

CLAIMS

What is claimed is:

1. A heat exchanger system comprising:
a cooling system comprising:
a heat generating apparatus configured to transfer heat to a process fluid;
a heat rejection apparatus configured to remove heat from the process fluid;
a sensor configured to detect a variable of the cooling system; and
processor circuitry operably coupled to the sensor and configured to provide the variable and a plurality of potential operating parameters of the cooling system to a machine learning model representative of the cooling system to estimate at least one of energy consumption, water usage, and chemical usage of the cooling system for the potential operating parameters;
the processor circuitry configured to determine, based at least in part on the estimated at least one of energy consumption, water usage, and chemical consumption for the potential operating parameters, an optimal operating parameter of the cooling system to satisfy a target optimization criterion; and
the processor circuitry configured to cause the cooling system to utilize the optimal operating parameter.
2. The heat exchanger system of claim 1 wherein the target optimization criterion is minimizing energy consumption, minimizing water usage, minimizing chemical consumption, or minimizing cost.
3. The heat exchanger system of claim 1 wherein the heat rejection apparatus includes at least one cooling tower.
4. The heat exchanger system of claim 1 wherein the optimal operating parameter includes at least one of an operating mode of the heat rejection apparatus, a temperature of the process fluid leaving the heat rejection apparatus, a pressure of the process fluid leaving the heat rejection apparatus, and a flow rate of the process fluid.

5. The heat exchanger system of claim 1 wherein the processor circuitry is configured to provide the plurality of potential operating parameters of the cooling system to the machine learning model to estimate energy consumption and water usage based on the potential operating parameters; and

the processor circuitry is configured to determine, based at least in part on the estimated energy consumption and water usage, the optimal operating parameter of the cooling system to satisfy the target optimization criterion.

6. The heat exchanger system of claim 5 wherein the plurality of potential operating parameters includes a first plurality of potential operating parameters and a second plurality of potential operating parameters;

wherein the machine learning model includes a first machine learning model to estimate energy consumption of the cooling system and a second machine learning model to estimate water usage; and

wherein the processor circuitry is configured to provide the first plurality of potential operating parameters to the first machine learning model to estimate energy consumption of the cooling system and provide the second plurality of potential operating parameters to the second machine learning model to estimate water usage of the cooling system.

7. The heat exchanger system of claim 1 wherein the processor circuitry is configured to provide the plurality of potential operating parameters of the cooling system to the machine learning model to estimate chemical consumption based on the potential operating parameters; and

the processor circuitry is configured to determine, based at least in part on the chemical consumption, the optimal operating parameter of the cooling system to satisfy the target optimization criterion.

8. The heat exchanger system of claim 1 wherein the processor circuitry is configured to estimate a future operating condition;

wherein the processor circuitry is configured to provide a plurality of future potential operating parameters of the cooling system associated with the future operating condition to the machine learning model to estimate at least one of future energy consumption, future water usage, and future chemical consumption, based on the future potential operating parameters;

the processor circuitry is further configured to determine the optimal operating parameter of the cooling system to satisfy the target optimization criterion based on at least one of:

- energy consumption;
- water usage;
- chemical consumption;
- future energy consumption;
- future water usage; and
- future chemical consumption.

9. The heat exchanger system of claim 1 wherein the plurality of potential operating parameters provided to the machine learning algorithm include a range of operating parameters within operating constraints of the cooling system.

10. The heat exchanger system of claim 1 wherein the plurality of potential operating parameters include at least one of a fan speed operating parameter and a water usage operating parameter of the heat rejection apparatus.

11. The heat exchanger system of claim 1 wherein the sensor includes a plurality of sensors configured to detect a plurality of variables including:

- a water usage variable of the cooling system;
- an energy consumption variable of the cooling system; and
- at least one of a leaving process fluid temperature variable of the heat rejection apparatus and a leaving process fluid pressure variable of the heat rejection apparatus.

12. The heat exchanger system of claim 1 wherein the sensor includes sensors configured to detect a variable of a process fluid leaving the heat rejection apparatus and a variable of an environment of the cooling system.

13. The heat exchanger system of claim 1 wherein the processor is configured to identify a malfunction of the cooling system, the processor configured to determine the plurality of potential operating parameters to provide to the at least one machine learning model representative based at least in part on the identified malfunction.

