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(71) Applicant: **UNIVERSITY OF IOWA RESEARCH FOUNDATION** [US/US]; 112 N. Capital Street, 6 Gilmore Hall, Iowa City, Iowa 52242 (US).

(72) Inventors: **JUST, Craig L.**; 310 Stanley Hydraulics Lab, 300 S. Riverside Drive, Iowa City, Iowa 52242 (US). **SCHROER, Hunter W.**; 310 Stanley Hydraulics Lab, 300 S. Riverside Drive, Iowa City, Iowa 52242 (US).

(74) Agent: **GREENBAUM, Michael C.**; Blank Rome LLP, 1825 Eye Street N.W., Washington, District of Columbia 20006 (US).

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(54) **Title:** MACHINE LEARNING-ENABLED OPTIMIZATION OF BIOGAS PRODUCTION

(57) **Abstract:** A biogas optimization system, including a machine learning model trained to identify features indicative of biogas production based on past biogas production and the composition and flow of past substrates provided to a digester. Using the machine learning model, the biogas optimization system predicts biogas production from a digester in view of the composition of substrates provided to the digester (determined, for example, using sensor data from diffuse reflectance detectors). Some embodiments also predict an optimal composition of the digester for optimizing biogas production (e.g., optimal percentages of lipids, protein, and/or carbohydrates) and adjust the flow and/or volume of a substrate to the digester. To predict the optimal composition of the digester, the machine learning model may also be trained on a physics-based model of the anaerobic digestion processes (e.g., Anaerobic Digestion Model No. 1 (ADM1)) and/or data captured during laboratory simulations of the anaerobic digestion processes.

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MACHINE LEARNING-ENABLED OPTIMIZATION OF BIOGAS PRODUCTION

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application claims priority to U.S. Prov. Pat. Appl. No. 63/471,684, filed June 7, 2023, which is hereby incorporated by reference in its entirety.

FEDERAL FUNDING

[0002] This invention was made with government support under contract number X1-97792601-0 awarded by the U.S. Environmental Protection Agency. The government has certain rights in the invention.

BACKGROUND

[0003] Anaerobic digestion can turn organic wastes that would otherwise be landfilled into valuable biogas that can be used onsite or upgraded into renewable natural gas. An estimated 20 percent of municipalities with wastewater treatment facilities, for instance, collect and "co-digest" industrial organic wastes to collect disposal fees, generate methane for heat and renewable energy, and meeting ambitious sustainability goals.

[0004] Despite the long-standing use of anaerobic digestion, the process still has practical difficulties due to the complexity of the heterogeneous microbial consortia and substrates involved. Existing systems and methods have difficulty accurately predicting the flow of biogas produced from anaerobic digestion, let alone identifying the flow and composition of substrates needed for optimal digester health and biogas production. Meanwhile, changes in the composition and/or loading rates of substrates can cause digester foaming, digester upsets, and even complete digester failure.

[0005] Accordingly, there is a desire to accurately predict the flow of biogas produced from anaerobic digestion of substrates and, in particular, to predict the composition of substrates needed for optimal digester health and biogas production.

SUMMARY

[0006] Disclosed is a biogas optimization system that includes a machine learning model trained to identify features indicative of biogas production based on past biogas production and the composition and flow of past substrates provided to a digester. Using the machine learning model, the biogas optimization system predicts biogas production from a digester in view of the composition of substrates provided to the digester (determined, for example, using sensor data from diffuse reflectance detectors). Embodiments of the biogas optimization system also predict an optimal composition of the digester for optimizing biogas production (e.g., optimal percentages of lipids, protein, and/or carbohydrates) and adjust the flow and/or volume of a substrate to the digester. To predict the optimal composition of the digester, the machine learning model may also be trained on a physics-based model of the anaerobic digestion processes (e.g., Anaerobic Digestion Model No. 1 (ADM1)) and/or data captured during laboratory simulations of the anaerobic digestion processes.

BRIEF DESCRIPTION OF THE DRAWINGS

[0007] Aspects of exemplary embodiments may be better understood with reference to the accompanying drawings. The components in the drawings are not necessarily to scale, emphasis instead being placed upon illustrating the principles of exemplary embodiments.

[0008] FIG. 1A is a diagram of an example environment for anaerobic digestion.

[0009] FIG. 1B is a diagram of an example environment of the disclosed system according to exemplary embodiments.

[0010] FIG. 2 is a block diagram of a biogas optimization system according to exemplary embodiments.

[0011] FIG. 3 is a block diagram of the biogas optimization system according to other exemplary embodiments.

[0012] FIG. 4 is a diagram of a laboratory simulation according to exemplary embodiments.

DETAILED DESCRIPTION

[0013] Reference to the drawings illustrating various views of exemplary embodiments is now made. In the drawings and the description of the drawings herein, certain terminology is used for convenience only and is not to be taken as limiting the embodiments of the present invention. Furthermore, in the drawings and the description below, like numerals indicate like elements throughout.

[0014] FIG. 1A is a diagram of an example facility 10 for anaerobic digestion. The example facility 10 is a wastewater treatment facility that includes a primary settling tank 20, activated sludge 25, a secondary settling tank 30, a thickening tank 40, a high-strength waste (HSW) tank 60, one or more digesters 80 having a temperature control device 84 (e.g., a heat exchanger), a burner 91, and a boiler 92. In the example facility 10, influent 110 (e.g., municipal wastewater) is provided to the primary settling tank 20 to form primary sludge (PS) 120 and thickened waste-activated sludge (TWAS) 140. The primary sludge 120 and thickened waste-activated sludge 140 are provided to the digester(s) 80 to form biogas 190 via anaerobic digestion.

