(19) Europäisches Patentamt
European Patent Office
Office européen des brevets

(11) **EP 4 148 105 A1**

(12) **EUROPEAN PATENT APPLICATION**

(43) Date of publication:
15.03.2023 Bulletin 2023/11

(21) Application number: **20020518.5**

(22) Date of filing: **11.11.2020**

(51) International Patent Classification (IPC):
C10G 9/36 *(2006.01)* ***C10G 75/00*** *(2006.01)*
G05D 23/00 *(2006.01)* ***C10G 9/20*** *(2006.01)*
C10G 9/16 *(2006.01)*

(52) Cooperative Patent Classification (CPC):
C10G 9/36; C10G 9/16; C10G 9/206; C10G 75/00

(84) Designated Contracting States:
AL AT BE BG CH CY CZ DE DK EE ES FI FR GB GR HR HU IE IS IT LI LT LU LV MC MK MT NL NO PL PT RO RS SE SI SK SM TR
Designated Extension States:
BA ME
Designated Validation States:
KH MA MD TN

(71) Applicant: **Linde GmbH**
82049 Pullach (DE)

(72) Inventors:
- **Schmidt, Gunther**
  82041 Deisenhofen (DE)
- **Kröner, Andreas**
  82515 Wolfratshausen (DE)
- **Heinzerling, Thomas**
  81369 München (DE)
- **Kracker, Gunther**
  83629 Weyarn (DE)
- **Merk, Malte**
  80469 München (DE)
- **Slaby, Oliver**
  81547 München (DE)
- **Verschinin, Valentin**
  81373 München (DE)

(74) Representative: **Lu, Jing**
Linde GmbH
Intellectual Property EMEA
Dr.-Carl-von-Linde-Straße 6-14
82049 Pullach (DE)

(54) **METHOD FOR STEAM CRACKING AND CORRESPONDING SYSTEMS**

(57) The invention relates to method for steam cracking, comprising: operating a steam cracking plant and using a model (100), representing at least part of the steam cracking plant, wherein the steam cracking plant and the model (100) are operated in parallel, wherein operational input data (210) is used for both, the steam cracking plant and the model (100), and wherein output data for at least one process variable are obtained from the model (100) as simulated output data (120), and wherein values (220) for at least one process variable for the plant are measured and fed into at least part of the model (100) as additional input data for improving quality of the simulated output data (120), and to corresponding systems.

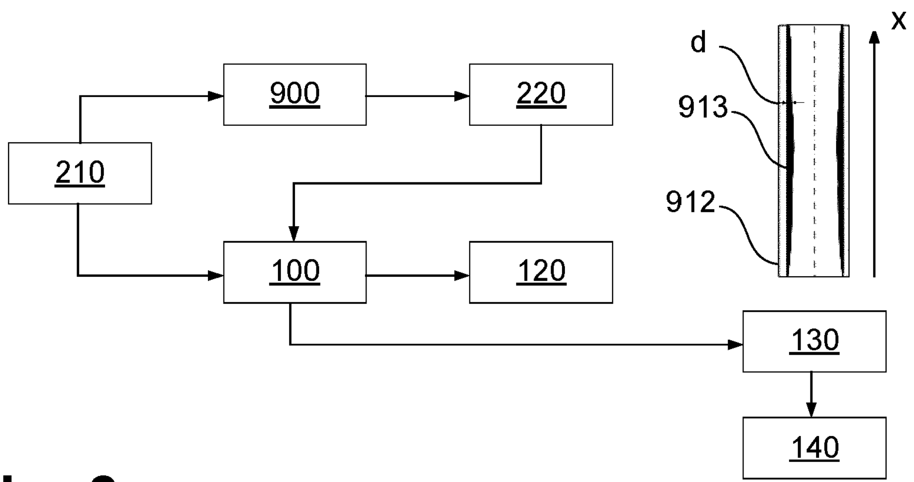

Fig. 3a

Description

[0001] The present invention relates to a method and a system for steam cracking according to the preambles of the independent claims.

Background of the invention

[0002] The present invention is based on steam cracking technology for the production of olefins and other base chemicals, as e.g. described in the article "Ethylene" in Ullmann's Encyclopedia of Industrial Chemistry, online publication 15 April 2009, DOI: 10.1002/14356007.a10_045.pub2. Plants adapted for steam cracking are often simply referred to as "ethylene plants" even if they produce other olefins.

[0003] Presently, the thermal energy required for initiating and maintaining the endothermic cracking reactions in steam cracking is provided predominantly by the combustion of fuel gas in a firebox (a refractory lined box supported by a steel frame). The required process heat can also be provided by other energy sources, for example by electrical heating. The process gas initially containing steam and the hydrocarbons to be cracked is passed through so-called cracking coils placed inside the refractory lined box, also called radiant zone or section. On its flow path through the cracking coils the process gas is continuously heated, enabling the desired cracking reactions to take place in the cracking coils, and the process gas is continuously enriched in cracking products.

[0004] An unavoidable side-product of the chemical reactions occurring within the cracking coils is the formation of coke and its deposits at their inner surfaces. Over the runtime of a furnace the continuously growing coke layer is responsible for two negative effects regarding the furnace performance: The inner cross section of the cracking coils decreases with increasing coke thickness yielding an increased pressure drop across the cracking coils. Further, as the heat conductivity of coke is considerably lower than the heat conductivity of the metal from which the cracking coils are formed, the coke layer has an insulating effect. Consequently, for maintaining the same cracking conditions over time, which in turn requires the same amount of heat transferred to the process gas, the maximum outer metal temperature of the cracking coils increases over the runtime of the furnace.

