to generate a first type of the TSC outputs.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the sensor network further includes a second type of context sensor operable to generate a second type of the TSC outputs.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the first type of the TSC outputs include temperature data that represents ambient temperature of the triggering sensor; and the second type of the TSC outputs includes humidity data that represents ambient humidity of the triggering sensor.

According to another embodiment, a method of operating a detection assembly to detect a refrigerant leak event includes using a sensor network to generate sensor outputs that include triggering-sensor (TS) outputs and triggering-sensor context (TSC) outputs. A controller is used to perform a sensor-reading context analysis on the sensor outputs. The sensor-reading context analysis includes accessing a set of the sensor outputs that occurred within a context time window, along with determining that a pattern of the set of sensor outputs represents the refrigerant leak event.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the controller includes a classifier operable to execute a machine learning algorithm trained to perform the sensor-reading context analysis as a classification task.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the machine learning algorithm has been trained using a training dataset including experimental data that results from experimental tests applied to the detection assembly, along with in-use data that results from in-use operations of the detection assembly.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, accessing the set of the sensor outputs that occurred within the context time window is based at least in part on a determination that at least one of the TS outputs represents a triggering event.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the triggering event includes the at least one of the TS outputs exceeding a threshold.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the at least one of the TS outputs includes a parameter of a refrigerant flowing through a closed loop refrigeration circuit.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the parameter includes a concentration.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the sensor network includes a triggering sensor operable to generate the TS outputs, along with a first type of context sensor operable to generate a first type of the TSC outputs.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the sensor network further includes a second type of context sensor operable to generate a second type of the TSC outputs.

In addition to one or more of the features described above, or as an alternative to any of the foregoing embodiments, the first type of the TSC outputs include temperature data that represents ambient temperature of the triggering sensor; and the second type of the TSC outputs includes humidity data that represents ambient humidity of the triggering sensor.

BRIEF DESCRIPTION OF THE DRAWINGS

The following descriptions should not be considered limiting in any way. With reference to the accompanying drawings, like elements are numbered alike:

FIG. **1** is a block diagram of an exemplary heating, ventilation, and air conditioning (HVAC) system operable to implement a novel sensor-reading context analysis according to an embodiment;

FIG. **2** is a simplified plot diagram illustrating context windows and sensor network output patterns used in a novel sensor-reading context analysis according to an embodiment;

FIG. **3** is a flow diagram of an exemplary method of operating a detection assembly using a novel sensor-reading context analysis according to an embodiment;

FIG. **4** is a block diagram illustrating how the portions of the novel sensor-reading context analysis can be implemented using a classifier according to an embodiment;

FIG. **5** is a block diagram of learning phase functionality that can be used to train the classifier shown in FIG. **4**; and

FIG. **6** is a block diagram of a programmable computer system operable to implement aspects of a controller of the HVAC system shown in FIG. **1**.

DETAILED DESCRIPTION

A detailed description of one or more embodiments of the disclosed systems and methods are presented herein by way of exemplification and not limitation with reference to the Figures.

Embodiments of the present disclosure provide methods and systems that improve the trustworthiness of refrigerant sensors in refrigerant leak detection assemblies. Embodiments of the refrigerant leak detection systems and methods described herein utilize a novel sensor-reading context analysis to detect refrigerant leaks. In some aspects, the novel sensor-reading context analysis uses a sensor network that includes refrigerant sensors operable to detect parameters of a refrigerant (i.e., "refrigerant parameters"), along with context sensors operable to detect parameters that can impact how the refrigerant sensor operates (i.e., "refrigerant-sensor context parameters"). More specifically, the refrigerant-sensor context parameters can cause the refrigerant sensor to output false alarm data that indicates a refrigerant leak when in fact no refrigerant leak has occurred. By incorporating refrigerant-sensor context parameters into the leak detection determination, operating conditions that can impact how the refrigerant sensor operates are taken into account so that false alarm conditions can be reduced and, in most instances, averted.