[0015] In addition to the influent 110, the facility 10 may accept substrates that have historically been landfilled (e.g., fats, oils, and grease from local commercial sources, organic waste from food and feed processors, etc.) to instead "co-digest" them for energy recovery. Accordingly, in the example facility 10, high-strength waste 160 is also provided to the digester(s) 80. The example facility 10 also includes a supervisory control and data acquisition (SCADA) system 50 that collects supervisory data from various sensors 105, such as flow sensors 105f, liquid height sensors 105h, digester lid height monitors 105h, temperature sensors 105t, etc.

[0016] FIG. 1B is a diagram of an example facility 100 for exemplary embodiments of the disclosed biogas optimization system 200 (described below with reference to FIGS. 2-5). In the example facility 100, individual organic components (e.g., lipids 161, protein 162, and carbohydrates 163) are provided via pumps 171, 172, and 173 (generically and collectively referred to herein as pumps 170).

[0017] FIG. 2 is a block diagram of a biogas optimization system 200 according to exemplary embodiments. As shown in FIG. 2, the biogas optimization system 200 includes an optimization engine 260 and an automation system 280.

[0018] In anaerobic digestion, biogas production 190 is a function of digester health, which is function of the composition and flow of the substrates provided to the digester 80. Accordingly, the optimization engine 260 includes a machine learning model 270 (including, for example, a reinforcement learning model) trained to optimize biogas production 190 while avoiding digester foaming, digester upsets, and/or complete digester failure. To do so, the machine learning model 270 may be trained using supervisory data 250 indicative of past biogas production 190 and the flow of each substrate provided to the digester 80 as well as composition data 220 indicative of the composition of each substrate.

[0019] The supervisory data 250 may include, for example, time series data that includes the flow and/or volume of high-strength waste 160 provided to the digester 80, the height of the high-strength waste tank 60, the height of the digester 80 lid, the temperature of the digester 80, the flow and/or volume of biogas 190 provided to the burner 91 and/or boiler 92, etc. In the example facility 100 of FIG. 1B, for example, the supervisory data 250 may also include the flow and/or volume of thickened waste-activated sludge 140 provided to the digester 80, the flow and/or volume of primary sludge 120 provided to the digester 80, the flow of influent 110, etc.

[0020] The composition data 220 includes HSW composition data 226 indicative of the composition of the high-strength waste 160 and digester composition data 228 indicative of the composition of the digester 80. The HSW composition data 226 may include, for example, the percentage of volatile solids in the high-strength waste 160, the chemical oxygen demand of the high-strength waste 160, etc. The digester composition data 228 may include, for example, the pH of the digester 80, the alkalinity of the digester 80, the density of volatile fatty acids in the digester 80. In the example facility 100 of FIG. 1B, the composition data 220 may also include TWAS composition data 224 indicative of the composition of the thickened waste-activated sludge 140 (e.g., the percentage of volatile solids in the thickened waste-activated sludge 140), PS composition data 222 indicative of the composition of the primary sludge 120 (e.g., the percentage of volatile solids in the primary sludge 120), and/or influent composition data 221 indicative of the composition of the influent 110 (e.g., the biochemical oxygen demand of the influent 110).

[0021] The machine learning model 270 is trained on past biogas production 190 data, past composition data 220, and past supervisory data 250 to identify the features in the past composition data 220 and past supervisory data 250 that data that are predictive of biogas production 190 and predict the current biogas production 190 based on current composition data 220 and supervisory data 250. Additionally, the machine learning model 270 can be trained to generate predictions for optimizing biogas production 190 in view of the current composition data 220 and supervisory data 250, for example by increasing the volume and/or flow of individual components to the high-strength waste 160 (e.g., lipids 161, protein 162, and carbohydrates 163) and/or adjusting the temperature of the digester 80, and the automation system 280 can autonomously output instructions in view of those predictions to the pumps 170 and/or the temperature control device 84 of the digester 80.

[0022] Some or all of the composition data 220 may be determined based on laboratory analysis of samples taken of each substrate (e.g., the high-strength waste 160, the thickened waste-activated sludge 140, the primary sludge 120, etc.). Additionally, in some embodiments, the biogas optimization system 200 includes one or more hardware sensors for capturing composition data 220 in near real time.

[0023] FIG. 3 is a block diagram of a biogas optimization system 200 according to other exemplary embodiments. In the embodiment of FIG. 3, the biogas optimization system 200 includes a diffuse reflectance detector 326 for capturing some or all of the HSW composition data 226 and/or a diffuse reflectance detector 328 for capturing some or all of the digester composition data 228. The diffuse reflectance detectors 326 and 328 may determine, for example, the total solids, total suspended solids, total dissolved solids, volatile solids, biochemical oxygen demand, chemical oxygen demand, total organic carbon, acetic acid, volatile acids (e.g., C1-C6 fatty acids such as acetic, propionic, butyric), alkalinity, volatile fatty acids, potassium, phosphorus, etc. in the high-strength waste 160 and/or digester 80.

