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(71) Applicant: **Paneratech, Inc.**
Chantilly, Virginia 20151 (US)

(72) Inventors:
- **BAYRAM, Yakup**
  Falls Church, VA (US)
- **BAYRAM, Suat**
  Ankara (TR)
- **ALP, Hande**
  Ankara (TR)
- **DAMA, Elif Rana**
  Ankara (TR)
- **TÜRER, Öncel Umut**
  Ankara (TR)

(74) Representative: **FRKelly**
Waterways House
Grand Canal Quay
Dublin D02 PD39 (IE)

(54) SYSTEM AND METHOD FOR PREDICTION OF OPERATIONAL SAFETY OF MANUFACTURING VESSELS

(57) Disclosed is a system and a method for estimating a level of risk of operation of a manufacturing vessels used in the formation of certain materials. The system and method are operative to determine a condition and level of degradation of the refractory material of the vessel to early warn a user of the operational risk of continuing operating the vessel, based on thermal scanning and the use of artificial intelligence. The system is capable of determining the presence of certain flaws within the refractory material and the remaining thickness of such material by correlating the results of processing thermal data corresponding to the external surface of the vessel with a machine learning-based mathematical model, according to a set of operational parameters related to the melting process and data from the user.

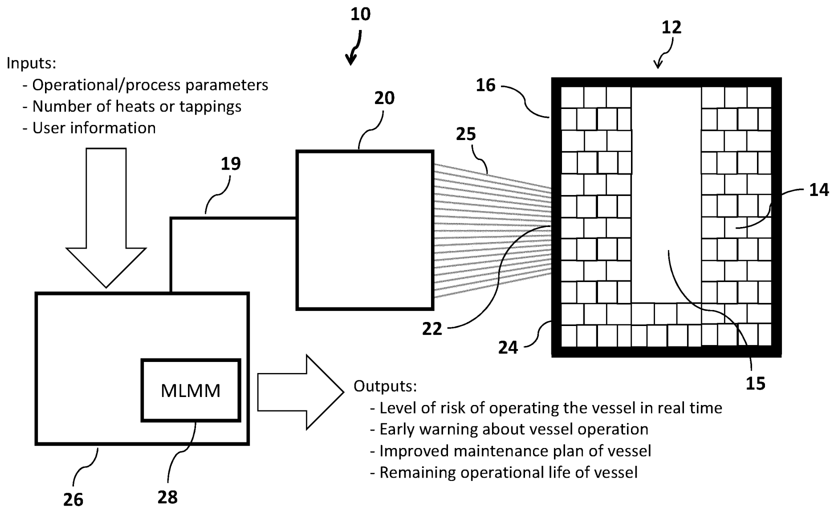


Figure 1

Description

CROSS REFERENCE TO RELATED APPLICATION

[0001] This application claims priority to the continuation-in-part U.S. patent application Ser. No. 18/518,863, filed on November 24, 2023, which is hereby incorporated by reference.

FIELD OF THE INVENTION

[0002] The present invention relates to systems and methods for evaluating the status of a material. More particularly, the present invention relates to sensing systems and methods, using machine learning, for estimating a safe operation condition of refractory-based vessels used in manufacturing.

BACKGROUND OF THE INVENTION

[0003] A number of evaluation systems and methods have been disclosed within various industries for measuring the status of certain materials, using a variety of devices, including thermal imaging cameras, infrared detectors, and laser scanners. As an example, thermal imaging cameras have been used to map roofs and walls of houses and buildings to show locations of anomalies comprising trapped moisture, roof cracks or openings causing thermal or water leaks, and compromised insulation. These cameras rely on the fact that moisture, cracks, and compromised insulation modify the thermal mass of the roof or wall, which makes the roof or wall to hold onto heat in a different fashion as compared to that of the unaffected material surrounding these anomalies.

[0004] Manufacturing industries use vessels, such as furnaces and ladles, to melt, treat, refine, and transport the raw material, such as metal, glass, or plastic, used for processing. They are key assets for manufacturers in terms of costs and operational functionality. In order to minimize the internal heat loss at high operating temperatures, these furnaces and ladles are constructed using refractory material, having very high melting temperatures and good insulation properties, to create a refractory melting chamber. However, the inner refractory walls of a manufacturing vessel will degrade during operation. The effects of this degradation include refractory erosion, refractory corrosion, stress cracks, and refractory material diffusion into the molten material. In addition, within the context of the present invention, a vessel may include a furnace or a ladle, and the terms furnace or ladle are used indistinctively as the invention applies to either one or both.

[0005] On the other hand, as the refractory material degrades over time, the molten material may accumulate on the degraded surface of or penetrate into the refractory material accelerating the degradation process and creating a higher risk for molten material leakage through the refractory wall with potentially devastating consequences. As a result, manufacturers may be misled and face an increased risk of experiencing either an unexpected leakage of molten material through the vessel wall or an increased uncertainty to conservatively shut down the vessel for re-build to reduce the likelihood of any potential leakage, based on the manufacturer's experience of the expected lifetime of the vessel.

[0006] In manufacturing vessels, the surface condition of internal and external walls, slag buildup, refractory material thickness and homogeneity, rate of erosion of the refractory material, and level and rate of penetration of molten material into the refractory material are some of the important aspects that may require monitoring and evaluation. The importance of these aspects relies on their role to provide useful information to estimate the remaining operational life of the vessel. Typically, collecting this information involves a plurality of sensors that may include one or a combination of more than one of an ultrasound unit, a laser scanner, a LIDAR device, an infrared camera, a stereovision camera, a radar, and a thermal scanning or imaging device to ultimately indicate whether the condition of the manufacturing vessel is suitable for operation.

[0007] Currently, most manufacturers use thermal scanning devices and visual inspections to monitor and assess the suitability of continuing operation of a manufacturing vessel. Laser scanning devices are also used by manufacturers to a lower extent due to their high cost as compared to thermal imaging systems. Laser scanning methods can provide refractory thickness, but they are not reliable to both determine the depth and size of cracks that may affect the refractory material of a vessel and estimate the penetration of molten material into the refractory material, due to the inherent slag buildup occurring on the surface of the refractory material in contact with the molten material and the lack of resolution needed for detecting very fine cracks.

[0008] The advent of artificial intelligence in recent years has provided means to develop and use machine learning-based techniques in multiple fields. In particular, the combination of machine learning algorithms with a thermal imaging device and operational and process parameters of the manufacturing vessel may be helpful to predict a level of risk of operating the vessel. In other words, a system and a method can be used to provide an early warning as to how the refractory material of the vessel is deteriorating to establish a level of risk of operating the vessel.

[0009] Specifically, the use of artificial intelligence to process data or images have been addressed in the prior art, as described in U.S. Pat. No. 11,144,814 to Cha et al., for performing structure defect detection using computer implemented arrangements employing machine learning algorithms in the form of neural networks, and in U.S. Pat. No. 10,970,887 to Wang et al., which discloses tomographic and tomosynthetic image reconstruction systems and methods in the framework of machine learning, such as deep learning, wherein a machine learning algorithm can be used to obtain an improved tomographic image from raw data, processed data, or a preliminarily reconstructed intermediate image for biomedical imaging or any other imaging purpose. Likewise, an effort to develop systems, methods, and devices for training models or algorithms for classifying or detecting particles or materials in microscopy images have been described in U.S. Pat. No. 10,255,693 to Richard B. Smith. However, these systems and methods are primarily aimed to process data or images to correlate certain surface structural defects with surface image features, to obtain or improve images, or to classify images.

[0010] Additional attempts have been made to predict a future status of a refractory lining that is lined over an inner surface of an outer wall of a metallurgical vessel, as described in U.S. Pat. No. 10,859,316 to Richter et al. However, this approach is constrained to collecting multiple laser scans of the interior of the vessel prior and after each heat of the vessel, while the vessel is empty (not processing molten material), to determine an exposure impact of the heat on the refractory lining by comparing the collected pre-heat structural condition data with the collected post-heat structural condition data.

[0011] In addition, there are other limitations and challenges faced by this attempt. Firstly, there is a lack of practicality because laser scanning involves a lengthy process and most of the time operators do not perform laser scans prior and after each heat. Secondly, the refractory wear is typically less than the accuracy and resolution of the laser scans. Therefore, comparing successive laser scans is not a reliable indicator of refractory wear. Thirdly, the predictability of the refractory material condition is ineffective since determination of the exposure impact is based only on comparing laser scans prior and after each heat without considering all the heats in which the refractory material under evaluation has been involved. Further, laser scanning technology is insufficient to determine the presence, depth, and size of cracks, which are not only a significant source for potential refractory failure, but also are typically found in and progressively grow throughout the operational lifetime of the refractory lining. Thus, a penetration of molten material into the refractory material cannot be detected by a laser scanner, especially when there is a slag build-up on the refractory which almost always is the case. Moreover, the referenced attempt addresses the prediction of the future status of the refractory lining after one or more subsequent heats based on the determined exposure impact of the heat, while remains silent about the calculation of the level of risk of operating the vessel, particularly while the vessel is processing molten material, or the use of artificial intelligence-based models or algorithms.

[0012] Likewise, in U.S. Pat. No. 10,935,320 to Lammer et al., a method is described for determining the state of a refractory lining of a metallurgical vessel containing molten metal. In addition, although the method disclosed in this patent comprises generating a mathematical model that provides an indication of wear of the refractory lining based on at least a portion of three sets of data, these data neither require the measured temperatures of the external surface of the vessel during the processing of molten material nor the mathematical model or the method disclosed correlates these measured temperatures with a calculation of the level of risk of operating the vessel, especially while the vessel is processing molten material. Additionally, U.S. Pat. App. No. 2018/0347907 and U.S. Pat. App. No. 2016/0282049, both by Lammer et al., describe a similar method for determining the state of a fire-resistant lining of a vessel containing molten metal in particular in which maintenance data, production data, and wall thicknesses at least at locations with the highest degree of wear are measured or ascertained together with additional process parameters of at least one identical/similar vessel after the vessel has been used. The data is collected and stored in a data structure. A calculating model is generated from at least some of the measured or ascertained data or parameters, and the data or parameters are evaluated using the calculating model using calculations and subsequent analyses. Thus, related or integral ascertaining processes and subsequent analyses can be carried out, on the basis of which optimizations relating to both the vessel lining as well as the complete process of the molten metal in the vessel are achieved. In these methods, the reliability of the vessel is correlated with the remaining refractory thickness. However, this approach has severe limitations because a vessel might have a very thick refractory, which would be considered safe according to these methods, but a tiny crack, that is covered by a slag, might not be detected by a laser scanner. Molten material may leak through the crack and penetrate behind the refractory into the safety and insulation layers, which represents a significant risk of failure for the vessel that these methods would not be able to detect.