14. The heat exchanger system of claim 1 wherein the heat rejection apparatus includes a plurality of cooling towers, wherein at least one of the cooling towers is operable in a dry mode and at least one of the cooling towers is operable in a wet mode or an adiabatic mode.

15. The heat exchanger system of claim 1 wherein the heat rejection apparatus includes a plurality of cooling towers; and
wherein the target operating parameter includes a parameter indicative of whether the cooling towers operate in a series or parallel configuration.

16. The heat exchanger system of claim 1 wherein the heat rejection apparatus includes a thermal energy storage system; and
wherein the target operating parameter includes a parameter indicating whether the thermal energy storage system is charging thermal energy or discharging thermal energy.

17. A heat rejection apparatus for a cooling system, the heat rejection apparatus comprising:
a cooling tower comprising an evaporative heat exchanger operable to cool process fluid;
a sensor configured to detect a variable of the cooling tower;

a controller operably coupled to the cooling tower and the sensor, the controller configured to implement an optimal operating parameter for the cooling tower to satisfy a target optimization criterion;

the optimal operating parameter being determined at least in part by providing the variable and a plurality of potential operating parameters of the cooling tower to a machine learning model representative of the cooling tower to estimate power consumption and water usage for the potential operating parameters.

18. The heat rejection apparatus of claim 17 wherein the sensor variable of the cooling tower includes a variable of process fluid leaving the cooling tower; and

wherein the optimal operating parameter causes the cooling tower to operate such that the variable of the process fluid leaving the cooling tower corresponds to an optimal variable of the process fluid.

19. The heat rejection apparatus of claim 17 wherein the target optimization criterion is minimizing energy consumption, minimizing water usage, or minimizing cost.

20. The heat rejection apparatus of claim 17 wherein the optimal operating parameter includes at least one of an operating mode of the cooling tower, a temperature of the process fluid leaving the cooling tower, a pressure of the process fluid leaving the cooling tower, and a flow rate of the process fluid.

21. The heat rejection apparatus of claim 17 wherein the controller is configured to provide the variable and the plurality of potential operating parameters of the cooling tower to the machine learning model to estimate the energy consumption and water usage; and

wherein the controller is configured to determine, based at least in part on the estimated energy consumption and the water usage, the optimal operating parameter of the cooling system to satisfy the target optimization criterion.

22. The heat rejection apparatus of claim 21 wherein the controller is configured to implement a first target optimization criterion and implement a different, second target optimization criterion in response to a predetermined event.

23. The heat rejection apparatus of claim 21 wherein the controller is configured to estimate a future operating condition;

wherein the controller is configured to provide a plurality of future potential operating parameters of the cooling tower associated with the future operating condition to the machine learning model to estimate future energy consumption and future water usage based on the future potential operating parameters of the cooling tower;

wherein the controller is configured to determine the optimal operating parameter of the cooling tower to satisfy the target optimization criterion based on at least one of:

energy consumption;

water usage;

future energy consumption; and

future water usage.

24. The heat rejection apparatus of claim 21 wherein the plurality of potential operating parameters includes a first plurality of potential operating parameters and a second plurality of potential operating parameters;

wherein the machine learning model includes a first machine learning model to estimate energy consumption of the cooling tower and a second machine learning model to estimate water usage; and

wherein the processor circuitry is configured to provide the first plurality of potential operating parameters to the first machine learning model to estimate energy consumption of the cooling tower and provide the second plurality of potential operating parameters to the second machine learning model to estimate water usage of the cooling tower.

25. The heat rejection apparatus of claim 17 wherein the plurality of potential operating parameters provided to the machine learning algorithm include a range of operating parameters within operating constraints of the cooling tower.

26. The heat rejection apparatus of claim 17 wherein the plurality of potential operating parameters include fan speed and a water usage variable of the cooling tower.

27. The heat rejection apparatus of claim 17 wherein the sensor includes a plurality of sensors configured to detect variables including:

a water usage variable of the cooling tower;

an energy consumption variable of the cooling tower; and

at least one of a leaving process fluid temperature variable and a leaving process fluid pressure variable of the cooling tower; and

wherein the controller is configured to provide the variables and the plurality of potential operating parameters of the cooling tower to the machine learning model to estimate energy consumption and water usage.

28. The heat rejection apparatus of claim 17 wherein the evaporative heat exchanger includes an indirect heat exchanger configured to receive the process fluid and an evaporative liquid distribution system configured to distribute evaporative liquid onto the indirect heat exchanger.