In some aspects, the sensor-reading context analysis utilizes a classifier having machine learning algorithms trained to determine whether features of the refrigerant parameters and the refrigerant-context parameters match the features of a refrigerant leak event. In some aspects, the machine learning algorithms extract features from how the refrigerant parameters and the refrigerant context parameters change over time. In some aspects, the classifier is trained using a training dataset developed from lab-based experimental tests and in-use tests applied to the refrigerant sensor. As a non-limiting example, the refrigerant parameters can include refrigerant concentration; and the refrigerant-context parameters can include ambient humidity and/or ambient temperature of the refrigerant sensor. Accordingly, embodiments described herein improve the trustworthiness of refrigerant sensors by greatly reducing false alarm rates with no or little compromise in detection rate; reducing refrigerant system downtime; and reducing the need for service visits from technicians in response to leak detection system false alarms.

With reference now to FIG. **1**, embodiments of the disclosure can be applied to a wide variety of technologies for cooling applications, including but not limited to evaporative cooling, convective cooling, or solid state cooling such as electrothermic cooling. One of the most prevalent cooling technologies in use for residential and commercial refrigeration and air conditioning is the vapor compression refrigerant heat transfer loop. FIG. **1** illustrates an example of a heating, ventilation, and air conditioning (HVAC) system. **100** operable to incorporate a leak detection system **126** in accordance with aspects of the disclosure. For ease of illustration, the leak detection system **126** is depicted separately from the cabinet **102**. However, it is understood that some or all of the functionality of the leak detection system **126** can also be incorporated within the cabinet **102**.

The HVAC system **100** is depicted in FIG. **1** as a furnace coil or fan coil unit **100**. Although described herein as furnace or fan coil unit it should be appreciated that the HVAC system **100** can be any heating or cooling system. As shown, the furnace coil or fan coil unit **100** includes a cabinet or housing duct **102** within which various components of the HVAC system are located. For example, housed within the cabinet **102** of the furnace coil or fan coil unit **100** is a heat exchanger assembly **104** operable to heat and/or cool the adjacent air. A blower or fan assembly **106** can also be arranged within the cabinet **102** or alternatively, at a position outside of but in fluid communication with the cabinet **102**. The blower **106** is operable to circulate a flow of air A through the interior of the cabinet **102**, across the heat exchanger assembly **104**. Depending on the desired characteristics of the furnace coil or fan coil unit **100**, the blower **106** can be positioned either downstream with respect to the heat exchanger assembly **104** (i.e., a "draw through" configuration), or upstream with respect to the heat exchanger assembly **104** (i.e., a "blow through" configuration), as shown in FIG. **1**.

The heat exchanger assembly **104** is part of a closed loop refrigeration circuit through which refrigeration (not shown separately from the heat exchanger assembly **104**) flows. The heat exchanger assembly **104** can include any of a plurality of configurations. As illustrated in FIG. **1**, the heat exchanger assembly **104** includes one or more heat exchanger coils **108**, which can be arranged in a non-linear configuration. For example, the heat exchanger assembly **104** can have a generally V-shaped configuration, a generally A-shaped configuration, or a generally N-shaped configuration, or any other suitable configuration as is known in the art. In other embodiments, the heat exchanger assembly **104** can include a single heat exchanger coil **108** arranged at an angle with respect to the flow path of air A through the cabinet **102**. In embodiments where the furnace coil or fan coil unit **100** is operable to provide cool air, the heat exchanger assembly **104** absorbs heat from the air A passing through the heat exchanger assembly **104** and the resultant cool air A is provided to a space to be conditioned. It should be understood that the refrigeration system illustrated herein is intended as an example only and that a HVAC system **100** having any suitable configuration is within the scope of the disclosure.

With continued reference to FIG. **1**, the refrigerant circulating within the heat exchanger assembly **104** can, in rare instances, leak. When utilizing A2L refrigerants, a leak of refrigerant could lead to undesirable consequences due to the mildly flammable nature of A2L refrigerants. It should be appreciated that other refrigerants, beyond A2L refrigerants, are within the scope of the disclosure. Accordingly, the HVAC system **100** can include the leak detection system **126** operable to detect a refrigerant leak of the cabinet **102**. The leak detection system **126** includes a sensor network **110** and a controller **120**, configured and arranged as shown. The controller **120** includes a sensor-reading context analyzer **122**; and the sensor network **110** includes refrigerant sensor(s) (or triggering sensor) **112** and refrigerant-sensor context sensor(s) (or triggering-sensor context sensor(s)) **114**.