[0005] For these reasons, a so-called de-coking of the cracking coils is required regularly to avoid elevated pressure drops across the cracking coils and a thermal fatigue of the material of the cracking coils. However, de-coking should be triggered as less or late as possible since it comes along with a complete interruption of the furnace operations and significant energy expenditure for removing the coke from the cracking coils.

[0006] Offline computations of process variables of a steam cracking furnace are well established and commonly used by the applicant for design computations of an ethylene plant. These computations may be based on a white-box model approach.

[0007] White-box models are known in the art and frequently mentioned in literature. For example, as stated in H.A.B. te Braake et al., "Semi-Physical Modeling of Chemical Processes with Neural Networks", IFAC Proceedings, Volume 29, Issue 1, June-July 1996, Pages 6119-6124, white-box models are based on first principles and can therefore not only be used as a model to predict a certain process behavior but also have the capability to explain the underlying physical and chemical relationships of a process. In general these models are therefore, to a certain extent, applicable independently of the process scale. Such a white-box model is thus, e.g., based on thermo fluidic and/or thermo dynamic and/or phenomenological correlations and/or mechanical equations and geometry and/or topology of components of the plant it represents. On the contrary, as also mentioned in the literature cited, black-box models describe input-output relations solely based on measured data. As a disadvantage, black-box models only can be used for the operating regime they are identified for. It is mostly impossible to use the same identified black-box model for more than one specific process scale.

[0008] When to trigger a de-coking procedure for a steam-cracking furnace is not an obvious decision: The coke layer thickness cannot be measured during running operations. Also, the outer metal temperature of the reaction coils is currently difficult to measure during running furnace operation. Typically, this temperature must be measured manually by an operator via a pyrometer. Recommended de-coking cycles are based on design computations, which cannot consider the actual, non-constant plant operating conditions. The empirical correlations within the white-box design model are of general nature and not plant specific. Further, the history of the plant operating conditions over several operation cycles has an influence on the plant behaviour, which might significantly alter expectation values over the plant life time.

[0009] It is therefore an object of the present invention to provide an advanced model-based approach for operating a steam cracking or ethylene plant which overcomes at least some of these problems.

Disclosure of the invention

[0010] Against this background, the present invention proposes a method for steam cracking, a system for operation a steam cracking plant and a system for steam cracking with the features of the independent claims. Embodiments of the invention are the subject of the dependent claims and of the description that follows.

[0011] The invention relates to steam cracking and, in particular, a method for steam cracking comprising operating a steam cracking plant and using a model, representing at least part of the steam cracking plant.

[0012] In general, the basis of the model, representing at least part of the steam cracking plant, in particular, a cracking furnace, consists of a white-box model as it can be used offline for plant design computations as mentioned before. A difference within the present invention is, however, that the model is no longer operated offline with estimated plant operating values but is fed with actual plant data, i.e., it is operated or used in parallel with the operation of the steam cracking plant. Operational input data like flows of certain streams or parameters for operating burners is used for both, the steam cracking plant and the model. This already increases the prediction accuracy of the (white-box) model. Output data for at least one process variable are obtained from the model as simulated or predicted output data. In particular, the model allows providing output data for the future.

[0013] A possibility is to use that model as a (pure) white-box model; output data of process variables of the plant, that are measured, can be used to validate the white-box model and describe the discrepancy between model prediction and measurement.

[0014] Within the invention, however, values for at least one process variable for the plant are measured and fed into at least part of the model as additional input data for improving quality of the simulated output data. Preferably, the at least one process variable for the plant, for which values are measured, comprises a temperature in at least one part of a radiant zone of the plant. One or more thermal cameras can be used for that. While the invention will be described mainly referring to this specific process variable, the invention is not limited to such temperature, as will become apparent from the following.

[0015] In this way, that newly available information - which is or was a model output in the (pure) white-box model approach - is used to replace the uncertainty afflicted model or part of it (e.g., a part representing the coking). By solving an optimization problem that minimizes the discrepancy between measured and predicted (tube metal) temperature or other values while given measurement uncertainties may be respected, the specific parameters like coking model parameters can be given as target values. The resulting model is thus data-driven and replaces a pure white-box model. Accordingly, the resulting model becomes a so-called grey-box model since it no longer depends on first principles only but also on data driven sub-models.

[0016] Generally, also other parts or other sub-models of the model (based on a white-box model) can be replaced by measured-data-driven models, i.e. data-driven models based on measured data. The coking model, however, turned out to be (quite) uncertainty afflicted. Thus, it is a prominent candidate for a data-driven replacement. Additionally, the coke thickness and coke building velocity correlate strongly with the (tube metal) temperature in the radiant zone such that a data-driven model derivation is of particular interest for this sub-model part.

[0017] This allows, based on the coke layer thickness and, conversely, maximum tube metal temperature, to determine a point in time for de-coking the plant by far more precisely than with previous approaches mentioned above.

[0018] A further application within the invention is a coil life time prediction. In general, based on simulated data, a life time of at least part of the radiant zone, preferably, a cracking coil, is predicted. The total lifetime of the coils in a steam cracking furnace is controlled by the carburisation grade of the coil material and the resulting material fatigue. The carburisation rate, in turn, strongly depends on the tube metal temperature: the larger the tube metal temperature, the faster the carburisation.

[0019] As one of various outputs from the model is the maximal (tube) temperature, which is continuously computed and stored in, e.g., an online database, a full set of historic operation data is generated. By combining an empirical or analytical model for the coil life time prediction with the model, an estimation of the coil life time is possible.