[0024] Because biogas production 190 is a function of digester health, the machine learning model 270 may be trained to optimize the health of the digester 80. To that end, the machine learning model 270 may be trained on a physics-based model 360 of the anaerobic digestion processes (e.g., Anaerobic Digestion Model No. 1 (ADM1)) and use the physics-based model 360 to generate predictions for optimizing digester health (e.g., by increasing the volume and/or flow lipids 161, protein 162, and/or carbohydrates 163 and/or adjusting the temperature of the digester 80).

[0025] The physics-based model 360 may be constructed, for example, as a digital twin of the facility controlled by the biogas optimization system 200 (e.g., the example facility 100 of FIG. 1B) that receives inputs indicative of the composition and flow of substrates provided to the digester 80 and outputs state variables indicative of digester health (e.g., soluble inerts, monosaccharides, amino acids, long chain fatty acids, total valerate, total butyrate, total propionate, total acetate, hydrogen gas, methane gas, particulate inerts, composites, carbohydrates 163, proteins 162, lipids 161, sugar degraders, amino acid degraders, long chain fatty acid degraders, valerate and butyrate degraders, propionate degraders, acetate degraders, hydrogen degraders, inorganic nitrogen, inorganic carbon, anions, cations, etc.). The machine learning model 270 may then use any combination of those state variables, for example, as the "reward" and/or "penalty" function(s) of a reinforcement learning model. The predictions made by the machine learning model 270 may be validated or supplemented using data indicative of past digester health (e.g., as indicated by past biogas production 190) and/or laboratory simulation data 460 (as described below with reference to FIG. 4).

[0026] Specifically, the machine learning model 270 may be trained to estimate the current composition of the digester 80, predict an optimal composition of the digester 80 (e.g., optimal percentages of lipids 161, protein 162, and carbohydrates 163) to optimize digester health and biogas production 190, and output instructions to the automation system 280 to control the flow and volume of components provided to the digester 80 (e.g., by controlling the pumps 170 as shown in FIG. 1B) to reduce the difference between the estimated composition of the digester 80 and the optimal composition of the digester 80 predicted by the machine learning model 270. Additionally, the machine learning model 270 may be trained to predict an optimal temperature of the digester 80 and output instructions to the automation system 280 to reduce any difference between the current temperature of the digester 80 (included, for example, in the supervisory data 250 as described above) and the optimal temperature predicted by the machine learning model 270.

[0027] In some embodiments, the biogas optimization system 200 may also include a toxicity sensor 380 (e.g., a biofilm resistor) that detects toxic elements that, if introduced into the digester 80, can cause a rapid system death. Accordingly, the toxicity sensor 380 may be used by the optimization engine 260 (or directly by the automation system 280) to stop the anerobic digestion process and avoid digester failure.

[0028] The machine learning model 270 is trained to optimize digester health as described above. By extension, the machine learning model 270 is trained to make predictions and output instructions that avoid digester foaming, digester upsets, and complete digester failures. Additionally, the optimization engine 260 may be configured to identify digester composition data 228 (e.g., from the diffuse reflectance detector 326 described above) indicative of digester foaming, digester upset, and/or complete digester failure in real time. The digester 80 may fail because of unbalanced microbiological conditions (e.g., caused by an increase in organic loading rate, feeding, or a drastic change in feedstock composition) that allows the acidogenic bacteria to exceed the growth rate of the methanogenic bacteria, lowering the pH of the digester 80. Accordingly, composition data 228 indicative of a digester upset may include, for example, a reduction in the methane concentration of the biogas 190, a decrease in the total alkalinity content of the digestate, an increase in the concentration of volatile fatty acids VFAs and/or the ratio between VFAs and alkalinity, etc. Additionally, composition data 228 indicative of digester foaming may include data indicative of upset a sudden, rapid increase in organic loading, which may be indicative of solids floating on the digester surface, trapping air, and leading to the collection of foam on the surface of the digester 80.

[0029] FIG. 4 is a diagram of a laboratory simulation 400 according to other exemplary embodiments.

[0030] In the example of FIG. 4, the laboratory simulation 400 includes lipids 161, protein 162, and carbohydrates 173 provided to a laboratory digester 480 via pumps 471, 472, and 473. A laboratory simulation data acquisition system 450 collects laboratory simulation data 460 indicative of biogas production 190 and/or the health of the laboratory digester 480 (e.g., the amount of acetate, glutamate, and glucose in the laboratory digester 480 as captured using a diffuse reflectance detector 320). That laboratory simulation data 460 can then be provided to the machine learning model 270 to train the model to generate predictions for optimizing digester health (e.g., by increasing the volume and/or flow of lipids 161, protein 162, and/or carbohydrates 163 as described above).

[0031] The features indicative of digester health and/or biogas production 190 may be identified, for example, using multiple ridge regression, a tree-based machine learning pipeline, and/or multilayer perception (as described, for example, in Schroer et al., "Feature Engineering and Supervised Machine Learning to Forecast Biogas Production during Municipal Anaerobic Co-Digestion", ACS EST Engg. 2024, 4, 660-672, which is hereby incorporated by reference).

[0032] While the biogas optimization system 200 is described above with reference to a wastewater treatment facility 100 that co-digests high-strength waste 160 with primary sludge 120 and thickened waste activated sludge 140, the same principals may be used by the biogas optimization system 200 to optimize and control any anerobic digestion process or facility (e.g., agricultural digester, an ethanol plant, etc.). While embodiments of the biogas optimization system 200 described above include an automation system 280 that autonomously controls the composition of the digester 80 (e.g., by controlling the volume and/or flow of components to the digester 80 and/or the temperature of the digester 80), in other embodiments the predictions made by the machine learning model 270 and/or the optimization recommendations output by the optimization engine 260 may, additionally or alternatively, be output to a human operator to manually control the environment 100 and improve digester health and biogas production 190.