[0013] Further, in International Publication. No. WO 2020/254134 by Vesuvius Group SA, a system for tracking and assessing the condition of replaceable refractory elements in a metallurgic facility is disclosed comprising a plurality of identifiable metallurgical vessels and removable refractory elements along with a plurality of replacement refractory elements, which have a machine-readable identification tag with refractory element identification data for assessing the condition of refractory elements coupled to anyone of said metallurgical vessels. However, this system faces challenges as it relies on the specific information provided by refractory elements, which must be identifiable, replaceable, and requires a means to assess the conditions of such refractory elements.

[0014] Particularly in steel metallurgy either a basic oxygen furnace or an electric arc furnace is commonly used for high-speed melting of the steel and carrying out metallurgical reactions to adjust the final chemical composition of the steel. Later, molten steel is transported to a ladle for further refining, which includes the addition of deoxidizers, slag formers, desulfurizers, and alloying agents. These additives along with the high temperatures at which the ladle operate accelerate and contribute to a severe corrosion, wear, and degradation of the internal sidewalls and the bottom of the ladle, both of which are in contact with the molten material during the ladle operation. In particular, electric-arc furnaces, with a capacity of 50 tons or more, and ladles are largely used to produce steel. These ladles need to be maintained for removal of residues and inspection, and sometimes repaired as often as on a weekly basis.

[0015] Moreover, the flow of molten material, such as steel, glass, or plastic, at high temperatures erodes and degrades the inner surface of the refractory material and creates a high risk for molten material leakage through the refractory wall or a severe damage to the outer shell of the vessel. Furthermore, a leak of molten material may cause significant damage to the equipment around the vessel and, most importantly, put at risk the health and life of workers. For these reasons, in most cases vessel relining is conducted at a substantially earlier time than needed. This leads to significant costs for manufacturers in terms of their initial investment and the reduced production capacity over the operational life of the vessel.

[0016] Thus, it is critical for manufacturing vessel operators to efficiently plan maintenance and monitor refractory material degradation of the vessel walls to extend the operational life of the vessel and plan required outages of the vessel when it is really necessary. The lifetime and operational capability of a ladle or furnace, as a result of the degradation of refractory material, might be affected by a number of factors, including the operational age, the average temperature of operation, the heating and cooling temperature rates, the range of temperatures of operation, the number of heats or tappings, the type and quality of the refractory material, the slag buildup on the inner refractory walls as well as the load and type of the molten material and additives in contact with the refractory material. Each of these factors is subject to uncertainties that make it difficult to create accurate estimates of the expected lifetime of a furnace and when to perform the corresponding maintenance tasks.

[0017] As a consequence of the foregoing there is a need to replace the lining after 30 to 100 heats or in some instances, even sooner when refractory wear accelerates. It is not unusual for a manufacturing vessel, especially in the metallurgical industry, to be shut down for maintenance multiple times a year. Further, each shut down can last up to several days, translating into a negative impact on the operational life of the vessel. On the other hand, a typical ladle may comprise a six-inch refractory layer in certain areas, and manufacturers look to operationally use the ladle until the refractory thickness is reduced to about one to two inches.

[0018] In particular, prediction of the level of risk associated to the operation of a vessel is crucial to industries where asset uptime is critical and asset downtime must be maintained to a minimum, while operating safely. Accurate operational risk prediction will enable manufacturers to minimize repairs and keep the asset uptime. In particular, current methods and techniques for measuring refractory thickness and slag buildup in manufacturing vessels, including ladles and electric arc furnaces, are primarily based on visual observations, laser scanning, thermal scanning, infrared, stereovision, radar, or acoustic technologies.

[0019] Currently, manufacturers use infrared scans of the external surface of a vessel as an alarm monitor. Once the measured temperature exceeds a predefined threshold, typically in the order of 700°F, an alarm is automatically triggered, and the vessel is taken out of service. Specifically, U.S. Pat. App. No. 2013/0120738 by Bonin et al., describes devices and methods to monitor the integrity of a container protected by a refractory material by using a sensor to measure an external surface temperature of the container, a source to measure a thickness of the refractory material, and a controller to display to a user these measurements. The document discloses exemplary embodiments for identifying potential failure locations in a metallic container configured to hold materials at elevated temperatures based only on the measurements of both the external surface temperature of the container and the thickness of the refractory material. However, this approach has faced limitations, which rendered it unsuccessful, because the outer temperature of the vessel has little dependence on the refractory thickness for determining the state of a refractory lining of a metallurgical vessel containing molten metal. Specifically, for a vessel in which molten metal has penetrated through cracks into the refractory material, an alarm may be triggered too late because during an actual operation of the vessel using a more corrosive process may cause a major leak of the vessel before the operator has a chance to catch the leak. Likewise, depending on how long the ladle has been empty, the overall shell temperature of the vessel may actually decline during operation, even though the refractory material gets thinner. As a result, in this critical situation, the alarm will not even be triggered despite the substantial risk of operating the vessel.

[0020] Therefore, there is a need, which is fulfilled by the present invention, not only to monitor the temperatures of the external surface of the vessel, but also to capture cracks, identified either visually or by means of a second sensor, and along with a set of operational and process parameters determine a compromised safety of the vessel well in advance of a possible leakage of molten material. This provides the ability to early warn vessel operators about molten material penetration into the refractory material before this penetration is observed using infrared scans. As a result, vessel operators will have ample time to properly plan for maintenance and more safely operate the vessel. In particular, as the refractory material gets thinner, the likelihood of a leakage of molten material gets higher. Therefore, refractory risk assessment becomes extremely critical towards the end of the campaign of the vessel.

[0021] Additionally, a pattern of reference or "normal temperatures" within a predefined range of values can be identified to provide a benchmark for the optimal operating condition of the vessel corresponding to a set of operational parameters, the characteristics of the refractory material and molten material being processed, and the type of vessel used. Specifically, the measured temperatures over a region of interest of the external surface of a vessel after being initially heated up; operational parameters, including the time the vessel has been empty or in operation, and at what temperatures; and the residual refractory thickness or the number of heats during the vessel's current campaign can be used to establish such a pattern of normal temperatures.

[0022] Over time, certain flaws may appear in the refractory material or the outer shell of the vessel. These flaws may include or may be due to cracks, erosion of materials, thickness variations, defects, and slag buildup. As a result of these flaws, the pattern of measured temperatures deviates from the pattern of normal temperatures. Accordingly, manufacturers set up a safety margin of temperature deviations from the pattern of normal temperatures to safely operate the vessel. Normally, once at least one of the measured temperatures over the region of interest of the external surface of the vessel exceeds the predefined safety margin, the operation of the vessel is stopped until the appropriate maintenance or repair of the vessel is performed.

[0023] Currently, there is no well-established system or method that can deterministically estimate the level of risk of operating a manufacturing vessel using a thermal data scanner along or combined with operational or process data. The lack of such system or method impairs the ability to operate the vessel with a higher safety confidence and to estimate more accurately both the remaining operational life and the maintenance plan of a vast number of furnaces and ladles. Thus, there remains an opportunity for a system and method, based on the integration of at least one first sensor with at least one customized machine learning-based mathematical model and a data processing component, to calculate the level of risk of operating such vessel.

SUMMARY OF THE INVENTION

[0024] A system and a method for estimating a level of risk of operation of a manufacturing vessel used in the formation of metals and other types of materials, such as glass and plastic, are disclosed herein. One or more aspects of exemplary embodiments provide advantages while avoiding disadvantages of the prior art. The system and method are operative to determine a condition and level of degradation of the refractory material of the vessel to early warn a user of the operational risk of continuing operating the vessel, based on thermal scanning and the use of artificial intelligence. The system is capable of determining the presence of molten material penetration into the refractory and the insulation by correlating the results of processing thermal data corresponding to the external surface of the vessel with a machine learning-based mathematical model, according to a set of operational parameters related to the melting process, data possibly inputted by a user, and residual thickness of the refractory material or number of heats the vessel has experienced in the campaign.

[0025] The system for estimating a level of risk of operation of a manufacturing vessel, such as a furnace or a ladle, comprises a plurality of subsystems. A thermal scanning subsystem to collect data for determining the temperature, of a region of interest, of the external surface of a manufacturing vessel to be evaluated, a machine learning-based mathematical model for such region of interest, and a data processing subsystem to manage the collected data and to use the machine learning-based mathematical model and additional operational and possibly user's input parameters to correlate both the temperature of the external surface of the vessel and its variations with the level of risk of operating the vessel. The results of the evaluation of the vessel comprise one or more of a calculation of a qualitative or a quantitative level of risk of operating the vessel, a determination or estimation of the molten material penetration into the refractory or the insulation material behind the refractory, the surface profile, or the rate of degradation over time of the molten material penetration of the vessel, an early warning to the user about the future operation of the vessel, or the remaining operational life of the vessel.

[0026] The thermal scanning subsystem comprises a first sensor, such as a thermal scanner, a thermal imaging camera, or an infrared camera for determining the temperature of the external surface of the manufacturing vessel, which can be used to collect and communicate temperature data corresponding to a specific region of the vessel. The temperature data is mapped to have a representation of the temperature values over such region. In particular, within the context of the present invention, a vessel may include a furnace or a ladle, and the terms furnace or ladle are used indistinctively as the invention applies to either one or both.