[0020] As mentioned, not only the measured data from the thermal camera(s) can be used in the (grey-box) model for data-driven model derivation, but all (or at least other parts of) the plant data measurements available might be used for model training. By replacing all first-principle (sub-) models and describing the process only by its input-output behaviour, a so-called black-box model results. Algorithmical approaches like artificial neural networks are of particular interest for the black-box model description. However, also other self-learning algorithms like decision trees or Support-Vector-Machines can be used.

[0021] It is to be emphasized that the possibility of deriving a black-box model description of the entire process (or also a grey-box model) is only enabled by continuous data collection of the online model. Over time, this data collecting procedure establishes a sufficiently large data set, which finally allows the training of a black-box model. The benefit of a well-trained black-box model is that it is trained with historic data across several de-coking cycles. Thus, also long-term trends of the plant process variables are taken into account. Hence, the black-box model is generally capable of extrapolating these trends to future plant operating conditions.

[0022] A possible model training strategy will be described in the following, exemplarily, for an artificial neural network. It would be similar, however, for other self-learning algorithms training: After an initial data collection phase, the gathered data will be split into a training data set and a validation data set. Based on the training data set, different network configurations will be evaluated with varying number of layers and neurons per layer. The input neurons coincide with the inputs of the white-box model, i.e. feed composition, coil inlet temperature, flow rate, etc.

[0023] The most promising models trained on the training data set, i.e. the ones with the smallest prediction error for, e.g., the H2 norm (a particular norm typically used in model training), are selected for further evaluation on validation data set. It is tested how well the models generalize on inputs they have not seen yet, as the validation data set was not used during training. The model configuration, which generalizes best on the validation set, will finally be used for deployment.

[0024] During the deployment phase, the model will, preferably, be continuously trained with incoming data to further increasing the model's accuracy. At the same time, the model prediction errors will be continuously monitored. This helps to detect possibly biased training due to corrupted input data.

[0025] The invention also relates to a system for operating a steam cracking plant, comprising processing means configured for running a model, representing at least part of the steam cracking plant, and measurement means configured for measuring values of at least one process variable of the plant. The processing means are configured for running the model in parallel to operation of the steam cracking plant, such that operational input data for the steam cracking plant is also used for the model, and the processing means are further configured for providing output data of at least one process variable obtained from the model as simulated output data. The processing means are also configured to receive the measured values for at least part of the model as additional input data for improving quality of the simulated output data. The processing means can include or provide a so-called cloud (central server providing access via internet or the like), and a local computer for user access.

[0026] A corresponding system for steam cracking comprises a steam cracking plant and the mentioned system with processing means and measurement means. The processing means (or at least a local part thereof) can also be used as control system for the plant.

[0027] With respect to further embodiments and advantages of the systems, it is referred to the remarks above for the method, which apply correspondingly.

[0028] To summarize, a main aspect of the invention is the incorporation of actual plant data measurement to optimize the prediction accuracy of an online model. Instead of using the available plant measurement data only for validation purpose of a plain white-box model, the available data is used for a data-driven model tuning. The more the online prediction model relies on data-driven model correlations, the more the white-box model shifts towards a grey-box model approach or, finally, even a black-box model, if it relies on data-driven correlations only.

[0029] Especially, the measurement data from the thermal camera, which will be installed for the first time into the firebox of a cracking furnace, improves the data availability significantly. With such data at hand the formulation of a data-based coking model becomes possible, as the coking formation and coke thickness correlate strongly with the tube metal temperature measured by the thermal camera. As this measurement data usually is not available for cracking furnaces, rigours data-driven formulations for the coking model were not feasible until now. Moreover, continuously collecting plant operation data establishes a data basis suitable for the formulation of a black-box model that describes the output process variables only on the basis of the input variables. As such a black-box model takes into account the complete plant history, long-term evolution of a plant can be predicted.

[0030] The advantages and improvements achieved by the invention are again summarized in the following: The coke-thickness cannot be measured during plant operation. However, the online virtual furnace (the model) provides correlation that allow to predict the coke layer thickness based on known and available input process variables only Besides other model outputs, e.g., the cracked gas composition, the coke layer thickness is accessible as a so-called soft sensed quantity, meaning a quantity that is not (continuously) measured but derived instead from other process variables. The online model can be used accordingly as a soft sensor to provide additional insight into the physical processes involved.

[0031] The continuous monitoring of the tube metal temperature via a thermal camera increases the measurement accuracy (compared to manual tube temperature measurements via pyrometer and operator) and consequently the process safety.

[0032] Compared to an offline design computation of a plant, the proposed online model runs in parallel to the actual plant operation and is consequently fed with actual plant data. This means that, for example, changes in the feedstock or cracking conditions are inherently considered in the online model. Consequently, the estimation of the coke layer thickness becomes more reliable compared to the offline design estimation with fixed operating conditions. As a result, a more robust and quantitative measure is available for triggering a de-coking procedure. Considering the de-coking procedure being energy extensive and requiring a full stop of the operations, postponing the de-coking (or even de-coke less frequently) is a significant improvement. Additionally, the de-coking schedule can be optimized to avoid de-coking of several furnaces at the same time.

[0033] Having data for a specific plant at hand allows deriving data-driven correlations for the virtual furnace, which are specifically tailored to the real plant conditions. For example, a plant specific, data-driven coking model can replace the uncertainty afflicted design coking model. For the given plant the resulting grey-box model would then be superior to the general white-box model yielding increased prediction accuracy.

[0034] Collecting data across several operation cycles allows capturing long term trends with a black-box model formulation. By considering the history of plant operation data, the influence of cycle-to-cycle variations could additionally be taken into account. The model's accuracy is further increased.