[0033] For simplicity, the biogas optimization system 200 is described above as optimizing digester health and biogas production 190 by controlling the volume and flow of homogeneous components (lipids 161, protein 162, and/or carbohydrates 163). In other embodiments, however, the biogas optimization system 200 may be trained to predict the optimal volume and/or flow of any substrate having any composition of any number of components (determined, for example, using laboratory analysis of samples and/or sensor data as described above).

[0034] While preferred embodiments have been described above, those skilled in the art who have reviewed the present disclosure will readily appreciate that other embodiments can be realized within the scope of the invention. Accordingly, the present invention should be construed as limited only by any appended claims.

CLAIMS

What is claimed is:

1. A biogas optimization system for an anerobic digestion facility having at least one digester, the optimization system comprising:

non-transitory computer readable storage media that stores:

supervisory data indicative of the flow of substrates provided to the digester;

composition data indicative of the composition of substrates provided to the digester; and

data indicative of past biogas production; and

an optimization engine comprising a machine learning model, trained on past biogas production data, past composition data, and past supervisory data, to identify features that are predictive of past biogas production, the optimization engine configured to:

estimate, based on the supervisory data and the composition data, a current composition of the digester; and

predict biogas production based on the estimated composition of the digester.

2. The biogas optimization system of claim 1, further comprising:

a diffuse reflectance detector that outputs data indicative of the current composition of the digester.

3. The biogas optimization system of claim 1, wherein the optimization engine configured to:

predict an optimal composition of the digester for optimizing biogas production.

4. The biogas optimization system of claim 3, wherein the optimal composition of the digester predicted by the optimization engine comprises optimal percentages of lipids, protein, and/or carbohydrates.

5. The biogas optimization system of claim 3, wherein the optimization engine configured to:

identify a composition of at least one substrate; and reduce a difference between the estimated current composition of the digester and the predicted optimal composition of the digester by outputting instructions to adjust a flow and/or volume of the at least one substrate to the digester.

6. The biogas optimization system of claim 5, wherein the composition of the at least one substrate comprises a percentage of lipids, a percentage of protein, and/or a percentage of carbohydrates.

7. The biogas optimization system of claim 5, further comprising:

a diffuse reflectance detector that outputs data indicative of the composition of the at least one substrate.

8. The biogas optimization system of claim 5, further comprising:

an automation system that autonomously adjusts the flow and/or volume of the at least one substrate to the digester in response to the instructions output by the optimization engine.

9. The biogas optimization system of claim 3, wherein the machine learning model is trained to predict the optimal composition of the digester based on data captured during laboratory simulations of the anaerobic digestion processes.

10. The biogas optimization system of claim 3, wherein the machine learning model is trained to predict the optimal composition of the digester based on a physics-based model of the anaerobic digestion processes.

11. A method of optimizing biogas production at an anerobic digestion facility having at least one digester, the method comprising:

training a machine learning model on data indicative of past biogas production, flows and/or volumes of past substrates provided to the digester, and compositions of the past substrates provided to the digester;

identifying, by the machine learning model, features predictive of past biogas production;

receiving data indicative of flows and/or volumes of one or more substrates provided to the digester;

receiving data indicative of compositions of the one or more substrates provided to the digester;

estimating a current composition of the digester; and

predicting biogas production based on the estimated composition of the digester.

12. The method claim 11, further comprising:

receiving sensor data, from a diffuse reflectance detector, indicative of the current composition of the digester,

wherein the current composition of the digester is estimated at least in part based on the received sensor data.

13. The method claim 11, further comprising:

predicting, by the machine learning model, an optimal composition of the digester for optimizing biogas production.

14. The method claim 13, wherein predicting the optimal composition of the digester comprises predicting an optimal percentage of lipids, protein, and/or carbohydrates.

15. The method claim 13, further comprising:

identify a composition of at least one substrate; and

outputting instructions to adjust a flow and/or volume of the at least one substrate to the digester to reduce a difference between the estimated current composition of the digester and the predicted optimal composition of the digester.

16. The method claim 15, wherein identifying the composition of the at least one substrate comprises identifying a percentage of lipids, protein, and/or carbohydrates.

17. The method claim 15, wherein estimating the composition of the at least one substrate comprises receiving sensor data, from a diffuse reflectance detector, indicative of the composition of the at least one substrate.

18. The method claim 15, further comprising:

autonomously adjusting the flow and/or volume of the at least one substrate to the digester, by an automation system, in response to the instructions.

19. The method claim 13, further comprising:

training the machine learning model on data captured during laboratory simulations of the anaerobic digestion processes to predict the optimal composition of the digester.

20. The method claim 13, further comprising:

training the machine learning model on a physics-based model of the anaerobic digestion processes to predict the optimal composition of the digester.