[0027] The system further comprises a machine learning-based mathematical model for providing a range of temperatures of the external surface of the vessel over such region of interest correlated to a level of risk of operation of the vessel. This model is developed and trained using a dataset comprising data that include refractory material size, type, and chemical composition, vessel shell material type and size, operational parameters, duration when the vessel is empty, the duration when the vessel is full with molten material, number of heats, and temperature of molten material, possibly other user's inputs, ambient temperature surrounding the vessel, external surface temperatures associated to the heat and melting processes of a region of interest for a plurality of manufacturing vessels and molten materials, according to machine learning techniques.

[0028] The data processing subsystem comprises a main computer-based processor further comprising a data storage device and an executable computer code. The data processing subsystem code is configured to process the data collected by at least the first sensor and the input information, including the operational and process parameters, the number of heats during the vessel's current campaign or alternatively the remaining refractory material thickness, and possibly the user's input. The data processing subsystem is further configured to use the machine learning-based algorithm to compare the actual temperature measurements of the external surface of the vessel with the range of temperatures provided by the model, according to a set of operational parameters related to the melting process, data possibly inputted by a user, and number of heats or the contact time of molten material with the vessel during the ongoing campaign or the prior thickness of the refractory material. Likewise, the data processing subsystem may be configured to process data or information from a plurality of sensors that may include one or a combination of more than one of an ultrasound unit, a laser scanner, a LIDAR device, a stereovision camera, a fiber optic-based device, and a radar.

[0029] Accordingly, the system can calculate the level of risk of operating the vessel, based on the deviations of the measured values of temperatures of the external surface of the vessel from the values provided by the machine learning-based mathematical model. Additionally, the data processing subsystem may be configured to process the values of temperatures of the external surface of the vessel, according to a plurality of residual thicknesses over the region of the material under evaluation and for multiple heats of the vessel, to assess the variability of these temperatures and calculate the level of risk of operating the vessel. As a result, the system may determine the presence of certain flaws within the refractory material and the remaining thickness of such material to early warn a user of the operational risk of operating the vessel. This information may be further processed to estimate the remaining operational life and improve the maintenance plan of the vessel under evaluation.

[0030] In the present invention, the first sensor is disposed not in physical contact with the manufacturing vessel. However, any of the various types of sensors that may be used to collect information prior, during, or after operation of the vessel may be disposed not in physical contact with, embedded in the refractory material of, or in physical contact with the vessel, according to the type of sensor used. Particularly, the first sensor may comprise a mesh or grid formed by a plurality of sections of optical fiber laid out on or around the external surface of the vessel, such that first sensor is able to map the temperatures of the external surface of the vessel. In addition, different attachment mechanisms might be incorporated with any of these sensors to physically position the sensor inside or outside the vessel's chamber at one or more locations.

[0031] The method for calculating a level of risk of operating a manufacturing vessel and estimating the remaining operational life of such vessel involves the steps of collecting data, including size, type, chemical composition, operational parameters, duration when the vessel is empty, the duration when the vessel is full with molten material, status, and temperature of molten material, possibly user's input, and external surface temperatures, associated to the heat and melting processes, of a region of interest for a plurality of manufacturing vessels and molten materials as well as creating a machine learning-based mathematical model to correlate an operational condition of the vessel's refractory material, the external surface temperatures of the vessel, the type of molten material, and the corresponding operational parameters, as previously noted, for the given region of interest.

[0032] The method further includes the step of determining a distribution of temperature ranges of the external surface of the region of interest associated to a level of risk of operation of a specific vessel according to the machine learning-based mathematical model in a certain region of interest. The method also includes the steps of measuring the external surface temperatures of the specific vessel over such region of interest, comparing these measurements with the distribution of temperature ranges of the external surface of the specific vessel, and calculating the risk of operation of the vessel, according to the difference between the measured temperatures and the modeled distribution of temperature ranges. The method further includes processing the data collected, determined, measured, or calculated to analyze, forecast, and provide information useful to estimate the remaining operational life and improve the maintenance plan of the vessel under evaluation.

[0033] By integrating at least a thermal scanning subsystem with customized computer processing tools, such as customized machine learning algorithms and a computer-based processor, the system and method are able to calculate the risk of operating the vessel in real time, while the vessel is in operation or has completed a heat. This translates into more effective and accurate scheduling to better manage the costly processes of manufacturing vessel repairs, decommissioning, or replacement along with a significant reduction of the level of risk of an operational break or leakage of molten material or severe damage to the vessel metal outer shell. Thus, the system and method allow a more effective operational assessment of manufacturing vessels, which may translate into a reduction of operational uncertainty and safer operations along with a potential extent of the operational life and an improved maintenance scheduling of such costly assets. Both the system and the method subject of the invention are set out in the appended set of claims.

BRIEF DESCRIPTION OF THE DRAWINGS

[0034] The numerous advantages of the present invention may be better understood by those skilled in the art by reference to the accompanying drawings in which:

Figure 1 shows a schematic view of an exemplary embodiment of a system for calculating the level of risk of operating a manufacturing vessel.

Figure 2 shows a schematic view of a method for calculating the level of risk of operating a manufacturing vessel.

DETAILED DESCRIPTION OF THE INVENTION

[0035] The following description is of particular embodiments of the invention, set out to enable one to practice an implementation of the invention, and is not intended to limit the preferred embodiment, but to serve as a particular example thereof. Those skilled in the art should appreciate that they may readily use the conception and specific embodiments disclosed as a basis for modifying or designing other methods and systems for carrying out the same purposes of the present invention. Those skilled in the art should also realize that such equivalent assemblies do not depart from the spirit and scope of the invention in its broadest form.

[0036] The system for estimating a level of risk of operation of a manufacturing vessel integrates a plurality of subsystems, comprising a thermal scanning subsystem to collect data for determining the temperature, of a region of interest, of the external surface of a manufacturing vessel to be evaluated; a machine learning-based mathematical model for such region of interest; and a data processing subsystem to manage the collected data and to use the machine learning-based mathematical model and additional operational and possibly user's input parameters to correlate both the temperature of the external surface of the vessel and its variations with the level of risk of operating the vessel in real time, while the vessel is in operation or has completed a heat.

[0037] In addition, the results of using the system and method for evaluating a manufacturing vessel may comprise one or more of a calculation of a qualitative or a quantitative level of risk of operating the vessel; a determination or estimation of the remaining thickness, the surface profile, or the rate of degradation over time of the refractory material of the vessel; an early warning to the user about the future operation of the vessel; the remaining operational life of the vessel; and an improved maintenance plan of the vessel.

[0038] In accordance with certain aspects of an embodiment of the invention, Figure 1 shows a schematic view of an exemplary embodiment of a system 10 for estimating a level of risk of operation of a manufacturing vessel 12. Usually, vessel 12 comprises a plurality of layers of a refractory material 14. Typically, the various layers of refractory material 14 are formed using bricks disposed side-by-side from the bottom to the top of vessel 12. In other words, refractory material 14 is disposed in one or more layers between a chamber 15, wherein melting of a material, such as steel, glass, or plastic, takes place during operation of the vessel, and the external bottom and external side walls of vessel 12.

[0039] Accordingly, refractory material 14 forms one or more walls at least partly surrounding chamber 15 of vessel 12. Thus, refractory material 14 has an innermost surface, which might be contiguous to (i.e., in contact with) a molten material, contained within chamber 15 during operation of vessel 12, and an outermost surface closer to the exterior region surrounding vessel 12. Typically, vessel 12 has an outer shell 24 surrounding refractory material 14. However, in certain applications, there might be no outer shell. As a result, an external surface 16 of vessel 12 may comprise either the outermost surface of refractory material 14 or at least part of outer shell 24. Usually, outer shell 24 of vessel 12 is made of steel, but those skilled in the art will realize that outer shell 24 may be made using other types of material and alloys.

[0040] In this particular configuration, a thermal scanning subsystem is used to collect data for determining the temperatures over a region of interest 22 of external surface 16 of vessel 12. The thermal scanning subsystem comprises at least one first sensor 20 able to detect the radiation emitted by an object in a band of the electromagnetic spectrum, including the infrared band, wherein the amount of emitted radiation can be correlated with the physical temperature of such object as well-known in the prior art.

[0041] Specifically, first sensor 20 is properly positioned to detect a radiation 25 emitted by region 22 of external surface 16 of vessel 12. First sensor 20 is a non-contact subsystem that allows collecting temperature data over region 22 of external surface 16 of vessel 12 at a distance from vessel 12. Preferably, first sensor 20 is part of a thermal data scanner configured to measure the temperatures over region 22. More preferably, first sensor 20 is part of a thermal imaging system capable of mapping the values of the measured temperatures over region 22 by converting these values into a range of tonalities to form an image.

[0042] Importantly, the measured temperatures over region 22 of external surface 16 of vessel 12 might be representative of a condition of refractory material 14 and are collected while vessel 12 is in operation. In particular, certain flaws, including cracks and voids, the presence of molten material inside of refractory material 14, slag buildup on the inner wall of refractory material 14, or a degradation of refractory material 14 may translate into a variation of measured temperature values over region 22, as compared to a set of reference temperature values. Thus, by measuring the temperatures over region 22 and computing the difference of the measured values with reference values, it might be possible to identify a degradation of the operational condition of vessel 12 while in operation processing a molten material.

[0043] System 10 further comprises a data processing subsystem 26 to manage input data associated to operational or process data of vessel 12, additional input parameters which may be provided by a user or preset, recorded, or historical data, and the data collected by first sensor 20 to calculate the level of risk of operating vessel 12. In addition, system 10 further comprises a machine learning-based mathematical model (MLMM) 28 integrated with data processing subsystem 26.

[0044] During normal operation of system 10, the temperature data collected by first sensor 20 is transferred to data processing subsystem 26 by means of a set of cables 19. In addition, set of cables 19 may be used to carry control, communications, and power signaling between first sensor 20 and data processing subsystem 26. Data processing subsystem 26, comprises a number of hardware components, such as a data storage device and a main computer-based processor, both of which can be integrated with first sensor 20 to process the data generated during the operation of system 10. The computer-based processor of data processing subsystem 26 is configured to operate machine learning-based mathematical model 28. In addition, data processing subsystem 26 is able to integrate and process a plurality of input data to allow system 10 to calculate the risk of operating vessel 12 and to determine the presence of certain flaws in and the remaining thickness of refractory material 14, in real time, during operation of vessel 12.