[0035] Short description of the figures

Fig. 1 illustrates a steam cracking plant that can be used within the present invention-

Fig. 2a shows a flow diagram of a method to operate a steam cracking plant.

Fig. 2b shows a diagram with measured and simulated values according to the method shown in Fig. 2a.

Fig. 3a shows a flow diagram of a method to operate a steam cracking plant according to a preferred embodiment of the invention.

Fig. 3b shows a diagram with measured and simulated values according to the method shown in Fig. 3a.

Fig. 4 shows an illustration of a method to operate a steam cracking plant according to a further preferred embodiment of the invention.

Detailed description of the figures

[0036] For reference, and to further illustrate the background of the invention, a steam cracking plant 900 is illustrated in Figure 1 in a simplified, partial representation.

[0037] The steam cracking plant 900 illustrated in Figure 1 comprises, as illustrated with a reinforced line, one or more cracking furnaces 90. For conciseness only, "one" cracking furnace 90 is referred to in the following, while typical steam cracking plants 900 may comprise a plurality of cracking furnaces 90 which can be operated under the same or different conditions. Furthermore, cracking furnaces 90 may comprise one or more of the components explained below.

[0038] The cracking furnace 90 comprises a radiant zone 91 and a convection zone 92. In other embodiments than that shown in Figure 1, also several radiant zones 91 may be associated with a single convection zone 92, etc.

[0039] In the example illustrated, several heat exchangers 921 to 925 are arranged in the convection zone 92, either in the arrangement or sequence shown or in a different arrangement or sequence. These heat exchangers 921 to 925 are typically provided in the form of tube bundles passing through the convection zone 92 and are surrounded by a flue gas from the radiant zone 91.

[0040] In the example illustrated, the radiant zone 91 is heated by means of a plurality of burners 911 arranged on the floor and wall sides of a refractory forming the radiant zone 91, which are only partially designated. In other embodiments, the burners 911 may also provided solely at the floor side.

[0041] In the example illustrated, a gaseous or liquid feed stream 901 containing hydrocarbons is provided to the steam cracking plant 900. It is also possible to use several feed streams 901 in the manner shown or in a different manner. The feed stream 901 is preheated in the heat exchanger 921 in the convection zone 92.

[0042] In addition, a boiler feed water stream 902 is passed through the convection zone 92 or, more precisely, the heat exchanger 922, where it is preheated. The boiler feed water stream 902 is thereafter introduced into a steam drum 93. In the heat exchanger 923 in the convection zone 92, a process steam stream 903, which can also be provided using the steam drum 93, is further heated and, in the example illustrated in Figure 1, thereafter combined with the feed stream 901.

[0043] A stream 904 of feed and steam formed accordingly is passed through a further heat exchanger 925 in the convection zone 92 and is thereafter passed through the radiant zone 91 in typically several cracking coils 912 to form a cracked gas stream 905. The illustration in Figure 1 is highly simplified. Typically, a corresponding stream 904 is divided up into a number of cracking coils 912 and a cracked gas formed therein is collected to form the cracked gas stream 905.

[0044] As further illustrated in Figure 1, a steam stream 906 can be withdrawn from the steam drum 93 and can be (over)heated in a further heat exchanger 924 in the convection zone 92, generating a high-pressure steam stream 907. The high-pressure steam stream 907 can be used in the steam cracking plant 900 at any suitable location and for any suitable purpose as not specifically illustrated.

[0045] The cracked gas stream 905 from the radiant zone 12 or the cracking coils 912 is passed via one or more transfer lines to a quench exchanger 94 where it is rapidly cooled for the reasons mentioned. The quench exchanger 94 illustrated here represents a primary quench (heat) exchanger. In addition to such a primary quench exchanger 94, further quench exchangers may also be present.

[0046] The cooled cracked gas stream 907 is passed to further process units 95 which are shown here only very schematically. These further process units 95 can, in particular, be process units for scrubbing, compression and fractionation of the cracked gas, and a compressor arrangement including a steam turbine, which may be operated using steam from the steam drum 93, being indicated with 96.

[0047] In the example shown, the quench exchanger 94 is operated with a water stream 908 from the steam drum 93. A steam stream 909 formed in the quench exchanger 94 is returned to the steam drum 93.

[0048] Further, processing means 101, 102 are provided which comprise local processing means 101 and remote processing means 102 like a cloud service or the like. The local processing means 101 can be used for operating the plant 900 and operating measurement means 200 like thermal cameras in order to acquire process variables like the temperature of cracking coils 912. The remote processing means 102 can be used to run or operate a model 100 of the plant as will be explained in more detail later.

[0049] In Fig. 2a, a flow diagram of a method to operate a steam cracking plant like plant 900 of Fig. 1 is shown. Input data 210 comprising, e.g., set values for different flows of certain streams or parameters for operating burners and the like (e.g., feed composition, fuel gas composition, coil inlet temperature, hydrocarbon flow rate, dilution, coil outlet pressure) are used for operation of the plant 900. In addition, the same input data 210 are used in or fed into model 100 representing at least part of the plant 900. In this case, model 200 is a white-box model.

[0050] During operation of plant 900, measured output data 220 for different process variables are acquired. These measured output data 220 can include, in particular, temperature values of cracking coils 912 of plant 900. The temperature can be measured using the thermal cameras mentioned with respect to Fig. 1. In parallel, model 100 is operated or run, and provides simulated output data 120 for different process variables. These process variables can coincide with those of the measured output data 220 of the plant or at least overlap with them. In particular, simulated output data 120 also include temperature values of cracking coils 912 of plant 900.