In embodiments, the refrigerant sensor(s) **112** can be coupled to the cabinet **102** in a way that allows the refrigerant sensor **112** to measure parameters of the refrigerant (not shown separately) that can provide an indication of a refrigerant leak. As a non-limiting example, the refrigerant parameter can be a concentration of the refrigerant in the heat exchanger assembly **104** because the concentration of the refrigerant in the heat exchanger assembly **104** can provide an indication of whether or not refrigerant is leaking from the system **100** (i.e., refrigerant concentration in the system **100** increases where fluid is leaking from the system **100**). Examples of the refrigerant sensor(s) **112** include but are not limited to a point sensor and a line of sight or beam sensor. Further, the technologies used by one or more of the refrigerant sensors **112** can include non-dispersive infrared (NDIR), photoacoustic spectroscopy (PAS), quantum cascade laser spectroscopy (QCLS), tunable diode laser spectroscopy (TDLS), thermal conductivity (TC), metal oxide semiconductor (MOS), ultrasonic, speed of sound, and ultraviolet spectroscopy for example. However, it should be understood that any suitable type of refrigerant sensor **112** is within the scope of the disclosure.

In embodiments, the refrigerant-sensor context sensor(s) **114** can be any suitable sensor or sensor assembly that measures parameters of the context or conditions in which the refrigerant sensor(s) **112** operate. For example, refrigerant sensor(s) **112** can be positioned near the heat exchanger assembly **104** so that the refrigerant sensor(s) **112** will be exposed to the high/low humidity and temperature cycles that result from the heat exchanger assembly **104** cycling through blowing cold air, warm air, cold air, warm air, etc. These high/low humidity and temperature cycles can result in condensation forming on the refrigerant sensor(s) **112**, which can result in the refrigerant sensor(s) **112** registering a false positive (i.e., signaling that refrigerant is leaking when in fact no refrigerant leakage has occurred). In some embodiments, the refrigerant-sensor context sensor(s) **114** can include any suitable sensor for measuring ambient humidity to which the refrigerant sensor(s) are exposed. In some embodiments, the refrigerant-sensor context sensor(s) **114** can include any suitable sensor for measuring ambient temperature to which the refrigerant sensor(s) are exposed.

In embodiments, the controller **120** includes the sensor-reading context analyzer module **122**, which is operable to analyze the outputs from the sensor network **110** to determine whether or not refrigerant is leaking from the system **100**. Because the outputs from the sensor network **110** include outputs from the refrigerant-sensor context sensor(s) **114**, operating conditions that can impact how the refrigerant sensor(s) **112** operate are taken into account by the sensor-reading context analyzer **122** so that false alarm conditions can be reduced and, in most instances, averted.

In some aspects, the sensor-reading context analyzer **122** utilizes a classifier having machine learning algorithms (e.g., classifier **410** and machine learning algorithms **412** shown in FIG. **4**) trained to determine whether features of the outputs from the sensor network **110** match the features of a refrigerant leak event. In some aspects, the machine learning algorithms extract features from how the outputs from the sensor network **110** change over time. In some aspects, the classifier is trained using a training dataset developed from lab-based experimental tests and in-use tests applied to the refrigerant sensor(s) **112**. As a non-limiting example, outputs from the refrigerant sensor(s) **112** can include refrigerant concentration; and the outputs from the refrigerant-sensor context sensor(s) **114** can include ambient humidity and/or ambient temperature to which the refrigerant sensor(s) **112** are or have been exposed. Accordingly, embodiments described herein improve the trustworthiness of the refrigerant sensor(s) **112** by greatly reducing false alarm rates with no or little compromise in detection rate; reducing refrigerant system downtime; and reducing the need for service visits from technicians in response to leak detection system false alarms.

In embodiments, the controller **120** is operably coupled to the sensor network **110** and to a motor (not shown separately) of the blower **106**. In addition, a thermostat **130** for selecting a temperature demand of the area to be conditioned by the HVAC system **100** is arranged in communication with the controller **120**. The controller **120** is operable to control operation of the furnace coil or fan coil unit **100** in response to the temperature setting of the thermostat **130**.