[0045] In this particular configuration, machine learning-based mathematical model 28 comprises a software architecture further comprising machine learning algorithms. Model 28 is configured to receive at least one input, consisting of data, and to generate at least one output. Model 28 is configured to receive as input at least three sets of data corresponding to multiple vessels, if possible, including various types, and one or more types, sizes, and chemical compositions of molten and refractory materials under a variety of operational and process conditions. These three sets of data include a first set of preset, recorded, or historical data, which may comprise user's input information; a second set of data comprising operational or process parameters; and a third set of data including the measured temperatures in at least one region of the external surface of the multiple vessels during their operation. Preferably, the collection of input data corresponds to a plurality of regions of these multiple vessels. The input data are used for training and validating one or more customized machine learning-based algorithms to create customized machine learning-based model 28.

[0046] The first set of data may include preset, recorded, or historical data, which may comprise information inputted by a user into data processing subsystem 26. This first set of data may include the number of heats or tappings, remaining thickness, rate of degradation, erosion profile of internal walls, type, quality, original and actual chemical composition, and operational age of, the presence of cracks in, and the level of penetration of one or more types of molten material into, refractory material 14, before processing one or more types of molten material using vessel 12. Likewise, the first set of data may also include historical information related to the maintenance of refractory material 14, such as replacement or repair of a part of refractory material 14 including the type, amount, and location of additives or replaced parts applied to refractory material 14, and the physical design of refractory material 14. Particularly, the physical design of refractory material 14 may include the type, shape, size, dimensions, number of layers, and layout of the physical disposition of refractory material 14 as part of vessel 12. Importantly, the first set of data may further comprise any operational and process parameters, as disclosed in the second set of data below, used during a prior operation of vessel 12.

[0047] The second set of data comprises operational and process parameters such as type and properties, including amount, average and peak processing temperatures, heating and cooling temperature profiles, treatment times, and chemical composition, of the molten material being or to be processed using vessel 12; thickness and composition of the slag buildup in vessel 12; ambient temperature surrounding vessel 12, tapping times using vessel 12; how the molten material is or will be poured or tapped into or out of vessel 12; preheating temperature profile while vessel 12 is empty; time during which the molten material is in contact with refractory material 14 (residence time); stirring time, level of pressure and flow rate of inert gas applied to vessel 12 during stirring; physical and chemical attributes and amounts of additives used or to be used in processing the molten material to produce a desired steel or other material grade; and any other relevant operational parameter for production of steel or other material using vessel 12. Those skilled in the art will realize that the additives used in steel or other material processing may include charging mix components, alloys, slag formers, and flux chemicals.

[0048] The third set of data includes the measured temperatures over at least one region of the external surface of a plurality of manufacturing vessels during the processing of one or more types of molten materials at various heats in a single or multiple campaign. The information from these three sets of data provides the basis to create customized machine learning-based mathematical model 28 by correlating both the temperatures over region 22 of external surface 16 of vessel 12 and its variations from reference, normal temperature values with the level of penetration of one or more types of molten material within refractory material 14 and/or the level of risk of operating vessel 12.

[0049] It is noted that the measured surface temperatures of vessel 12 immediately preceding and during the current heat as well as the residence time, the thickness and composition of the slag buildup in vessel 12, the remaining thickness of refractory material 14, and the temperature profile and duration while vessel 12 was empty, immediately preceding the current heat are extremely relevant. Alternatively, the surface temperatures of vessel 12 do not have to be measured immediately preceding the current heat, as long as the empty time vessel time, residence time and molten material temperature are tracked from the time surface temperatures of vessel 12 are measured and the current heat.

[0050] Likewise, at least a portion of the data in the first, second, and third sets of data may be obtained by measurements performed using a variety of measurement devices available in the marketplace or by using recorded information, as well known to one skilled in the art. Moreover, those skilled in the art will realize that any of the information pertaining to the first, second, and third sets of data may be inputted into data processing subsystem 26 by a user.

[0051] According to the invention, customized machine learning-based model 28 is trained, using at least part of the first, second, and third sets of data as input data, to correlate the input data to generate at least one output comprising a distribution of temperature ranges corresponding to the at least one region of the external surface of multiple vessels. After training is completed, model 28 is capable of generating an output, consisting of a distribution of temperature ranges over region 22 of external surface 16 of vessel 12, for a given input consisting of a specific first set of data and a specific second set of data, as noted above. Moreover, model 28 correlates this distribution of temperature ranges with both the level of penetration of one or more types of molten material within refractory material 14 and the level of risk of operating vessel 12. Accordingly, for vessel 12 and specific first and second sets of data, data processing subsystem 26 is capable of estimating a level of penetration of one or more types of molten material within refractory material 14 and calculating a level of risk of operating vessel 12 for a given temperature over region 22 of external surface 16 of vessel 12, based on at least one output of model 28.

[0052] In particular, model 28 determines the expected safe range of external temperatures, at least in part, by processing the first set of data and the second set of data, including the measured temperatures over region 22 for one or more heats prior to the ongoing heat, under multiple operational scenarios of vessel 12 and fitting these data to one of a plurality of probability distribution functions. Specifically, probability distributions are useful in quantifying and visualizing the uncertainty and variability of the data, and for statistically characterizing and estimating the expected temperature values and the range of variance of the temperature values. Those skilled in the art will realize that a number of probability distribution functions are available to fit these data, including the Gaussian, lognormal, F, beta, gamma, binomial, Fatigue Life, geometric, hypergeometric, Bernoulli, Poisson, Cauchy, Frechet, Levy, Rayleigh, Pareto, Weibull, Chi-Square, logistic, exponential, and uniform distributions, and any combination thereof.

[0053] Furthermore, model 28 is also configured for processing the first set of data and the second set of data under multiple operational scenarios of vessel 12 to produce a customized, unique probability distribution function generated to fit these particular data by means of an algorithm to optimize a function to get the largest statistical coefficient of determination such as R-squared and the smallest statistical mean squared error. The coefficient of determination and the mean squared error are statistical metrics well-known in the prior art. The generation of a customized, unique probability distribution function that fits these data and situation, allows to calculate more accurately various measures of risk, such as the expected value and the statistical variance, which are indicative of the most likely outcome and the level of uncertainty of that outcome. In addition, model 28 is configured to estimate percentiles and confidence intervals, which show the range of possible outcomes and the probability of achieving them. Accordingly, model 28 is also configured to generate at least one output that allows data processing subsystem 26 determining an expected safe range of external surface temperatures over region 22 during operation of vessel 12 for a given set of operational and structural conditions of vessel 12, including the measured external surface temperatures over region 22 during one or more heats prior to the current heat.

[0054] Therefore, by measuring the external surface temperatures over region 22 of external surface 16 during operation of vessel 12 and comparing these temperatures with the expected safe range of external surface temperatures, data processing subsystem 26, can not only determine whether the vessel is operating within a safe range of external surface temperatures, but also compute the difference between the measured temperatures and the temperatures at which operating vessel 12 is unsafe. Even further, based on the output of model 28, data processing subsystem 26 can calculate a level of risk of operating vessel 12, according to the difference between the measured temperatures and the temperatures at which operating vessel 12 is unsafe, in real time while vessel 12 is processing a molten material.

[0055] For example, if the data are distributed according to the customized, unique probability distribution function generated by model 28 over region 22, a difference between the measured actual temperature and the predicted temperature resulting in a variance larger than a predefined threshold might be considered statistically significant. If that is the case, a customized second-level algorithm is activated to further evaluate the measured temperatures for identifying a potential development of a hotspot in a specific locality within region 22.

[0056] In particular, based on, at least in part, the measured temperatures data from the current heat and at least one prior heat, the customized second-level algorithm may calculate the temperature variations in the specific locality within region 22 where a hotspot might be developing. Then, the calculated temperature variations are compared to a predefined temperature variation threshold. If the calculated temperature variations exceed the temperature variation threshold, the potential development of a hotspot is confirmed.

[0057] Alternatively, where measured temperatures over region 22 of vessel 12 are recorded at consistent intervals over a period of time rather than intermittently or randomly, the customized second-level algorithm may determine the development of a potential hotspot by conducting a time series analysis. Specifically, the customized second-level algorithm may perform this analysis by calculating the Kendall rank correlation coefficient or the Euclidean distance, applying an outcome of a dynamic time warping, relying on an outcome of any other time series analysis algorithm, or a combination thereof, as known in the prior art, and in reference to the measured temperature changes over time to confirm the potential development of a hotspot.

[0058] In particular, a customized second-level algorithm may be implemented based on a machine learning algorithm, which may be trained using measured temperatures data and their variations from multiple heats and a plurality of regions of one or more vessels and the corresponding time series analysis data as well-known to those skilled in the art.

[0059] Once a a potential development of a hotspot is identified, model 28 generates an output such that data processing subsystem 26 generates a warning message to a user. As a result, the output of the customized second-level algorithm can be used to determine more accurately a potential development of a hotspot and calculate the risk of operation of vessel 12, to predict the degradation of and molten material penetration into refractory material 14 of vessel 12, and to estimate the remaining operational life and optimize the maintenance plan of vessel 12.

[0060] Thus, according to the invention, model 28 is generated from data which are evaluated by calculations and subsequent analyses using at least a machine learning-based algorithm. In particular, these data include measured temperatures over at least one region of the external surface of at least a manufacturing vessel during the processing of at least a molten material. Importantly, where these measured temperatures data do not correspond to real time measurements, these data are used by model 28 to generate at least one output for reference and/or predicting a level of risk of operating vessel 12. However, where these measured temperatures data correspond to vessel 12 while processing a molten material, these data are used by model 28 to generate at least one output to calculate a level of risk of operating vessel 12 in real time while vessel 12 is in operation.

[0061] Preferably, the number of heats undergone by vessel 12 during an ongoing campaign is part of the specific first set of data or the specific second set of data used as input into data processing subsystem 26 to calculate the level of risk of operating vessel 12. Alternatively, the contact time of molten material with vessel 12 or the thickness of refractory material 14 prior to the processing of a molten material in vessel 12 is preferably part of the specific first set of data or the specific second set of data used as input to data processing subsystem 26 to calculate the level of risk of operating vessel 12.