[0051] In Fig. 2b, a diagram with measured and simulated values according to the method as illustrated in Fig. 2a is shown. The diagram shows a temperature T of (e.g., a certain) cracking coil of plant 900 versus a length x of (or a position within) the coil. The measured temperature is indicated with solid line T_M and the simulated temperature is indicated with dashed line T_S.

[0052] As can be seen in the diagram, the measured and the simulated temperature differ from each other. Nevertheless, the measured temperature - a temperature of the cracking coils could not be measured at all before the use of the thermal cameras - can be used to validate model 200 and - if required - model 200 can be adapted.

[0053] In Fig. 3a, a flow diagram of a method to operate a steam cracking plant according to a preferred embodiment of the invention is shown. Input data 210 comprises, e.g., set values for different flows of certain streams or parameters for operating burners and the like (e.g., feed composition, fuel gas composition, coil inlet temperature, hydrocarbon flow rate, steam dilution rates, coil outlet pressure) and are used for operation of plant 900. In addition, the same input data 210 are used or fed into the model 100 representing at least part of plant 900. This is similar or even equivalent to the situation illustrated in Fig. 2a.

[0054] During operation of plant 900, measured output data 220 for different process variables are acquired. These measured output data 220 include, at least, temperature values of cracking coils 912 of plant 900. The temperature is measured using the thermal cameras mentioned with respect to Fig. 1. The temperature values - or, if desired, also values of further process variables - are fed into model 200 which is operated or run in parallel. Thus, model 200, in this case, is not a white-box model but a grey-box model as explained above. Nevertheless, model 200 provides simulated output data 120 for different process variables. These process variables can coincide with those of the measured output data 220 of the plant or at least overlap. In particular, simulated output data 120 also include temperature values of cracking coils 912 of plant 900.

[0055] In Fig. 3b, a diagram with measured and simulated values according to the method illustrated in Fig. 3a is shown. The diagram shows a temperature T of (e.g., a certain) cracking coils of plant 900 versus a length x of (or a position within) the coil. The measured temperature is indicated with solid line T_M and the simulated temperature is indicated with dashed line T_S.

[0056] As can be seen in the diagram, the measured and the simulated temperature differ from each other only slightly. The simulated temperature is much closer to the measured temperature than without feeding the measured values into the model, as can be seen in Fig. 2b. This shows that a prediction of the temperature of the cracking coils - or other process variables - by means of model 200 will be much better than without feeding the measured values into the model.

[0057] This allows an additional step 130 in the method shown in Fig. 3a, determining a coke layer thickness d of coke 913 at the inside of the cracking coil 912. This also allows determining a point in time 140 in the future at which a de-coking procedure shall be made.

[0058] In Fig. 4, an illustration of a method to operate a steam cracking plant according to a further preferred embodiment of the invention is shown. In particular, an online architecture to be used within such method is illustrated.

[0059] In a customer database 401, which might be operated on the local processing means 101 shown in Fig. 1, plant data 411 is stored and will be transmitted to an online database 403. Such plant data 411 can comprise set values and measurement data, the latter in particular including measured temperature values of the cracking coils.

[0060] From online database 403, model input data 412 is transmitted to model 100. Model input data 412 can comprise the set values for, e.g., flows, streams, inlet temperatures and outlet pressures. Model 100 can include different sub models 420, 421 for different parts or components of the plant. For example, sub model 420 can represent the burners (or a firebox) and sub model 4321 can represent the cracking coils. Model 100 includes, e.g., values 414 for an outer temperature that is fed from sub model 421to sub model 420 and values 413 for a heat flux fed vice versa.

[0061] Model 100 or the sub models can continuously be tuned or trained (see step 415) by using history data 430 about the pant or plant operation (including values for feedstock, coke, runtime and the like) and/or corresponding measurements (including data from the thermal cameras, other temperatures, pressures and the like).

[0062] From model 100 model output data 416 can be transmitted to online database 403. Such model output data 416 can comprise simulated data like inlet pressures, fuel amounts, coke thicknesses or profiles, temperature profiles, pressure profiles, cracked gas composition and the like. From model output data 416 visual output data 417 can be computed or determined to be visualized on a web interface 405 for customers. Such visual output data 417 can comprise specific trends of process variables, runtime predictions, advices and the like.

[0063] Online database 402, model 100 and web interface 405 can be operated in a cloud or be run on corresponding processing means like the processing means 102 shown in Fig. 1.

Claims

1. A method for steam cracking, comprising: operating a steam cracking plant (900) and using a model (100), representing at least part of the steam cracking plant (900),
characterized in that the steam cracking plant (900) and the model (100) are operated in parallel, wherein operational input data (210) is used for both, the steam cracking plant (900) and the model (100), and wherein output data for at least one process variable (T) are obtained from the model (100) as simulated output data (120),
wherein values (220) for at least one process variable (T) for the plant (900) are measured and fed into at least part of the model (100) as additional input data for improving quality of the simulated output data (120).

2. The method of claim 1, wherein the at least one process variable for the plant, for which values are measured, comprises a temperature (T) in at least one part of a radiant zone (91) of the plant (900).

3. The method of claim 2, wherein the at least one process variable (T), for which the values are obtained from the model (100), comprises a temperature in at least one part of a radiant zone (91) of the plant (900), wherein the simulated data (120) comprises temperature values predicted for the future, based on which a coke layer (d) thickness is determined.

4. The method of claim 3, wherein, based on the coke layer thickness (d), a point in time (140) for de-coking the plant is determined.