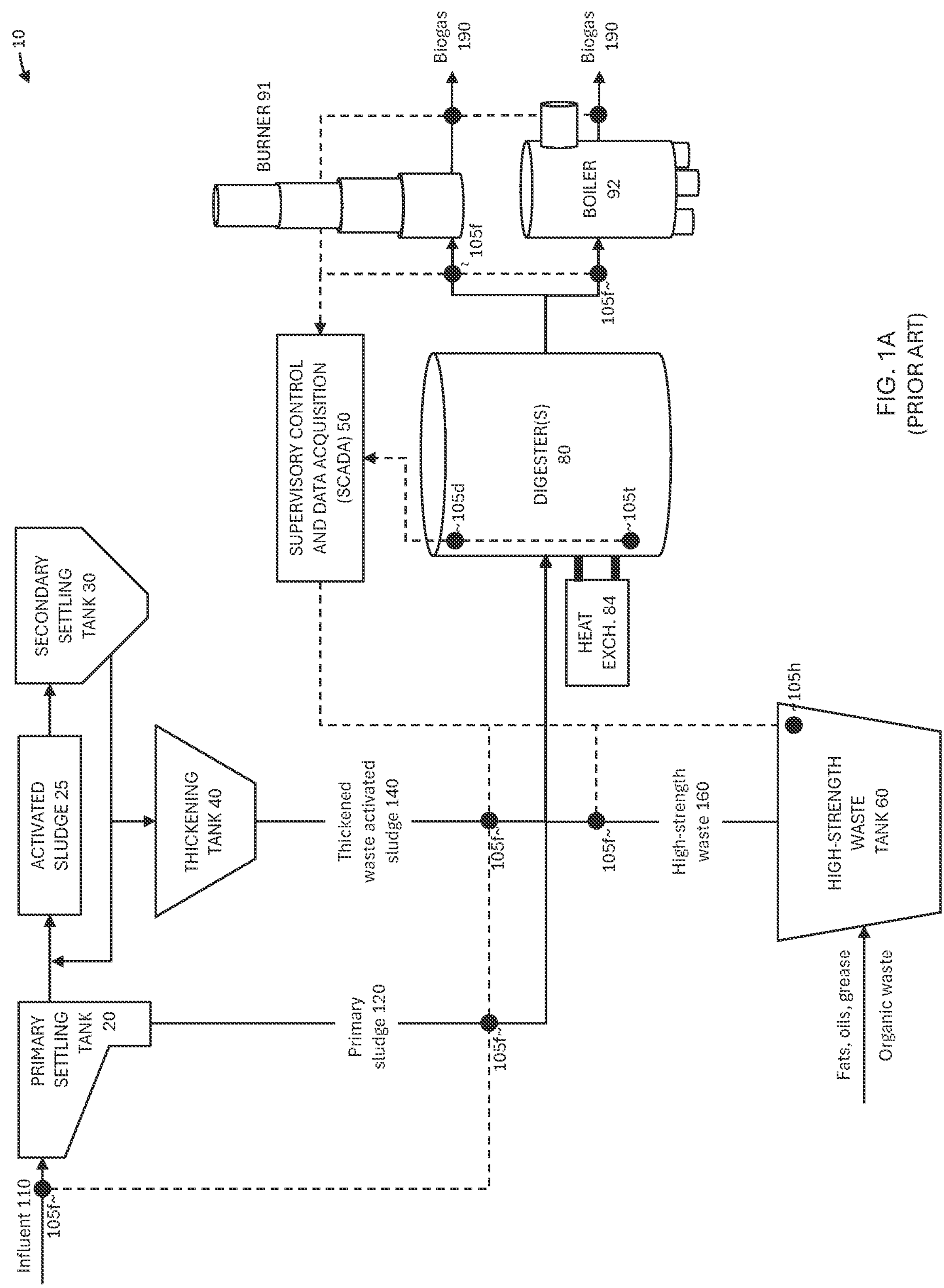

FIG. 1A
(PRIOR ART)