[0062] Accordingly, by calculating the level of risk of operating vessel 12 after processing a molten material, data processing subsystem 26 is capable of determining the thickness of refractory material 14 and estimating the remaining operational life and the maintenance plan of vessel 12. Alternatively, based on at least one output of model 28, data processing subsystem 26 can estimate the remaining thickness of refractory material and molten material penetration 14 from the thickness of refractory material 14 prior to the processing of a molten material in vessel 12 and by factoring in the operational and process parameters used in the actual processing of such molten material in vessel 12, without the need of external temperature readings.

[0063] In general, those skilled in the art will realize how to create a mathematical model and will recognize that calculation methods exist for the assessment of refractory material 14 using operational information or empirical data to generate mathematical models. However, the possibilities for mathematically determining an effective level of risk of operating vessel 12 for the input data, as done by model 28 as described above, are not available in the prior art. As a result, typically the decisions regarding safety operation, remaining operational life, and maintenance of vessel 12 must be taken manually. In particular, prior art mathematical models lack the capability to effectively calculate the level of risk of operating vessel 12, based on the temperatures measured over region 22 of external surface 16 of vessel 12, while processing a molten material, for a given set of user's information or preset, recorded, or historical data, operational and process data, and conditions regarding vessel 12, as noted above.

[0064] Specifically, this invention discloses system 10, which comprises model 28, wherein model 28 is generated by correlating the specific data as mentioned above. In addition, model 28 allows warning users and providing safety margins of operation of vessel 12, according to the calculated level of risk of operating vessel 12, determining a level or rate of penetration of one or more types of molten material into refractory material 14, estimating the remaining operational life of vessel 12, and determining what and when to perform preventive and corrective maintenance actions, regarding vessel 12, in real time, during operation of vessel 12 or after vessel 12 complete a heat.

[0065] More specifically, by correlating a specific set of input data to generate a customized machine learning-based model 28, as disclosed above, one skilled in the art at the time the invention was made would readily understand how to make and use the invention. Thus, customized machine learning-based mathematical model 28 may be implemented or programmed in multiple ways by those skilled in the art in view of the disclosure herein and their knowledge of artificial intelligence and mathematical models.

[0066] In particular, the output from data processing subsystem 26, as a result of evaluating vessel 12 using model 28, comprises a qualitative assessment of the level of risk of operating vessel 12. As an example, this qualitative assessment may involve identifying the risk of operating vessel 12 as very high, high, medium, low, or very low, according to the measured temperatures over region 22 of external surface 16 of vessel 12. In addition, data processing subsystem 26 may provide an early warning to the user about the risk of operating vessel 12 as an alert notification or red flag signaling. The output from data processing subsystem 26 comprises a quantitative assessment of the level of risk of operating vessel 12. As an example, this quantitative assessment may involve identifying the risk of operating vessel 12 as a probability or percentage of the potential failure of vessel 12 during processing a molten material.

[0067] Preferably, the output from data processing subsystem 26 further comprises a determination of the presence of penetration of one or more types of molten material into refractory material 14 of vessel 12 or the remaining thickness, the surface profile, or the rate of degradation over time of refractory material 14 of vessel 12 to estimate the remaining operational life and or an improved maintenance plan of vessel 12, including preventive or corrective maintenance of vessel 12. Moreover, data processing subsystem 26 may control the operation of first sensor 20. It is noted that the additional hardware components of data processing subsystem 26 have not been shown as these components are not critical to the explanation of this embodiment and the functions and configurations of these components are well-known in the prior art. Furthermore, in reference to Figure 1, those skilled in the art will realize that set of cables 19 may be replaced with a wireless system to couple first sensor 20 to data processing subsystem 26.

[0068] According to the invention, data processing subsystem 26 further comprises a customized artificial intelligence-based software. This software may comprise one or more customized machine learning-based algorithms developed to predict the degradation and wearing of the material under evaluation as well as to estimate the remaining operational life and to improve the maintenance plan of the vessel.

[0069] In particular, the number of heats undergone by a vessel during an ongoing campaign, the estimates of the thickness of a refractory material and slag buildup, temperature measurements using the first sensor at certain locations and various heats using different refractory and molten materials as well as when the vessel is empty, operational parameters (including the residence time) and observations, and previous knowledge of the thickness of the refractory material, provide a data set that can be used to train these algorithms. Once the customized algorithms are trained for each of the different zones of a predefined region of interest of vessel 12, their performance can be improved with additional estimations of the refractory thickness at different stages of the vessel's life. Alternatively, the degradation of refractory material 14 as a function of the number of heats undergone by a vessel during an ongoing campaign for a plurality of scenarios and operational parameters or all the thickness estimation data of refractory material 14, collected over time, may be used for training or model-building of one or more of the specific artificial intelligence algorithms.

[0070] Furthermore, data processing subsystem 26 may also provide a status of refractory material 14 comprising a level or rate of degradation of such material due to various factors, including operational wear, age, and presence of one or more types of molten material within, flaws, cracks, corrosion, and erosion of refractory material 14. Accordingly, data processing subsystem 26 may enable system 10 to estimate the remaining thickness of refractory material 14, which is useful to estimate the remaining operational life and to improve the maintenance plan of vessel 12.

[0071] In addition, system 10 may further comprise a software subsystem configured to enable a user to control one or more computer-based processors for handling the collected data. This data handling includes measuring, storing, monitoring, recording, processing, mapping, visualizing, transferring, analyzing, tracking, and reporting of these data for calculating the risk of operating vessel 12 and to determine the presence of certain flaws and the remaining thickness of refractory material 14. Accordingly, an estimation of the overall health of vessel 12 might be obtained, even while vessel 12 is processing a molten material. In addition, a software subsystem might be configured to monitor and control the system operations not only locally, but also remotely through a computer network or a cloud computing environment.

[0072] Moreover, data processing subsystem 26 may further comprise a signal processing technique including data processing and image processing algorithms implemented by using one or a combination of more than one technique. These techniques may include Fourier transform, spectral analysis, frequency- and time-domain response analyses, digital filtering, convolution and correlation, decimation and interpolation, adaptive signal processing, waveform analysis, and data windows and phase unwrapping for data processing; and time domain, back projection, delay and sum, synthetic aperture radar imaging, back propagation, inverse scattering, and super-resolution, either with or without the application of differential imaging, for image processing. The signal processing technique may be selected according to a characteristic of the refractory material under evaluation, such as thickness, number of layers, type, and dimensions of the refractory material, and the type of molten material to be processed.

[0073] In an alternative configuration, system 10 may further comprise at least one second sensor that can provide information as an input to data processing subsystem 26 to either improve machine learning-based mathematical model 28 to calculate the level of risk of operating vessel 12 or to estimate the remaining operational life and maintenance plan of vessel 12 once the level of risk of operating vessel 12 has been calculated. The information provided by the at least one second sensor may replace or complement one or more input data included as part of the first set of data or the second set of data typically used as input to data processing subsystem 26.

[0074] The second sensor may include one or a combination of more than one of an ultrasound unit, a laser scanner, a LIDAR device, a radar, and a stereovision camera. As an example, the information provided by the second sensor may include a surface profile of the internal walls of refractory material 14, obtained from measurements using a LIDAR or a laser scanning device. As another example, the second sensor may provide the thickness of refractory material 14, obtained from a radar or multiple measurements obtained from a LIDAR or a laser scanner. As an additional example, the second sensor may provide an estimate of the slag buildup on the internal walls of refractory material 14 obtained by using a radar.

[0075] The various embodiments have been described herein in an illustrative manner, and it is to be understood that the terminology used is intended to be in the nature of words of description rather than of limitation. Any embodiment herein disclosed may include one or more aspects of the other embodiments. The exemplary embodiments were described to explain some of the principles of the present invention so that others skilled in the art may practice the invention.

Method

[0076] The method for calculating a level of risk of operating a manufacturing vessel and estimating the remaining operational life of such vessel is operative to combine a plurality of data with a machine learning-based mathematical model to estimate the operational condition of the vessel and provide information to estimate the remaining operational life and to improve the maintenance plan of the vessel.

[0077] Figure 2 shows a schematic view of a method for calculating the level of risk of operating a manufacturing vessel while processing a molten material. The information used may include data collected prior to, during, or after the operation of multiple vessels and regions of these vessels along with data related to a plurality of molten materials processed or to be processed. Then, a machine learning-based mathematical model is created to correlate these data and to determine a distribution of external temperature ranges of specific vessels according to a level of risk of operating the vessel or a level of penetration of molten material within the refractory material of the vessel under certain current or expected conditions and operational parameters. Finally, the comparison of actual temperature measurements of the external surface of a particular vessel during operation and the corresponding pre-determined distribution of the external surface temperature ranges determined by the model allows to calculate the risk of operation, estimate the remaining operational life, and improve the maintenance plan of the vessel, in real time during operation of such vessel, according to the following steps:

1. At step 100, collecting a plurality of data prior to, during, or after the operation of multiple manufacturing vessels corresponding to at least one region of these vessels along with data related to a plurality of molten materials. A first set of data may include information, which might be provided by a user, available prior to the operation of the vessel, regarding the refractory material and the manufacturing vessel, such as size, type, and operational condition, including the number of heats during the vessel's current campaign, the thickness of and the presence, location, and characteristics of certain flaws, such as cracks, in the refractory material, operational parameters, vessel empty and full times, and temperature of molten material. A second set of data may comprise one or more operational or process parameters, including ambient temperature, of the vessel during the heating and melting processes for a specific molten material to be processed or under processing. A third set of data may entail the measured temperatures in such at least one region of the external surface of the multiple vessels during their operation. Preferably, the collection of data corresponds to a plurality of regions of these multiple vessels for a variety of molten materials. More preferably, the second set of data comprises measurements of the external surface temperatures of the region of interest of the specific vessel corresponding to at least one prior heat. Most preferably, this prior heat is the one immediately preceding the current heat.
2. Next, at step 200, creating a machine learning-based mathematical model, using a customized machine learning-based algorithm, wherein such model is based on the data collected in Step 100, to correlate an operational condition of a refractory material, the type of molten material, the operational parameters, and the external surface temperatures of the vessel, corresponding to such at least one region of these vessels. Preferably, the model is created to characterize a plurality of regions of these multiple vessels for a variety of molten materials. More preferably, the operational condition of the refractory material is based on the number of heats during the current campaign of the vessel.
3. Next, at step 300, determining a distribution of temperature ranges corresponding to the external surface of a region of interest of a specific vessel associated to a level of risk of operation of such vessel, according to the machine learning-based mathematical model. By entering the information related to the first set of data and the second set

of data, as described in Step 100 for a specific vessel, the model is used to determine an expected safe range of external surface temperatures of the vessel during operation and a level of risk of operating the vessel as a function of the external surface temperatures of the region of interest of the vessel during operation. The machine learning-based mathematical model determines the expected safe range of external temperatures in part by processing the first set of data and the second set of data and fitting these data to one of a plurality of probability distribution functions in order to statistically characterize and estimate the expected temperature values and the range of statistical variance of the temperature values. Moreover, the probability distribution function is customized and uniquely generated by the machine learning-based mathematical model, as previously described.