5. The method of any one of claims 2 to 4, wherein, based on measured or simulated data (120), a remaining life time of at least part of the radiant zone, preferably, a cracking coil (912), is predicted.

6. The method of any one of the preceding claims, wherein, using the measured values of the at least one process parameter (T), the model (100) is improved or trained, preferably, by solving an optimization problem, in order to reduce a discrepancy between the simulated output data (120) and corresponding measured output data (220) obtained from the plant (900).

7. The method of any one of the preceding claims, wherein, the model (100) is based on a self-learning algorithm, in particular, an artificial neural network.

8. A system for operating a steam cracking plant (900), comprising processing means (101, 102) configured for running a model (100), representing at least part of the steam cracking plant (900), and measurement means (200) configured for measuring values of at least one process variable (T) of the plant,
wherein the processing means (101, 102) are configured for running the model (100) in parallel to operation of the steam cracking plant (900), such that operational input data (210) for the steam cracking plant (900) is also used for the model (100), and the processing means (101, 102) further configured for providing output data of at least one process variable (T) obtained from the model (100) as simulated output data (120),
wherein the processing means (101, 102) are configured to receive the measured values (220) for at least part of the model (100) as additional input data for improving quality of the simulated output data (120).

9. The system of claim 8, wherein the at least one process variable for the plant, for which values are measured, comprises a temperature (T) in at least one part of a radiant zone (91) of the plant.

10. The system of claim 8 or 9, wherein the at least one process variable, for which the values are obtained from the model (100), comprises a temperature in at least one part of a radiant zone (91) of the plant, wherein the simulated output data (120) comprises temperature values predicted for the future, wherein processing means (101, 102) are configured to determine, based on the simulated data, a coke layer thickness (d)..

11. The system of claim 10, wherein the processing means are configured to determine, based on the coke layer thickness (d), a point in time (140) for decoking the plant (900).

12. A system for steam cracking, comprising a steam cracking plant (900) and the system of any one of claims 8 to 11.

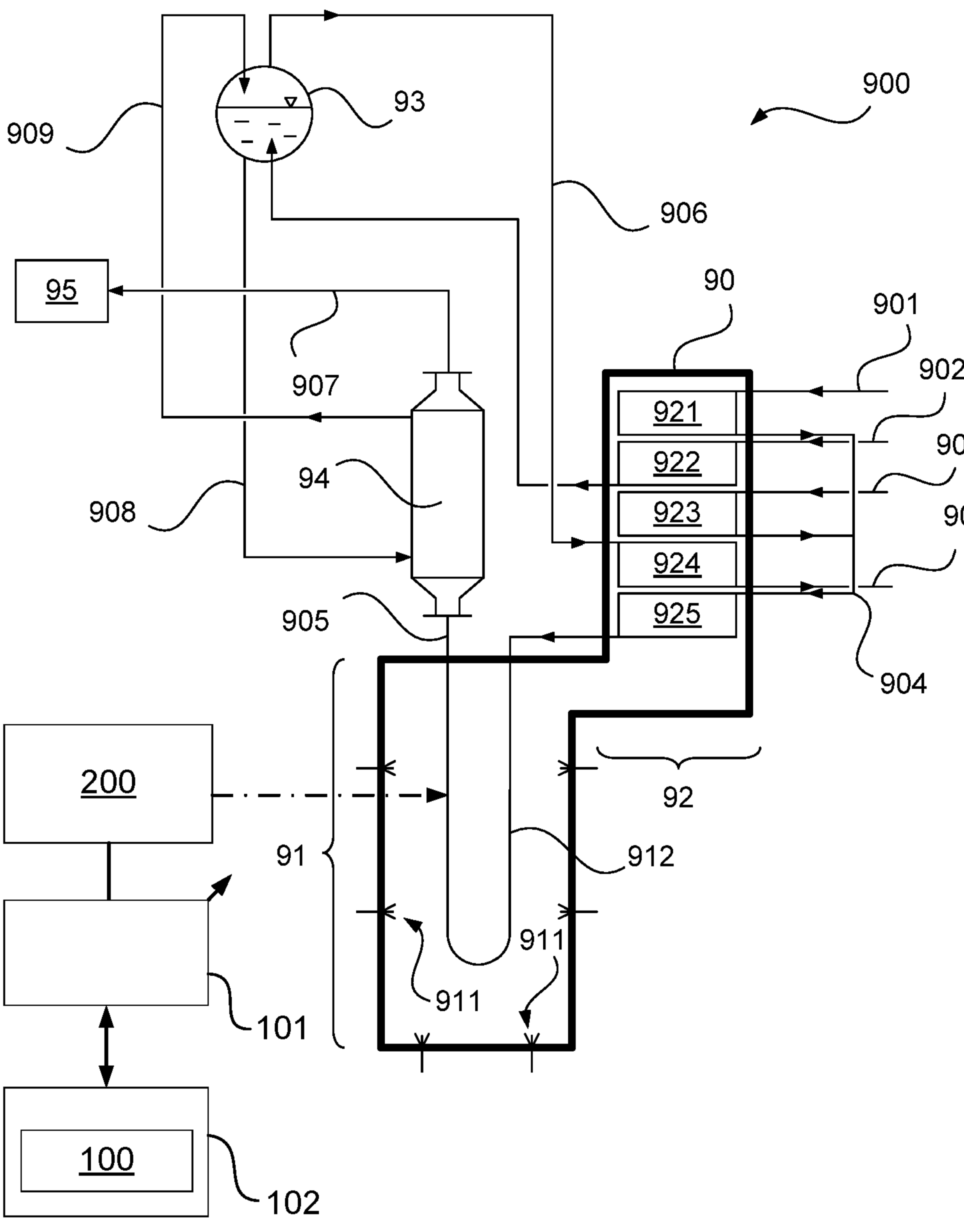
900
93
909
906
95
90
901
902
907
921
922
923
924
925
903
94
908
907
905
904
200
92
91
912
911
911
101
100
102