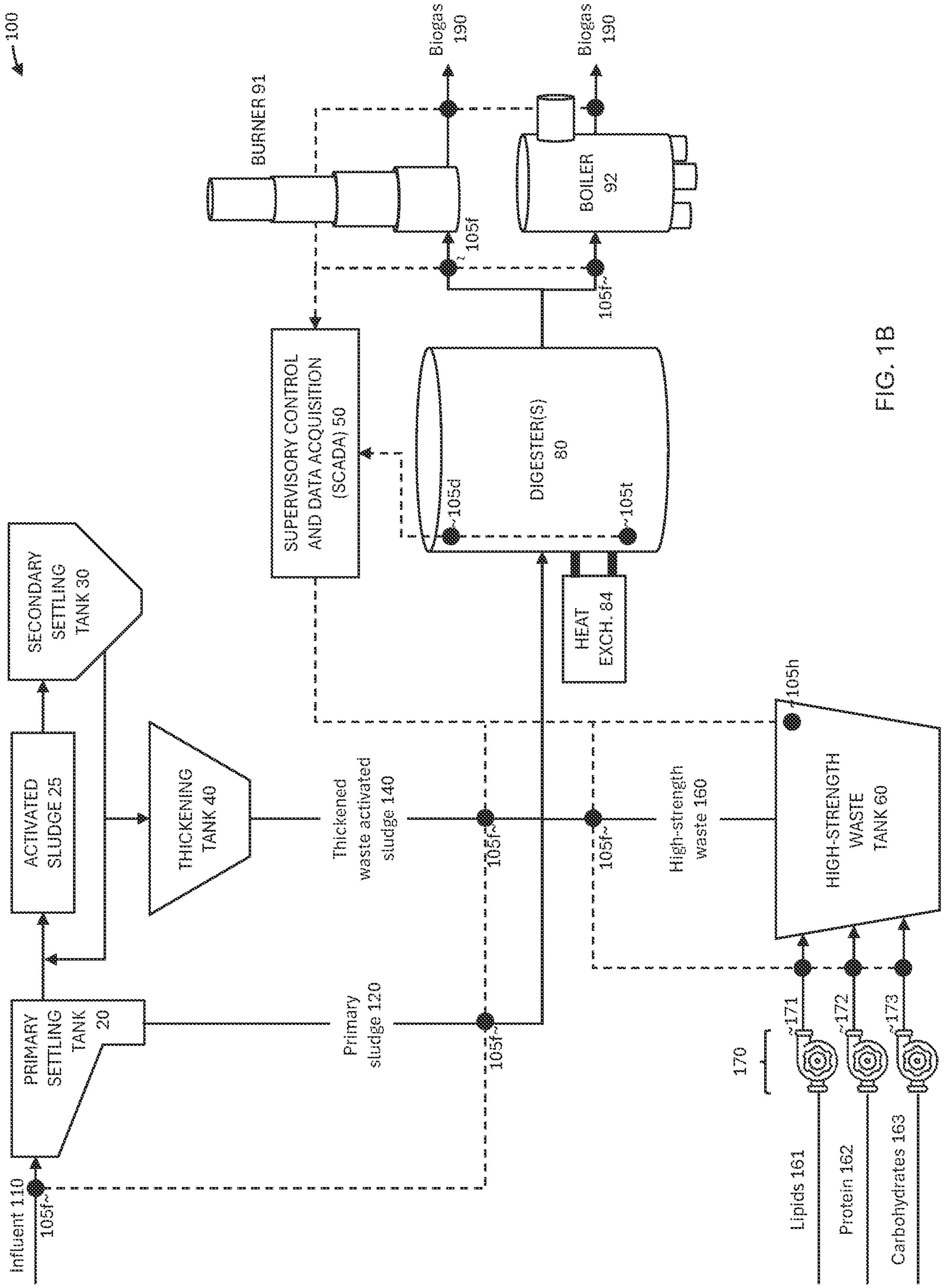
100
Influent 110
105f
PRIMARY SETTLING TANK 20
ACTIVATED SLUDGE 25
SECONDARY SETTLING TANK 30
THICKENING TANK 40
Primary sludge 120
Thickened waste activated sludge 140
High-strength waste 160
HIGH-STRENGTH WASTE TANK 60
105h
SUPERVISORY CONTROL AND DATA ACQUISITION (SCADA) 50
DIGESTER(S) 80
105d
105t
HEAT EXCH. 84
BURNER 91
BOILER 92
Biogas 190
170
171
172
173
Lipids 161
Protein 162
Carbohydrates 163

FIG. 1B

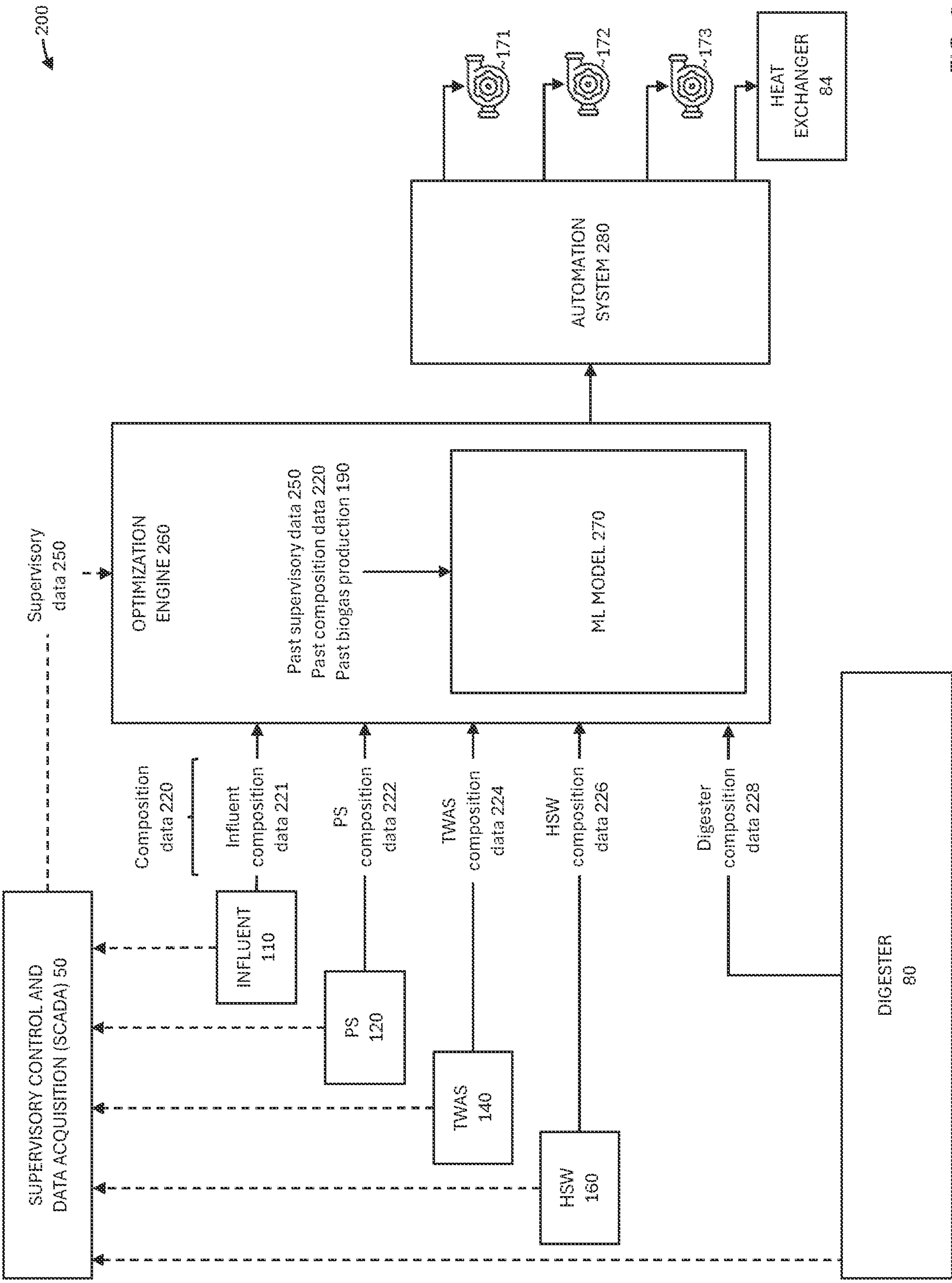
200
SUPERVISORY CONTROL AND DATA ACQUISITION (SCADA) 50
INFLUENT 110
PS 120
TWAS 140
HSW 160
DIGESTER 80
Supervisory data 250
Composition data 220
Influent composition data 221
PS composition data 222
TWAS composition data 224
HSW composition data 226
Digester composition data 228
OPTIMIZATION ENGINE 260
Past supervisory data 250
Past composition data 220
Past biogas production 190
ML MODEL 270
AUTOMATION SYSTEM 280
171
172
173
HEAT EXCHANGER 84