Responsive to the controller **120** determining that a refrigerant leak event has occurred, the leak detection system **126** enters an alarm state and the controller **120** is operable to operate the HVAC system **100** in a first mode. In the first mode, the controller **120** can be made operable to isolate one or more possible ignition sources by turning off the HVAC system **100** as needed. For example, in embodiments where the HVAC system **100** includes a non-communicating thermostat, the controller **120** could cut power to the thermostat **130** to prevent calls for heat and/or cooling provided to the thermostat **130** from being communicated to the controller **120** and activating the HVAC system **100**. In embodiments where the thermostat is a communicating thermostat, isolating one or more possible ignition sources includes de-energizing HVAC operating circuits directly, such as the furnace ignition circuit, AC compressor circuit, etc. In addition, during operation in the first mode, the controller **120** can be made operable to initiate operation of a blower **106**. Operation of the blower **106** is intended to dissipate the refrigerant within the atmosphere.

Additional details of how embodiments of the leak detection system **126** can be implemented are shown in FIGS. **2** and **3**. FIG. **2** is a simplified plot diagram, and FIG. **3** is a flow diagram illustrating a methodology **300**. More specifically, FIG. **2** is a plot diagram illustrating a simplified example of sensor output(s) **220** of the sensor network **110**, content windows **230**, **240**, sensor patterns A, B, and a leak threshold (Th), that can be utilized by the sensor-reading context analyzer **122** (shown in FIG. **1**) to perform the methodology **300** shown in FIG. **3**.

The methodology **300** will now be described with reference to the leak detection system **126** shown in FIG. **1**, the simplified plot diagram shown in FIG. **2**, and the flow diagram shown in FIG. **3**. Turning first to FIG. **3**, the methodology **300** begins at block **302** by using the sensor network **110** (shown in FIG. **1**) to make continuous sensor readings or measurements, and by using the controller **120** (shown in FIG. **1**) to receive and store the sensor readings or measurements. FIG. **2** provides a simplified representation of the sensor readings of the sensor network **110** as sensor output(s) **220**. The sensor output(s) **220** are simplified in that they represent a combination of sensor readings generated over time by the refrigerant sensor(s) **112** and the refrigerant-sensor context sensor(s) **114**. In practice, each instance of the refrigerant sensor(s) **112** and the refrigerant-sensor context sensor(s) **114** generates its own sensor output. The sensor output(s) **220** are further simplified in that the change in magnitude over time in FIG. **2** is random and provided for ease of illustration and explanation. The pattern of the output(s) **220** is not intended to represent an actual or expected change in magnitude over time for the sensor readings generated by the sensor network **110**. The output(s) **220** are intended to illustrate that the magnitude of the sensor readings from the sensor network **110** change over time, and are further intended to illustrate that the magnitude of the output(s) can exceed a leak threshold (Th) value. In some embodiments, the leak Th corresponds to a threshold for sensor readings from the sensor network **110**, where the threshold functions as a trigger to capture the context window (e.g., context window **230** and/or context window **240** shown in FIG. **2**) and the associated sensor output pattern (e.g., sensor output pattern A and/or context output pattern B shown in FIG. **2**) that will be analyzed by the sensor-readings context analyzer **122** (shown in FIG. **1**). In some embodiments, sensor readings from the refrigerant sensor(s) **112** function as the trigger, and the leak Th is a value of sensor reading from the refrigerant sensor(s) **112** that provide a preliminary indication that the refrigerant sensor(s) **112** may or may not have detected a refrigerant leak in the system **100** (shown in FIG. **1**). In accordance with embodiments, the sensor-reading context analyzer **122** performs additional analysis using the information depicted in FIG. **2** to determine whether the preliminary indication that the refrigerant sensor(s) **112** may or may not have detected a refrigerant leak represents an actual refrigerant leak or a false alarm.