29. The heat rejection apparatus of claim 17 wherein the controller is configured to identify a malfunction in the cooling tower, the plurality of potential operating parameters of the cooling tower determined based at least in part on the identified malfunction.

30. The heat rejection apparatus of claim 17 wherein the optimal operating parameter is determined at least in part by providing the variable and the plurality of potential operating parameters of the cooling tower to the machine learning model representative of the

cooling tower to estimate power consumption, water usage, and chemical consumption for the potential operating parameters.

31. A method for operating a cooling system, the method comprising:
at a processor associated with a cooling system:
receiving a variable of the cooling system detected by a sensor of the cooling system;
providing the variable and a plurality of potential operating parameters of the cooling system to the machine learning model representative of the cooling system to estimate at least one of energy consumption, water usage, and chemical usage of the cooling system for the potential operating parameters;
determining, based at least in part on the estimated at least one of energy consumption, water usage, and chemical usage for the potential operating parameters, an optimal operating parameter of the cooling system to satisfy a target optimization criterion;
and
effecting utilization of the optimal operating parameter by the cooling system.
32. The method of claim 31 wherein effecting utilization of the optimal operating parameter by the cooling system includes communication circuitry operably coupled to the processor communicating the optimal operating parameter to the cooling system via a network.
33. The method of claim 31 wherein the cooling system includes a cooling tower;
and
wherein the optimal operating parameter includes a plurality of optimal operating parameters of the cooling tower.
34. The method of claim 31 wherein the target optimization criterion is minimizing energy consumption, minimizing water usage, minimizing chemical consumption, or minimizing cost.

35. The method of claim 31 wherein the optimal operating parameter includes at least one of an operating mode of a heat rejection apparatus of the cooling system, a temperature of process fluid leaving a heat rejection apparatus of the cooling tower, a pressure of the process fluid leaving the heat rejection apparatus, and a flow rate of the process fluid.

36. The method of claim 31 wherein providing the plurality potential operating parameters of the cooling system to the machine learning model includes providing the plurality of potential operating parameters to the machine learning model to estimate energy consumption and water usage based on the potential operating parameters;

wherein determining the optimal operating parameter to satisfy the target optimization criterion includes determining the optimal operating parameter based at least in part on the estimated energy consumption and the target optimization criterion.

37. The method of claim 31 wherein providing the plurality of potential operating parameters of the cooling system to the machine learning model includes providing the plurality of potential operating parameters to the machine learning model to estimate chemical usage based on the potential operating parameters;

wherein determining the optimal operating parameter to satisfy the target optimization criterion includes determining the optimal operating parameter based at least in part on the estimated chemical consumption.

38. The method of claim 31 wherein the plurality of potential operating parameters includes a first plurality of potential operating parameters and a second plurality of potential operating parameters;

wherein the machine learning model includes a first machine learning model to estimate energy consumption of the cooling system and a second machine learning model to estimate water usage; and

wherein providing the variable and the plurality of potential operating parameters to the machine learning model includes providing the first plurality of potential operating parameters to the first machine learning model to estimate energy consumption of the cooling system and

providing the second plurality of potential operating parameters to the second machine learning model to estimate water usage of the cooling system.

39. The method of claim 31 wherein the plurality of potential operating parameters include at least one of a fan speed operating parameter and a water usage operating parameter of a heat rejection apparatus of the cooling system.

40. The method of claim 31 wherein receiving the variable of the cooling system detected by the sensor of the cooling system includes receiving variables detected by sensors of the cooling system, the variables including:

a water usage variable of the cooling system;

an energy consumption variable of the cooling system; and

at least one of a leaving process fluid temperature variable of a heat rejection apparatus of the cooling system and a leaving process fluid pressure variable of the heat rejection apparatus.

41. The method of claim 31 further comprising:

at the processor associated with the cooling system:

estimating a future operating condition;

providing a plurality of future potential operating parameters of the cooling system associated with the future operating condition to the machine learning model to estimate at least one of future energy consumption, future water usage, and future chemical consumption; and

determining the optimal operating parameter of the cooling system to satisfy the target optimization criterion based on at least one of:

energy consumption;

water usage;

chemical consumption

future energy consumption;

future water usage; and

future chemical consumption.

42. The method of claim 31 further comprising changing the target optimization criterion in response to a predetermined event.

43. The method of claim 31 wherein the plurality of potential operating parameters of the cooling system are determined based at least in part on a detected malfunction in the cooling system.