FIG. 2

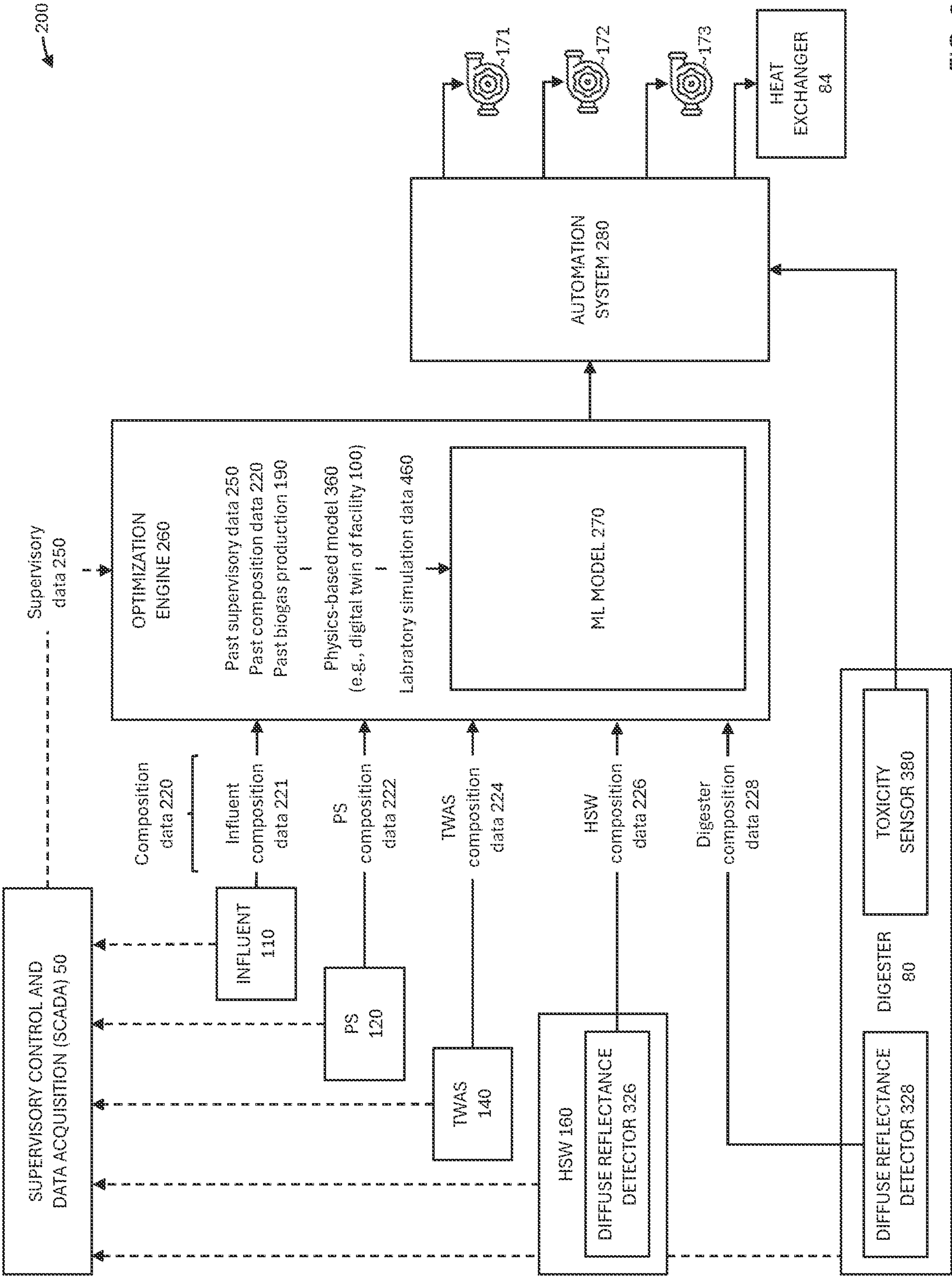
200
SUPERVISORY CONTROL AND DATA ACQUISITION (SCADA) 50
Supervisory data 250
INFLUENT 110
PS 120
TWAS 140
HSW 160
DIFFUSE REFLECTANCE DETECTOR 326
DIGESTER 80
DIFFUSE REFLECTANCE DETECTOR 328
TOXICITY SENSOR 380
Composition data 220
Influent composition data 221
PS composition data 222
TWAS composition data 224
HSW composition data 226
Digester composition data 228
OPTIMIZATION ENGINE 260
Past supervisory data 250
Past composition data 220
Past biogas production 190
Physics-based model 360
(e.g., digital twin of facility 100)
Laboratory simulation data 460
ML MODEL 270
AUTOMATION SYSTEM 280
171
172
173
HEAT EXCHANGER 84