Returning to the methodology **300** shown in FIG. **3**, from block **302** the methodology **300** moves to decision block **304** where the controller **120** (shown in FIG. **1**) monitors the sensor outputs stored at block **302** to determine when the portion of the sensor output(s) **220** generated by the refrigerant sensor(s) **112** exceeds the leak Th (shown in FIG. **2**). If the answer to the inquiry at decision block **304** is no, the methodology **300** returns to the input of decision block **304** and continues to monitor the sensor outputs stored at block **302**. If the answer to the inquiry at decision block **304** is yes, the methodology **300** moves to block **306** where the controller **120** determines, selects, and/or accesses a context window context window **230** and/or context window **240** shown in FIG. **2**) around the point in time where the portion of the sensor output(s) **220** generated by the refrigerant sensor(s) **112** exceeds the leak Th. In general, the width or duration of the context window needs to be large enough such that the sensor pattern (e.g., sensor output pattern A and/or sensor output pattern B shown in FIG. **2**) defined by the context window provides sufficient data for the sensor pattern analysis at decision block **312**. In some embodiments, the width or size of the context window is selected in advance of initiating the methodology **300**. In some embodiments, the width or size of the context window is determined dynamically by the sensor-reading, context analyzer **122** using the sensor output(s) **220**. For example, where the sensor-reading context analyzer **122** includes a classifier (e.g., classifier **410** shown in FIG. **4**), the classifier can be trained to dynamically selected the context window based on a dynamic determination of the width or duration of the sensor output pattern (e.g., sensor output pattern A and/or sensor output pattern B) needed in order to determine at a sufficiently high confident level whether sensor readings from the refrigerant sensor(s) **112** exceeding leak Th represent an actual refrigerant leak or a false alarm.

At decision block **308**, the controller **120** determines whether or not the selected or determined context window has ended. If the answer to the inquiry at decision block **308** is no, the methodology **300** returns to the input the decision block **308**. If the answer to the inquiry at decision block **308** is yes, the context window has closed or ended, and the methodology **300** moves to block **310** where the controller **120** captures the sensor output pattern (e.g., sensor output pattern A and/or sensor output pattern B shown in FIG. **2**) of the selected context window (e.g., context window **230** and/or context window **240** shown in FIG. **2**).

From block **310**, the methodology **300** moves to decision block **312**, where the controller **120** and the sensor-reading context analyzer **122** evaluate the sensor pattern captured at block **310** to determine whether the refrigerant sensor output exceeding leak Th at decision block **304** represents an actual refrigerant leak or a false alarm. In some embodiments, the analysis performed by the sensor-reading context analyzer **122** at decision block **304** utilizes a classifier (e.g., classifier **410** shown in FIG. **4**) having machine learning algorithms (e.g., machine learning algorithms **412** shown in FIG. **4**) trained to determine whether features of the sensor pattern match the features of a refrigerant leak event. In some aspects, the machine learning algorithms extract features from the sensor pattern changes over time. In some embodiments, the classifier is trained using a training dataset developed from lab-based experimental tests and in-use tests applied to the refrigerant sensor(s) **112**.

If the answer to the inquiry at decision block **312** is no, the methodology **300** moves to block **320** and logs the various aspects of the evaluations at decision block **304** and decision block **312** as a false alarm. From block **320**, the methodology **300** branches to block **318** and to another iteration of decision block **304** and the overall methodology **300**. In embodiments where the evaluation at decision block **312** is performed by a trained classifier (e.g., the classifier **410** shown in FIG. **4**), block **318** uses the false alarm event logged at block **320** to update the trained classifier of decision block **312**, If the answer to the inquiry at decision block **312** is yes, the methodology **300** moves to block **314** where the controller **120** initiates alarm and logs the alarm as an alarm event. From block **314**, the methodology **300** branches to block **318** and block **316**. In embodiments where the evaluation at decision block **312** is performed by a trained classifier, block **318** uses the alarm event logged at block **314** to update the trained classifier of decision block **312**. At block **316**, the methodology **300** initiates a refrigerant leak response strategy, Which can include shutting down the HVAC system **100** (shown in FIG. **1**) or initiating a service call.

Additional details of machine learning techniques that can be used to implement functionality of the controller **120** and/or the sensor-reading context analyzer **122** will now be provided. The various classification, prediction and/or determination functionality of the controllers or processors described herein can be implemented using machine learning and/or natural language processing techniques. In general, machine learning techniques are run on so-called "learning machines," which can be implemented as programmable computers operable to run sets of machine learning algorithms and/or natural language processing algorithms. Machine learning algorithms incorporate knowledge from a variety of disciplines, including neurophysiology, cognitive science/psychology, physics (statistical mechanics), control theory, computer science, artificial intelligence, statistics/mathematics, pattern recognition, computer vision, parallel processing and hardware (e.g., digital/analog/VLSI/optical).