Fig. 1

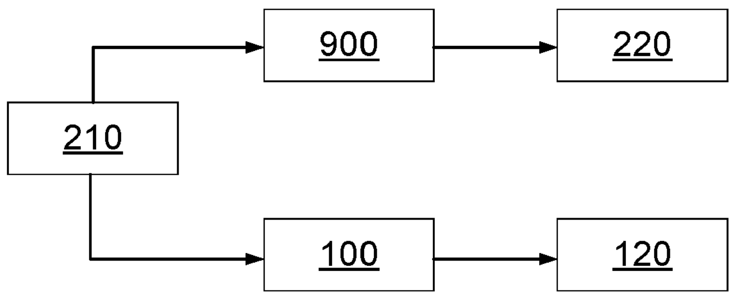

Fig. 2a

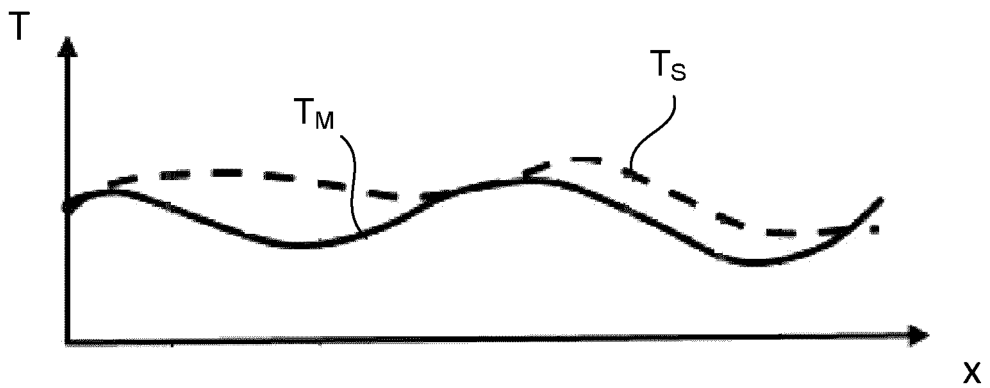

Fig. 2b

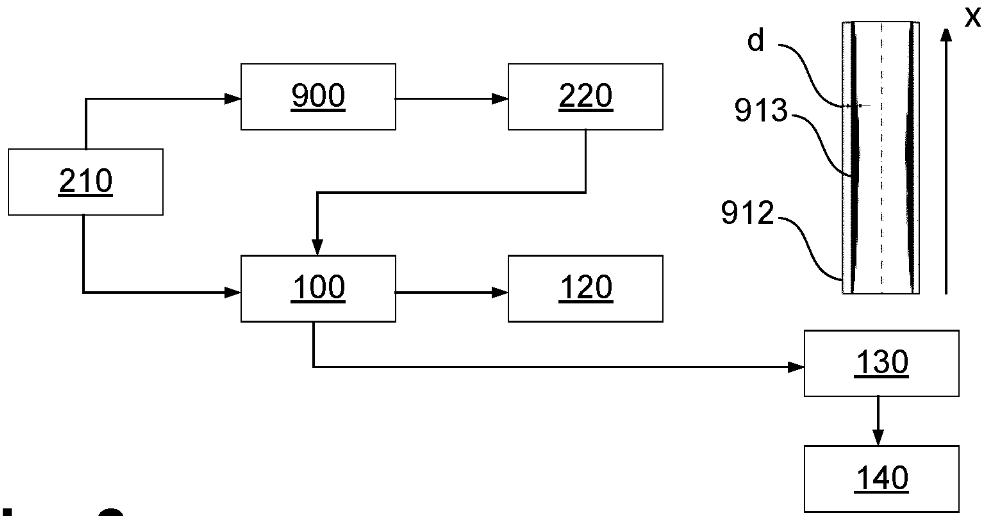

Fig. 3a

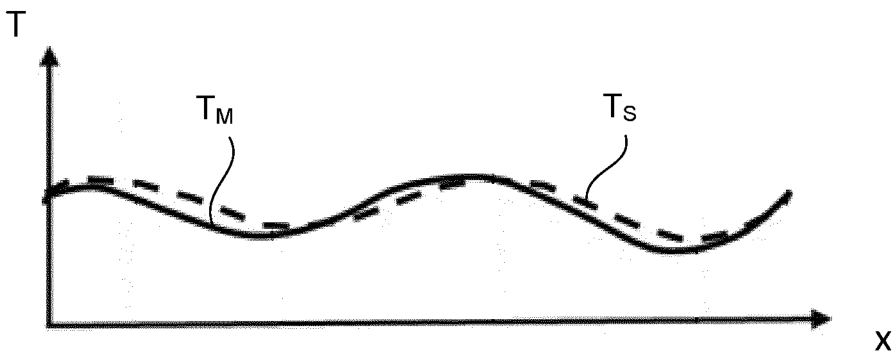

Fig. 3b

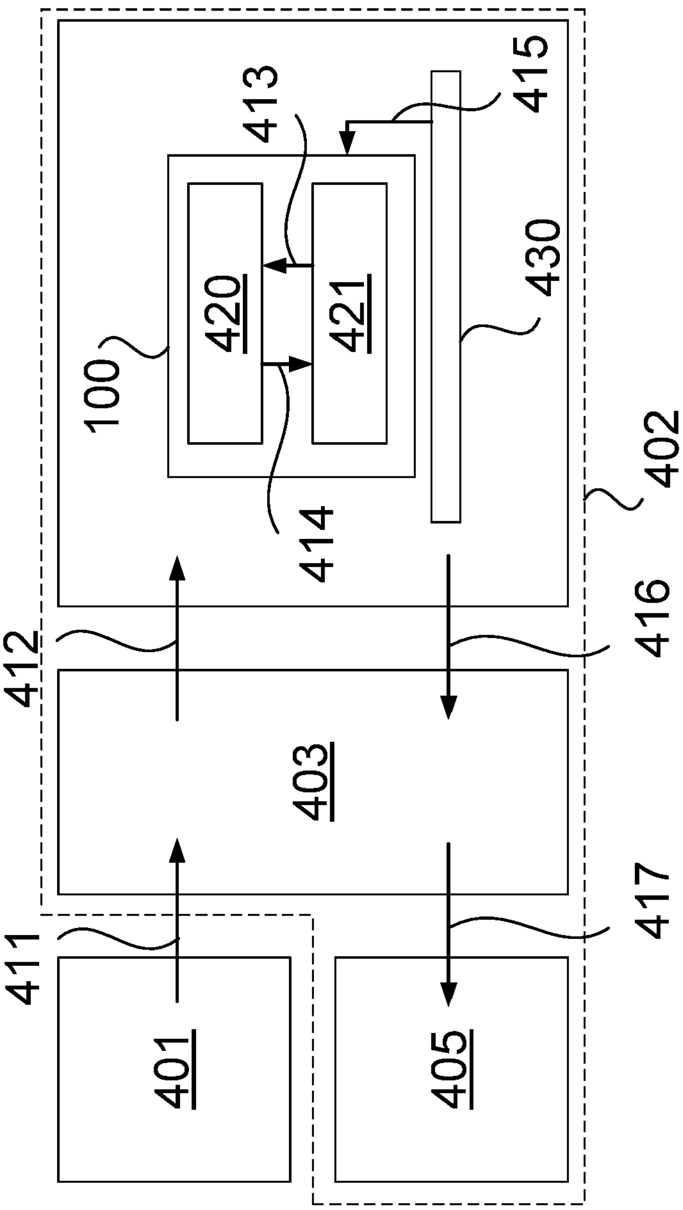

Fig. 4

Europäisches Patentamt
European Patent Office
Office européen des brevets

EUROPEAN SEARCH REPORT

Application Number
EP 20 02 0518

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	US 2017/101586 A1 (ILIYAS ABDULJELIL [SA] ET AL) 13 April 2017 (2017-04-13) * figures 1-15 * * paragraph [0041] - paragraph [0100] * -----	1-12	INV. C10G9/36 C10G75/00 G05D23/00 C10G9/20 C10G9/16
X	WO 2018/229621 A1 (SABIC GLOBAL TECHNOLOGIES BV [NL]) 20 December 2018 (2018-12-20) * figures 1-7 * * paragraph [0027] - paragraph [0051] * * example 1; tables 1-4 * -----	1-12	
A	US 2017/081594 A1 (SPICER DAVID B [US] ET AL) 23 March 2017 (2017-03-23) * figure 1 * * paragraph [0014] - paragraph [0031] * -----	1-12	

TECHNICAL FIELDS SEARCHED (IPC)

C10G
G05D

The present search report has been drawn up for all claims

Place of search	Date of completion of the search	Examiner
The Hague	26 March 2021	Bernet, Olivier

2

CATEGORY OF CITED DOCUMENTS

X : particularly relevant if taken alone
Y : particularly relevant if combined with another document of the same category
A : technological background
O : non-written disclosure
P : intermediate document

T : theory or principle underlying the invention
E : earlier patent document, but published on, or after the filing date
D : document cited in the application
L : document cited for other reasons