4. Next, at step 400, measuring the external surface temperatures of the region of interest of the specific vessel during operation while processing a molten material. Preferably, a thermal scanning device is used to measure the external surface temperature of the specific vessel.

5. Next, at step 500, comparing the measured external surface temperatures in Step 400 with the predetermined distribution of temperature ranges in Step 300, corresponding to the region of interest of the specific vessel. This comparison is performed by calculating a difference between the measured temperatures corresponding to the current heat and the temperature ranges pre-determined by the model after the heat immediately preceding the current heat. However, other comparison methods may be used as well-known in the prior art.

6. Next, at step 600, calculating the risk of operation of the specific vessel, in real time while the vessel is in operation processing a molten material, according to the comparison of the measured external surface temperatures with the pre-determined distribution of temperature ranges, performed in Step 500, corresponding to the region of interest of the specific vessel. The risk of operation of the specific vessel is calculated, in real time while the vessel is in operation processing a molten material, based on the difference between the measured temperatures and the temperature ranges pre-determined by the model.

7. Last, at step 700, processing the data collected, determined, measured, or calculated at Steps 100 and 300 to 600 to analyze, forecast, and provide information useful to estimate the remaining operational life and to improve the maintenance plan of the specific vessel. At least one signal processing technique, is selected to process the data according to a characteristic of the refractory material of the vessel, as previously noted. In addition, at least a customized second-level algorithm is used to further evaluate the measured temperature data in regions where the difference between the measured temperatures and the temperature ranges pre-determined by the model exceeds a predefined statistical variance, according to the fitted-data probability distribution function used in Step 300, in a locality within the region of interest of the specific vessel to identify a potential development of a hotspot, as previously noted. The output of the customized second-level algorithm can be used to determine more accurately a potential development of a hotspot and calculate the risk of operation of the specific vessel for predicting the degradation and wearing of the refractory material of the vessel as well as estimating the remaining operational life and optimize the maintenance plan of the vessel. Once the potential development of a hotspot has been identified, the customized second-level algorithm activates an alarm or communicates a priority-level warning message to a user, such as high, medium, or low or color-coded (red, yellow, or green), according to the severity of the development of a hotspot. Preferably, multiple evaluations over the remaining operational life of the vessel are performed to predict the degradation and wearing of the refractory material under evaluation more accurately to better estimate the remaining operational life and to improve the maintenance plan of the vessel.

[0078] In reference to Step 100 and Step 200 above, it is to be understood that these steps might need to be performed only during the initial set up of the machine learning-based mathematical model. Once the model has been created, a variety of specific vessels may be modeled and measured to calculate the risk of operating each of these specific vessels and provide information to estimate the remaining operational life and to improve the maintenance plan of the vessel. In other words, after steps 100 and 200 have been completed once, multiple assessments of a plurality of vessels may be performed starting at Step 300, with no need to go over steps 100 or 200 and without imposing any limitations or affecting the performance of the described method and the results obtained after applying such method.

[0079] Additionally, in reference to step 100 above, those skilled in the art would realize that a plurality of techniques and methods, based on a variety of sensors, including acoustic, radar, LIDAR, laser, infrared, thermal, and stereovision sensors, can be used to collect relevant data related to a manufacturing vessel. Those skilled in the art will also recognize that the steps above indicated can be correspondingly adjusted for a specific vessel and type of molten material, according to the specific machine learning-based algorithm used to create the machine learning-based mathematical model.

[0080] Once the risk of operating a specific vessel is calculated, and the remaining operational life and improvement of the maintenance plan of the vessel is estimated, the thickness and a level or rate of degradation of such material due to various factors, including operational wear, age, and presence of molten material, flaws, cracks, and erosion might also be estimated. In addition, multiple evaluations of the status of a material over time may be used to create trends to estimate such material degradation as well as forecast the remaining operational life and improve the maintenance plan of the vessel.

[0081] The present system and method for calculating the risk of operating a specific manufacturing vessel and provide information to estimate the remaining operational life and to improve the maintenance plan of the vessel have been disclosed herein in an illustrative manner, and it is to be understood that the terminology which has been used is intended to be in a descriptive rather than in a limiting nature. Those skilled in the art will recognize that many modifications and variations of the invention are possible in light of the above teachings. Obviously, many modifications and variations of the invention are possible in light of the above teachings. The present invention may be practiced otherwise than as specifically described within the scope of the appended claims and their legal equivalents.

Claims

1. A system (10) for calculating a risk of operation of a manufacturing vessel (12), wherein said manufacturing vessel comprises a refractory material (14) having at least one internal wall and at least one external wall opposite said at least one internal wall, wherein said at least one internal wall of said refractory material of said vessel is exposed to one or more types of molten material different from said refractory material, said system comprising:

    a. a thermal scanning subsystem comprising at least one first sensor (20) to collect data for measuring at least two groups of temperatures over a region of interest (22) of an external surface (16) of said vessel;
    b. a customized machine learning-based algorithm; and
    c. a data processing subsystem (26) comprising a computer-based processor further comprising a data storage device and an executable computer code configured to process a first set of data, comprising a first of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel, corresponding to at least one prior heat of said vessel; a second set of data comprising at least one operational parameter related to a processing of said one or more types of molten material; and a third set of data comprising a second of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel, corresponding to a current heat of an ongoing campaign of said vessel, and to create and operate said customized machine learning-based algorithm;

    wherein said risk of operation of said vessel is calculated, in real time while said vessel is in operation processing said one or more types of molten material, based on a correlation of said second of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel and a range of variations from said first of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel with a level of an element selected from a group consisting of said risk of operation of said vessel and a penetration of said one or more types of molten material within said refractory material of said vessel, according to at least one output of said customized machine learning-based algorithm, wherein said first set of data, said second set of data, and said third set of data for at least one of a plurality of vessels, including said vessel, are processed using said customized machine learning-based algorithm to create a customized machine learning-based mathematical model (28), and wherein said executable computer code operates said customized machine learning-based algorithm by providing one or more inputs to be used by said customized machine learning-based algorithm to create said machine learning-based mathematical model (28) and by processing one or more outputs of said customized machine learning-based mathematical model (28).

2. The system of claim 1, wherein said first set of data further comprises at least one element selected from a group consisting of a number of heats undergone by said vessel, a contact time of said one or more types of molten material with said refractory material of said vessel, and a thickness of said refractory material of said vessel, corresponding to said at least one prior heat of said vessel, wherein said at least one prior heat of said vessel (12) is immediately preceding said current heat of said ongoing campaign.

3. The system of claim 1, wherein said first set of data comprises at least one element selected from a group consisting of a remaining thickness, a rate of degradation, an erosion profile of said at least one internal wall, a type, a quality, an original and an actual chemical composition, an operational age, and a number of heats of, a presence of one or more cracks in, and a level or rate of penetration of said one or more types of molten material into said refractory material before operating said vessel, a

historical information related to a maintenance of an outer shell material of said vessel, including its audit reports, age, design and observed geometrical variations, a historical information related to a maintenance of said refractory material including a type, an amount, and a location of one or more additives and one or more replaced parts applied to said refractory material, a physical design of said refractory material, said at least one operational parameter, and at least one operational parameter in addition to said at least one operational parameter, corresponding to a prior operation of said at least one of said plurality of vessels, including said vessel, wherein said physical design of said refractory material (14) comprises one or more elements selected from a group consisting of said type, a shape, a dimension, a number of layers, and a layout of a physical disposition of said refractory material of said at least one of said plurality of vessels, including said vessel.

4. The system of claim 1, wherein said second set of data comprises at least one element selected from a group consisting of a remaining thickness of said refractory material prior to operating said vessel; an amount, an average and a peak processing temperatures; a heating and a cooling temperature profiles; a set of treatment times for said one or more types of molten material being or to be processed using said vessel; a type and a chemical composition of said one or more types of molten material being or to be processed using said vessel; a thickness and a composition of a slag buildup in said at least one internal wall of said refractory material of said vessel; an ambient temperature surrounding said vessel; a number of tapping times using said vessel; a pouring and a tapping method for said one or more types of molten material to be poured and tapped into and out of said vessel; a preheating temperature profile while said vessel is empty; a time during which said one or more types of molten material is in contact with said refractory material; a stirring time; intensity of stirring; a flow rate of inert gas applied to said vessel during stirring; an electric power applied; duration of electric power applied; duration of time between two tappings; a physical and a chemical set of attributes and amounts of one or more additives used or to be used in processing said one or more types of molten material to process a desired grade of said one or more types of molten material; said at least one operational parameter; and at least one operational parameter in addition to said at least one operational parameter, for processing said one or more types of molten material using said at least one of said plurality of vessels, including said vessel.

5. The system of claim 1, wherein said customized machine learning-based model (28) is created by determining a correlation of said first set of data and said second set of data with said third set of data for at least one element selected from a group consisting of said at least one of said plurality of vessels, one or more types of said refractory material, and said one or more types of said molten material.