The basic function of learning machines and their machine learning algorithms is to recognize patterns by interpreting unstructured sensor data through a kind of machine perception. Unstructured real-world data in its native form (e.g., images, sound, text, or time series data) is converted to a numerical form (e.g., a vector having magnitude and direction) that can be understood and manipulated by a computer. The machine learning algorithm performs multiple iterations of learning-based analysis on the real-world data vectors until patterns (or relationships) contained in the real-world data vectors are uncovered and learned. The learned patterns/relationships function as predictive models that can be used to perform a variety of tasks, including, for example, classification (or labeling) of real-world data and clustering of real-world data. Classification tasks often depend on the use of labeled datasets to train the classifier (i.e., the model) to recognize the correlation between labels and data. This is known as supervised learning. Examples of classification tasks include identifying objects in images (e.g., stop signs, pedestrians, lane markers, etc.), recognizing gestures in video, detecting voices, detecting voices in audio, identifying particular speakers, transcribing speech into text, and the like. Clustering tasks identify similarities between objects, which the clustering task groups according to those characteristics in common and which differentiate them from other groups of objects. These groups are known as "clusters."

An example of machine learning techniques that can be used to implement embodiments of the disclosure will be described with reference to FIGS. **4** and **5**. FIG. **4** depicts a block diagram showing a classifier system **400** capable of implementing various predicting and determining aspects of the embodiments described herein. More specifically, the functionality of the system **400** is used in embodiments of the disclosure to generate various models and/or sub-models that can be used to implement predicting and determining functionality in embodiments of the disclosure. The classifier system **400** includes multiple data sources **402** in communication (e.g., through a network **404**) with a classifier **410**. In some embodiments of the disclosure, the data sources **402** can bypass the network **404** and feed directly into the classifier **410**. The data sources **402** provide data/information inputs that will be evaluated by the classifier **410** in accordance with embodiments of the disclosure. The data sources **402** also provide data/information inputs that can be used by the classifier **410** to train and/or update model(s) **416** created by the classifier **410**. The data sources **402** can be implemented as a wide variety of data sources, including but not limited to, sensors operable to gather real time data, data repositories (including training data repositories), and outputs from other classifiers. The network **404** can be any type of communications network, including but not limited to local networks, wide area networks, private networks, the Internet, and the like.

The classifier **410** can be implemented as algorithms executed by a programmable computer such as the computing system **600** (shown in FIG. **6**). As shown in FIG. **4**, the classifier **410** includes a suite of machine learning (ML) algorithms **412**; and model(s) **416** that are relationship (or prediction) algorithms generated (or learned) by the ML algorithms **412**. The algorithms **412**, **416** of the classifier **410** are depicted separately for ease of illustration and explanation. In embodiments of the disclosure, the functions performed by the various algorithms **412**, **416** of the classifier **410** can be distributed differently than shown. In some embodiments of the disclosure, natural language processing (NLP) algorithms can be integrated within the ML algorithms **412**.

Referring now to FIGS. **4** and **5** collectively, FIG. **5** depicts an example of a learning phase **500** performed by the ML algorithms **412** to generate the above-described models **416**. In the learning phase **500**, the classifier **410** extracts features from the training data and coverts the features to vector representations that can be recognized and analyzed by the ML algorithms **412**. The features vectors are analyzed by the ML algorithm **412** to "classify" the training data against the target model (or the model's task) and uncover relationships between and among the classified training data. Examples of suitable implementations of the ML algorithms **412** include but are not limited to neural networks, support vector machines (SVMs), logistic regression, decision trees, hidden Markov Models (HMMs), etc. The learning or training performed by the ML algorithms **412** can be supervised, unsupervised, or a hybrid that includes aspects of supervised and unsupervised learning. Supervised learning is when training data is already available and classified/labeled. Unsupervised learning is when training data is not classified/labeled so must be developed through iterations of the classifier **410** and the ML algorithms **412**. Unsupervised learning can utilize additional learning/training methods including, for example, clustering, anomaly detection, neural networks, deep learning, and the like.