FIG. 3

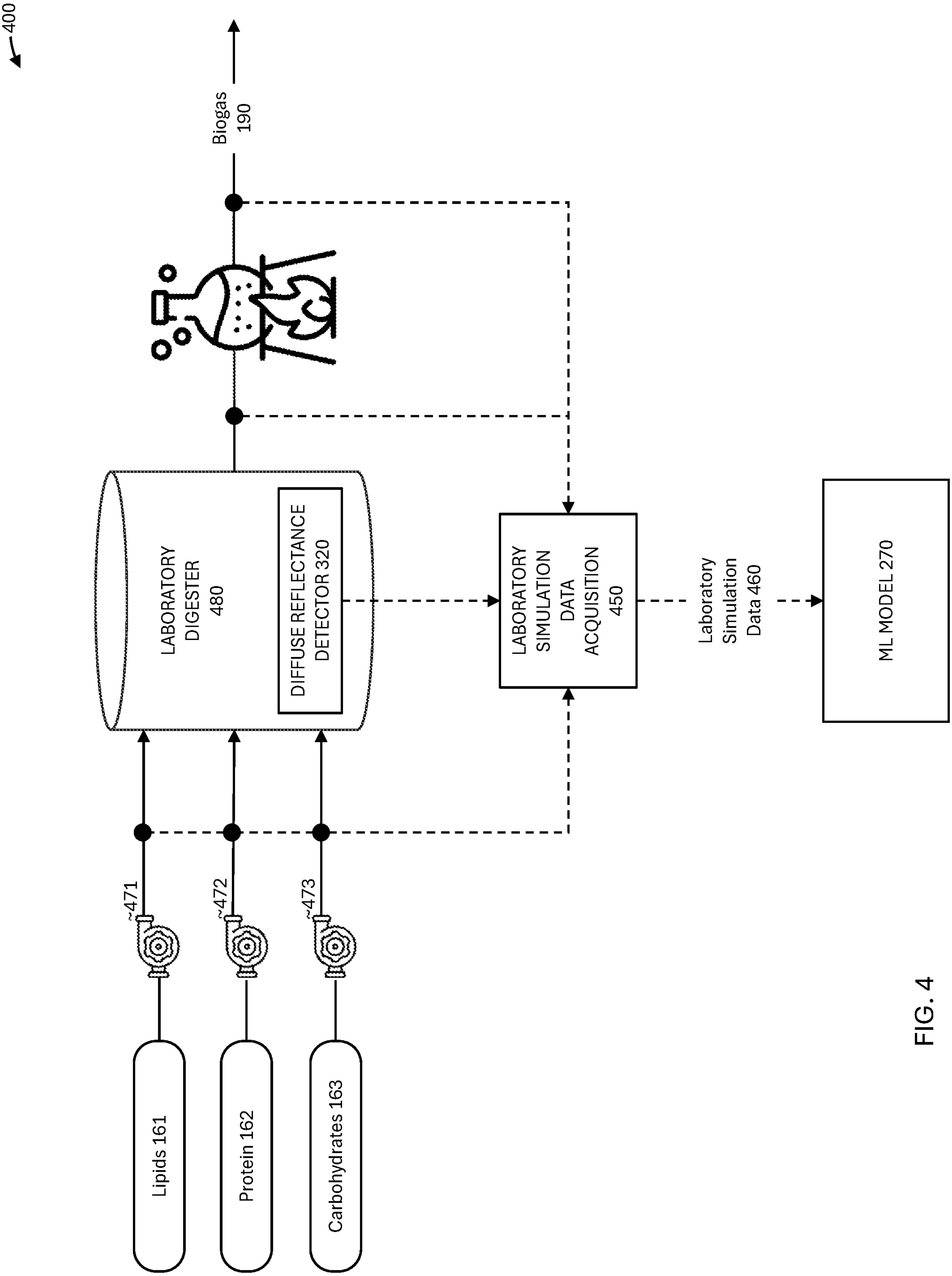
400
Biogas 190
LABORATORY DIGESTER 480
DIFFUSE REFLECTANCE DETECTOR 320
LABORATORY SIMULATION DATA ACQUISITION 450
Laboratory Simulation Data 460
ML MODEL 270
~471
~472
~473
Lipids 161
Protein 162
Carbohydrates 163

FIG. 4