6. The system of claim 1, wherein said data processing subsystem (26) is configured to process said at least two groups of temperatures over said region of interest (22) of said external surface (16) of said vessel, corresponding to a plurality of residual thicknesses of said region of interest of said external surface of said vessel for said at least one prior heat and said current heat of said vessel, to calculate said risk of operation of said vessel based on a variability of said at least two groups of temperatures over said region of interest of said external surface of said vessel for said at least one prior heat and said current heat of said vessel.

7. The system of claim 1, wherein said at least one first sensor (20) comprises an element selected from a group consisting of an infrared camera, a thermal scanner, a thermal imaging camera, and a mesh formed by one or more sections of optical fiber laid out in proximity to said external surface of said vessel.

8. The system of claim 1, further comprising at least one second sensor to collect information related to an element selected from a group consisting of said first set of data and said second set of data, wherein said at least one second sensor comprises an element selected from a group consisting of an ultrasound unit, a laser scanner, a LIDAR device, a radar, and a stereovision camera.

9. The system of claim 8, wherein said at least one second sensor comprises said at least one laser scanner configured to perform a plurality of laser scans of a predefined area of said at least one internal wall of said refractory material while said vessel is empty, and wherein said vessel has undergone a plurality of heats in between performing a first set of said plurality of laser scans and performing a second set of said plurality of laser scans to calculate a remaining thickness of said refractory material (14).

10. The system of claim 1, wherein said data processing subsystem (26) further comprises a second-level algorithm for identifying a potential development of a hotspot in a specific locality of said region of interest of said external surface of said vessel and said data processing subsystem (26) is further configured to perform an action selected from a group consisting of estimating a remaining operational life of said vessel and enhancing a maintenance plan of said vessel, after calculating said risk of operation of said vessel.

11. The system of claim 1, wherein said customized machine learning-based mathematical model (28) is configured to process at least a part of said first set of data and at least a part of said second set of data under multiple operational scenarios to produce a customized, unique probability distribution function that fits at least said part of said first set of data and at least said part of said second set of data, wherein said customized, unique probability distribution function is generated by optimizing a function to get the largest statistical coefficient of determination and the smallest statistical mean squared error of at least said part of said first set of data and at least said part of said second set of data to calculate an expected value and a statistical variance, which are indicative of the most likely outcome and a level of uncertainty of said outcome as well as an expected safe range of normal temperatures over said region of interest (22) of said external surface (16) of said vessel corresponding to said current heat of said ongoing campaign.

12. The system of claim 11, wherein a difference between said safe range of normal temperatures and said second of said at least two groups of temperatures measured over said region of interest (22) of said external surface (16) of said vessel, corresponding to said current heat of said ongoing campaign, that is larger than a predefined threshold, based on said statistical variance, activates a second-level algorithm for identifying a potential development of a hotspot in a specific locality of said region of interest of said external surface of said vessel, wherein said second-level algorithm confirms said potential development of said hotspot after performing an action selected from a group consisting of comparing a temperature variation of said second of said at least two groups of temperatures measured in said specific locality of said region of interest of said external surface of said vessel to a predefined threshold of said temperature variation and verifying that said temperature variation of said second of said at least two groups of temperatures measured in said specific locality of said region of interest (22) of said external surface (16) of said vessel exceeds said predefined threshold of said temperature variation; and conducting a time series analysis of said second of said at least two groups of temperatures measured at consistent intervals over a period of time in said specific locality of said region of interest (22) of said external surface (16) of said vessel, and determining an element selected from a group consisting of a calculation of a Kendall rank correlation coefficient, a calculation of an Euclidean distance, an outcome of application of a dynamic time warping, an outcome of an application of another time series analysis algorithm, and a combination thereof, and wherein said customized machine learning-based mathematical model produces an output such that said data processing subsystem generates a priority-level warning message after said potential development of said hotspot is confirmed.

13. A method for calculating a risk of operation of a manufacturing vessel (12), wherein said manufacturing vessel comprises a refractory material (14) having at least one internal wall and at least one external wall opposite said at least one internal wall, wherein said at least one internal wall of said refractory material of said vessel is exposed to one or more types of molten material different from said refractory material, said method comprising:

a. providing a thermal scanning subsystem comprising at least one first sensor (20) to collect data for measuring at least two groups of temperatures over a region of interest (22) of an external surface (16) of said vessel; a customized machine learning-based algorithm; a data processing subsystem (26) comprising a computer-based processor further comprising a data storage device and an executable computer code configured to process a first set of data, comprising a first of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel, corresponding to at least one prior heat of said vessel; a second set of data comprising at least one operational parameter related to a processing of said one or more types of molten material; and a third set of data comprising a second of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel, corresponding to a current heat of an ongoing campaign of said vessel, and to create and operate said customized machine learning-based algorithm; wherein said risk of operation of said vessel is calculated, in real time while said vessel is in operation processing said one or more types of molten material, based on a correlation of said second of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel and a range of variations from said first of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel with a level of an element selected from a group consisting of said risk of operation of said vessel and a penetration of said one or more types of molten material within said refractory material of said vessel, according to at least one output of said customized machine learning-based algorithm;

b. collecting said first set of data, said second set of data, and said third set of data corresponding to said region of interest for at least one of a plurality of vessels, including said vessel, along with data related to one or more types of said refractory material and said one or more types of molten material;

c. creating a customized machine learning-based mathematical model (28), using said customized machine learning-based algorithm, wherein said customized machine learning-based model is created based on said first set of data, said second set of data, and said third set of data to correlate an operational condition of said refractory material, a type of said one or more types of molten material, said at least one operational parameter, and at least one operational parameter in addition to said at least one operational parameter with said second of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel and a range of variations from said first of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel, according to at least one output of said customized machine learning-based algorithm, for calculating said level of said risk of operation of said vessel, while said vessel is in operation processing said one or more types of molten material.

14. The method of claim 13, further comprising the steps of:

d. determining a distribution of ranges of said first of said at least two groups of temperatures measured over said region of interest (22) of said external surface (16) of said vessel (12) associated to said level of said risk of operation of said vessel, according to said machine learning-based mathematical model (28), wherein said distribution of ranges of said first of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel provides an expected safe range of said second of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel while said vessel is in operation processing said one or more types of molten material and said level of said risk of operating said vessel;

e. measuring said second of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel while said vessel is in operation processing said one or more types of molten material;

f. comparing said second of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel while said vessel is in operation processing said one or more types of molten material with said distribution of ranges of said first of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel;

g. calculating said level of said risk of operation of said vessel, according to said comparison of said second of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel while said vessel is in operation processing said one or more types of molten material with said distribution of ranges of said first of said at least two groups of temperatures measured over said region of interest of said external surface of said vessel.

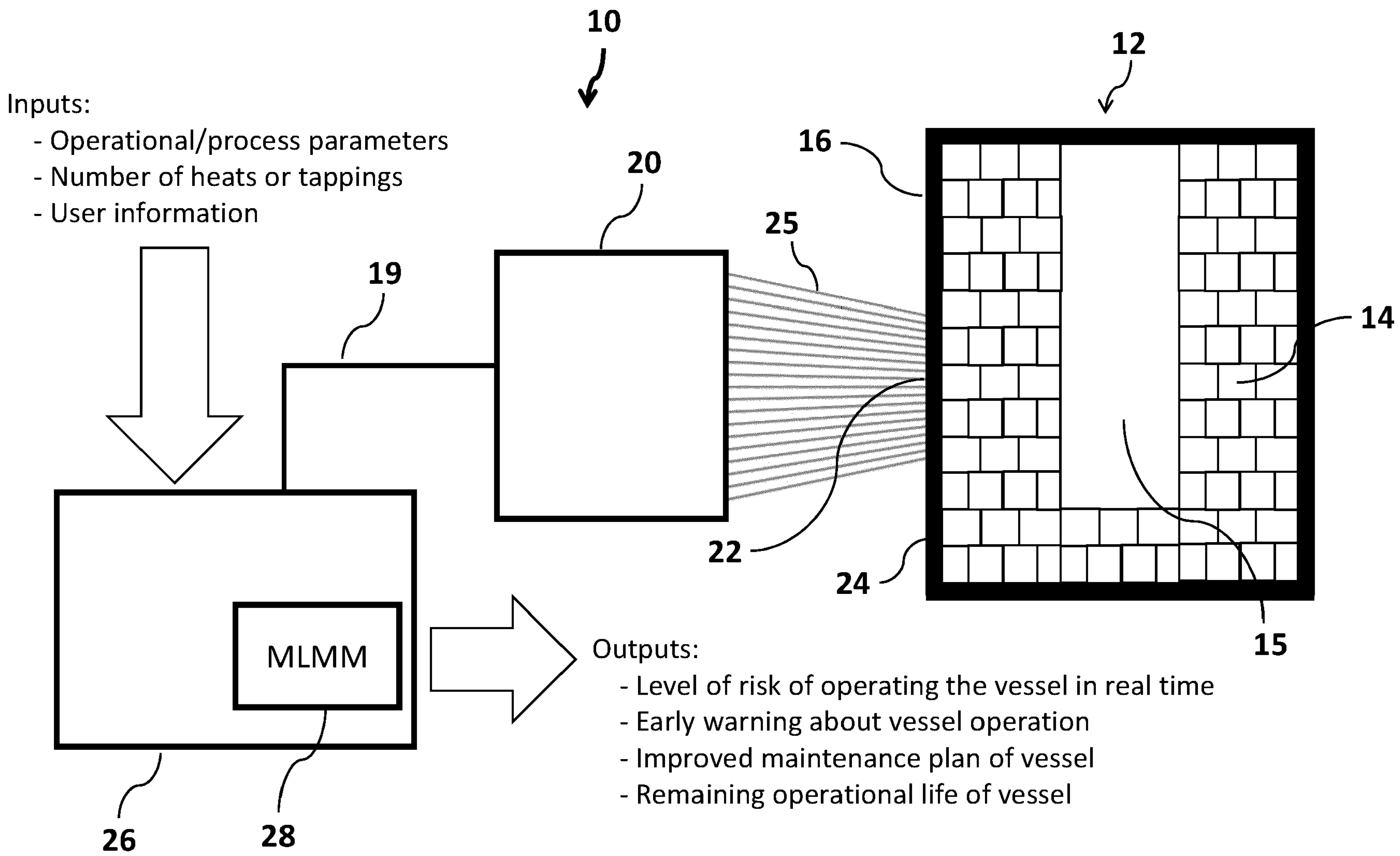
15. The method of claim 14, further comprising a step of processing at least one element selected from a group consisting of said first set of data, said second set of data, said third set of data, a range of normal temperatures over said region of interest (22) of said external surface (16) of said vessel corresponding to said current heat of said ongoing campaign, and said level of said risk of operating said vessel to analyze, forecast, and provide information to perform an action selected from a group consisting of estimating a remaining operational life of said vessel and improving a maintenance plan of said vessel.