When the models **416** are sufficiently trained by the ML algorithms **412**, the data sources **402** that generate "real world" data are accessed, and the "real world" data is applied to the models **416** to generate usable versions of the results **420**. In some embodiments of the disclosure, the results **420** can be fed back to the classifier **410** and used by the ML algorithms **412** as additional training data for updating and/or refining the models **416**.

FIG. **6** illustrates an example of a computer system **600** that can be used to implement the controller **120** described herein. The computer system **600** includes an exemplary computing device ("computer") **602** configured for performing various aspects of the content-based semantic monitoring operations described herein in accordance embodiments of the disclosure. In addition to computer **602**, exemplary computer system **600** includes network **614**, which connects computer **602** to additional systems (not depicted) and can include one or more wide area networks (WANs) and/or local area networks (LANs) such as the Internet, intranet(s), and/or wireless communication network(s). Computer **602** and additional system are in communication via network **614**, e.g., to communicate data between them.

Exemplary computer **602** includes processor cores **604**, main memory ("memory") **610**, and input/output component(s) **612**, which are in communication via bus **603**. Processor cores **604** includes cache memory ("cache") **606** and controls **608**, which include branch prediction structures and associated search, hit, detect and update logic, which will be described in more detail below. Cache **606** can include multiple cache levels (not depicted) that are on or off-chip from processor **604**. Memory **610** can include various data stored therein, e.g., instructions, software, routines, etc., which, e.g., can be transferred to/from cache **606** by controls **608** for execution by processor **604**. Input/output component(s) **612** can include one or more components that facilitate local and/or remote input/output operations to/from computer **602**, such as a display, keyboard, modem, network adapter, etc. (not depicted).

Embodiments of the disclosure described herein can be a system, a method, and/or a computer program product at any possible technical detail level of integration. The computer program product can include a computer readable storage medium (or media) having computer readable program instructions thereon for causing a controller or processor to carry out aspects of the embodiments of the disclosure.

The computer readable storage medium can be a tangible device that can retain and store instructions for use by an instruction execution device. The computer readable storage medium can be, for example, but is not limited to, an electronic storage device, a magnetic storage device, an optical storage device, an electromagnetic storage device, a semiconductor storage device, or any suitable combination of the foregoing. A non-exhaustive list of more specific examples of the computer readable storage medium includes the following: a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), a static random access memory (SRAM), a portable compact disc read-only memory (CD-ROM), a digital versatile disk (DVD), a memory stick, a floppy disk, a mechanically encoded device such as punch-cards or raised structures in a groove having instructions recorded thereon, and any suitable combination of the foregoing. A computer readable storage medium, as used herein, is not to be construed as being transitory signals per se, such as radio waves or other freely propagating electromagnetic waves, electromagnetic waves propagating through a waveguide or other transmission media (e.g., light pulses passing through a fiber-optic cable), or electrical signals transmitted through a wire.

The term "about" is intended to include the degree of error associated with measurement of the particular quantity based upon the equipment available at the time of filing the application.

The terminology used herein is for the purpose of describing particular embodiments only and is not intended to be limiting of the present disclosure. As used herein, the singular forms "a", "an" and "the" are intended to include the plural forms as well, unless the context clearly indicates otherwise. It will be further understood that the terms "comprises" 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, element components, and/or groups thereof.

While the present disclosure has been described with reference to an exemplary embodiment or embodiments, it will be understood by those skilled in the art that various changes may be made and equivalents may be substituted for elements thereof without departing from the scope of the present disclosure. In addition, many modifications may be made to adapt a particular situation or material to the teachings of the present disclosure without departing from the essential scope thereof. Therefore, it is intended that the present disclosure not be limited to the particular embodiment disclosed as the best mode contemplated for carrying out this present disclosure, but that the present disclosure will include all embodiments falling within the scope of the claims.