& : member of the same patent family, corresponding document

EPO FORM 1503 03.82 (P04C01)

ANNEX TO THE EUROPEAN SEARCH REPORT ON EUROPEAN PATENT APPLICATION NO. EP 20 02 0518

This annex lists the patent family members relating to the patent documents cited in the above-mentioned European search report. The members are as contained in the European Patent Office EDP file on
The European Patent Office is in no way liable for these particulars which are merely given for the purpose of information.

26-03-2021

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
US 2017101586 A1	13-04-2017	CN 106574191 A	19-04-2017
		EP 3149113 A1	05-04-2017
		JP 2017524041 A	24-08-2017
		US 2017101586 A1	13-04-2017
		WO 2015181638 A1	03-12-2015
WO 2018229621 A1	20-12-2018	EP 3638751 A1	22-04-2020
		US 2020096982 A1	26-03-2020
		WO 2018229621 A1	20-12-2018
US 2017081594 A1	23-03-2017	US 2017081594 A1	23-03-2017
		US 2019085249 A1	21-03-2019
		WO 2017052685 A1	30-03-2017

EPO FORM P0459

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

REFERENCES CITED IN THE DESCRIPTION

This list of references cited by the applicant is for the reader's convenience only. It does not form part of the European patent document. Even though great care has been taken in compiling the references, errors or omissions cannot be excluded and the EPO disclaims all liability in this regard.

Non-patent literature cited in the description

- Ullmann's Encyclopedia of Industrial Chemistry. 15 April 2009 **[0002]**
- **H.A.B. TE BRAAKE et al.** Semi-Physical Modeling of Chemical Processes with Neural Networks. *IFAC Proceedings,* June 1996, vol. 29 (1), 6119-6124 **[0007]**