16. The method of claim 13, wherein said at least one first sensor (20) comprises an element selected from a group consisting of an infrared camera, a thermal scanner, a thermal imaging camera, and a mesh formed by one or more sections of optical fiber laid out in proximity to said external surface of said vessel.

17. The method of claim 13, said data processing subsystem (26) further comprises a second-level algorithm for identifying a potential development of a hotspot in a specific locality of said region of interest (22) of said external surface (16) of said vessel.

18. The method of claim 13, wherein a second sensor is used to collect at least a portion of an element selected from a group consisting of said first set of data and said second set of data, and wherein said at least one second sensor comprises an element selected from a group consisting of an ultrasound unit, a laser scanner, a LIDAR device, a radar, and a stereovision camera.

19. The method of claim 13, wherein said first set of data comprises at least one element selected from a group consisting of a remaining thickness, a rate of degradation, an erosion profile of said at least one internal wall, a type, a quality, an original and an actual chemical composition, an operational age, and a number of heats of, a presence of one or more cracks in, and a level or rate of penetration of said one or more types of molten material into said refractory material before operating said vessel, a historical information related to a maintenance of an outer shell material of said vessel, including its audit reports, age, design and observed geometrical variations, a historical information related to a maintenance of said refractory material including a type, an amount, and a location of one or more additives and one or more replaced parts applied to said refractory material, a physical design of said refractory material, said at least one operational parameter, and at least one operational parameter in addition to said at least one operational parameter, corresponding to a prior operation of said at least one of said plurality of vessels, including said vessel; wherein said second set of data comprises at least one element selected from a group consisting of a remaining thickness of said refractory material prior to operating said vessel; an amount, an average and a peak processing temperatures; a heating and a cooling temperature profiles; a set of treatment times for said one or more types of molten material being or to be processed using said vessel; a type and a chemical composition of said one or more types of molten material being or to be processed using said vessel; a thickness and a composition of a slag buildup in said at least one internal wall of said refractory material of said vessel; an ambient temperature surrounding said vessel; a number of tapping times using said vessel; a pouring and a tapping method for said one or more types of molten material to be poured and tapped into and out of said vessel; a preheating temperature profile while said vessel is empty; a time during which said one or more types of molten material is in contact with said refractory material; a stirring time; intensity of stirring; a flow rate of inert gas applied to said vessel during stirring; an electric power applied; duration of electric power applied; duration of time between two tappings; a physical and a chemical set of attributes and amounts of one or more additives used or to be used in processing said one or more types of molten material to process a desired grade of said one or more types of molten material; said at least one operational parameter; and at least one operational parameter in addition to said at least one operational parameter, for processing said one or more types of molten material using said at least one of said plurality of vessels, including said vessel; and wherein said third set of data includes said measured set of temperatures of said region of interest (22) of said external surface (16) of said refractory material.


10
12
16
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MLMM
Inputs:
- Operational/process parameters
- Number of heats or tappings
- User information
Outputs:
- Level of risk of operating the vessel in real time
- Early warning about vessel operation
- Improved maintenance plan of vessel
- Remaining operational life of vessel

Figure 1

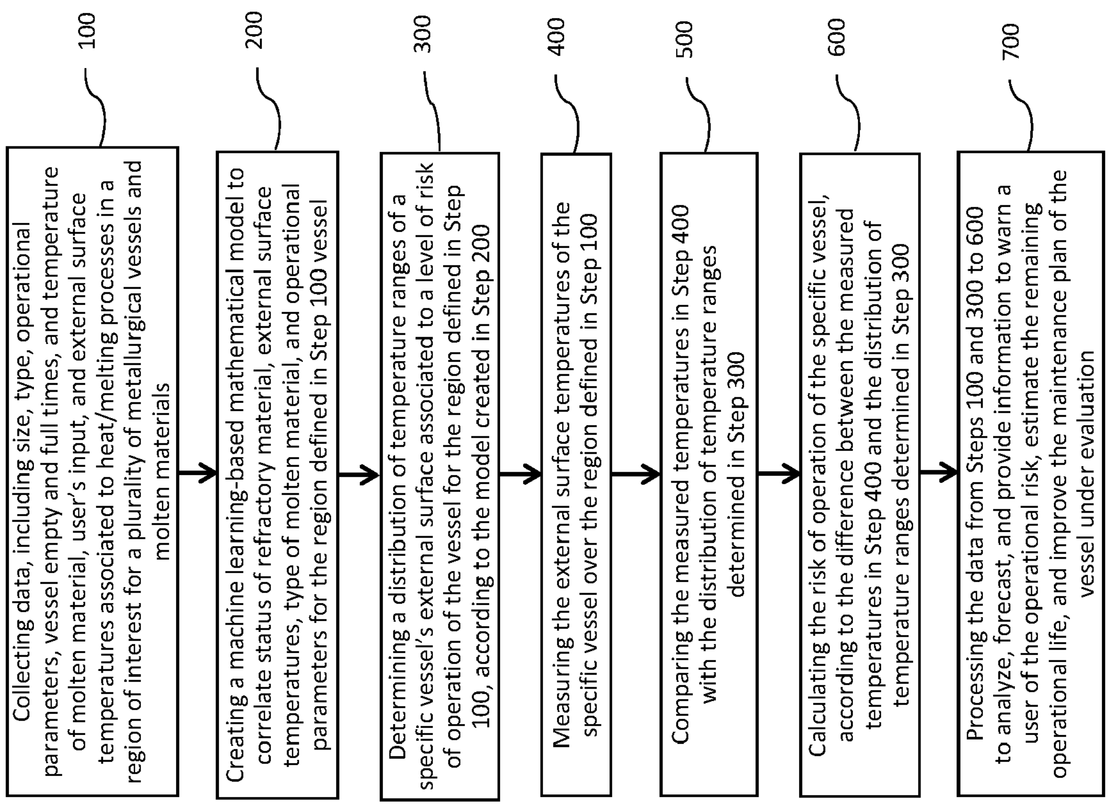
100
Collecting data, including size, type, operational parameters, vessel empty and full times, and temperature of molten material, user's input, and external surface temperatures associated to heat/melting processes in a region of interest for a plurality of metallurgical vessels and molten materials
200
Creating a machine learning-based mathematical model to correlate status of refractory material, external surface temperatures, type of molten material, and operational parameters for the region defined in Step 100 vessel
300
Determining a distribution of temperature ranges of a specific vessel's external surface associated to a level of risk of operation of the vessel for the region defined in Step 100, according to the model created in Step 200
400
Measuring the external surface temperatures of the specific vessel over the region defined in Step 100
500
Comparing the measured temperatures in Step 400 with the distribution of temperature ranges determined in Step 300
600
Calculating the risk of operation of the specific vessel, according to the difference between the measured temperatures in Step 400 and the distribution of temperature ranges determined in Step 300
700
Processing the data from Steps 100 and 300 to 600 to analyze, forecast, and provide information to warn a user of the operational risk, estimate the remaining operational life, and improve the maintenance plan of the vessel under evaluation

Figure 2

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EUROPEAN SEARCH REPORT

Application Number
EP 24 16 3212

DOCUMENTS CONSIDERED TO BE RELEVANT

Category	Citation of document with indication, where appropriate, of relevant passages	Relevant to claim	CLASSIFICATION OF THE APPLICATION (IPC)
X	CN 113 984 635 A (UNIV EAST CHINA SCIENCE & TECH) 28 January 2022 (2022-01-28) * Machine translation; paragraph [Summaryoftheinvention] * -----	1-19	INV. F27D21/00 G01N25/00
X	US 2023/160636 A1 (ISRAELSEN MARK [US]) 25 May 2023 (2023-05-25) * paragraph [0157] - paragraph [0239]; figures 1-6 * -----	1-19	
X	US 2023/289625 A1 (BAYRAM YAKUP [US]) 14 September 2023 (2023-09-14) * claims 1-26; figures 1-2 * -----	1-19	

TECHNICAL FIELDS SEARCHED (IPC)

F27D
G01N

The present search report has been drawn up for all claims

1

Place of search	Date of completion of the search	Examiner
The Hague	11 July 2024	Desvignes, Rémi

CATEGORY OF CITED DOCUMENTS

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D : document cited in the application
L : document cited for other reasons
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ANNEX TO THE EUROPEAN SEARCH REPORT ON EUROPEAN PATENT APPLICATION NO. EP 24 16 3212

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11-07-2024

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
CN 113984635 A	28-01-2022	NONE	
US 2023160636 A1	25-05-2023	US 2023160636 A1	25-05-2023
		US 2023358474 A1	09-11-2023
US 2023289625 A1	14-09-2023	EP 4242768 A1	13-09-2023
		US 2023289625 A1	14-09-2023
		WO 2023173049 A1	14-09-2023

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For more details about this annex : see Official Journal of the European Patent Office, No. 12/82

REFERENCES CITED IN THE DESCRIPTION

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Patent documents cited in the description

- US 51886323 **[0001]**
- US 11144814 B, Cha **[0009]**
- US 10970887 B, Wang **[0009]**
- US 10255693 B, Richard B. Smith **[0009]**
- US 10859316 B, Richter **[0010]**
- US 10935320 B, Lammer **[0012]**
- US 20180347907 A **[0012]**
- US 20160282049 A, Lammer **[0012]**
- WO 2020254134 A **[0013]**
- US 20130120738 A, Bonin **[0019]**