What is claimed is:

1. A detection assembly operable to detect a refrigerant leak event, the detection assembly comprising:

a sensor network operable to generate sensor outputs comprising triggering-sensor (TS) outputs and triggering-sensor context (TSC) outputs; and

a controller operable to perform a sensor-reading context analysis on the sensor outputs;

wherein the sensor-reading context analysis comprises:

accessing a set of the sensor outputs comprising the TS outputs and the TSC outputs that occurred within a context time window; and

determining that a pattern of the set of sensor outputs represents the refrigerant leak event.

2. The detection assembly of claim **1**, wherein the controller comprises a classifier operable to execute a machine learning algorithm trained to perform the sensor-reading context analysis as a classification task.

3. The detection assembly of claim **2**, wherein the machine learning algorithm has been trained using a training dataset comprising:

experimental data that results from experimental tests applied to the detection assembly; and

in-use data that results from in-use operations of the detection assembly.

4. The detection assembly of claim **1**, wherein the sensor-reading context analysis further comprises determining a duration of the context time window based at least in part on a determination of an amount of the sensor outputs that are needed to perform the determining that the pattern of the set of sensor outputs represents the refrigerant leak event.

5. The detection assembly of claim **1**, wherein:

accessing the set of the sensor outputs comprising the TS outputs and the TSC outputs that occurred within the context time window is based at least in part on a determination that at least one of the TS outputs represents a triggering event; and

the triggering event comprises the at least one of the TS outputs exceeding a threshold.

6. The detection assembly of claim **5**, wherein the at least one of the TS outputs comprises a parameter of a refrigerant flowing through a closed loop refrigeration circuit.

7. The detection assembly of claim **6**, wherein the parameter comprises a concentration.

8. The detection assembly of claim **1**, wherein the sensor network comprises:

a triggering sensor operable to generate the TS outputs; and

a first type of context sensor operable to generate a first type of the TSC outputs.

9. The detection assembly of claim **8**, wherein the sensor network further comprises a second type of context sensor operable to generate a second type of the TSC outputs.

10. The detection assembly of claim **9**, wherein:

the first type of the TSC outputs comprises temperature data that represents ambient temperature of the triggering sensor; and

the second type of the TSC outputs comprises humidity data that represents ambient humidity of the triggering sensor.

11. A method of operating a detection assembly to detect a refrigerant leak event, the method comprising:

using a sensor network to generate sensor outputs comprising triggering-sensor (TS) outputs and triggering-sensor context (TSC) outputs; and

using a controller to perform a sensor-reading context analysis on the sensor outputs;

wherein the sensor-reading context analysis comprises:

accessing a set of the sensor outputs comprising the TS outputs and the TSC outputs that occurred within a context time window; and

determining that a pattern of the set of sensor outputs represents the refrigerant leak event.

12. The method of claim **11**, wherein the controller comprises a classifier operable to execute a machine learning algorithm trained to perform the sensor-reading context analysis as a classification task.

13. The method of claim **12**, wherein the machine learning algorithm has been trained using a training dataset comprising:

experimental data that results from experimental tests applied to the detection assembly; and

in-use data that results from in-use operations of the detection assembly.

14. The method of claim **11**, wherein the sensor-reading context analysis further comprises determining a duration of the context time window based at least in part on a determination of an amount of the sensor outputs that are needed to perform the determining that the pattern of the set of sensor outputs represents the refrigerant leak event.

15. The method of claim **11**, wherein:

accessing the set of the sensor outputs comprising the TS outputs and the TSC outputs that occurred within the context time window is based at least in part on a determination that at least one of the TS outputs represents a triggering event; and

the triggering event comprises the at least one of the TS outputs exceeding a threshold.

16. The method of claim **15**, wherein the at least one of the TS outputs comprises a parameter of a refrigerant flowing through a closed loop refrigeration circuit.

17. The method of claim **16**, wherein the parameter comprises a concentration.

18. The method of claim **11**, wherein the sensor network comprises:

a triggering sensor operable to generate the TS outputs; and

a first type of context sensor operable to generate a first type of the TSC outputs.

19. The method of claim **18**, wherein the sensor network further comprises a second type of context sensor operable to generate a second type of the TSC outputs.

20. The method of claim **19**, wherein:

the first type of the TSC outputs comprises temperature data that represents ambient temperature of the triggering sensor; and

the second type of the TSC outputs comprises humidity data that represents ambient humidity of the triggering sensor.

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