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Machine learning solutions for maintenance of power plants

Master's Thesis

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Abstract

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The primary goal of this work is to present analysis of current market for predictive maintenance software solutions applicable to a generic coal/gas-fired thermal power plant, as well as to present a brief discussion on the related developments of the near future. This type of solutions is in essence an advanced condition monitoring technique, that is used to continuously monitor entire plants and detect sensor reading deviations via correlative calculations. This approach allows for malfunction forecasting well in advance to a malfunction itself and any possible unforeseen consequences.

Predictive maintenance software solutions employ primitive artificial intelligence in the form of machine learning (ML) algorithms to provide early detection of signal deviation. Before analyzing existing ML based solutions, structure and theory behind the processes of coal/gas driven power plants is going to be discussed to emphasize the necessity of predictive maintenance for optimal and reliable operation. Subjects to be discussed are: basic theory (thermodynamics and electrodynamics), primary machinery types, automation systems and data transmission, typical faults and condition monitoring techniques that are also often used in tandem with ML. Additionally, the basic theory on the main machine learning techniques related to malfunction prediction is going to be briefly presented.

Keywords: predictive maintenance, machine learning, power plant processes.	Publishing language: English

Contents

Abbreviations

AI – Artificial Intelligence

ANN – Artificial Neural Network

API – Application Programming Interface

CCGT – Combined Cycle Gas Turbine

CFB – Circulating Fluidized Bed

CHP – Combined Heat and Power

CM – Condition Monitoring

CPU – Central Processing Unit

DH – District Heating

EMF – ElectroMotive Force

GT – Gas Turbine

I/O – Input/Output

IoT – Internet of Things

IP – Intermediate Pressure

HP – High Pressure

LP – Low Pressure

LV – Low Voltage

ML – Machine Learning

MV – Medium Voltage

PD – Partial Discharge

PLC – Programmable Logic Controller

PM – Predictive Maintenance

PP – Power Plant

PWM - Pulse Width Modulation

rpm – revolutions per minute

RTU – Remote Terminal Unit

TG – Turbo-Generator

UI – User Interface

VFD - Variable Frequency Drive

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1. Introduction

Electricity generation across the world grows every year, thus increasing already significant numbers even beyond. This is imposed by various activities in human societies especially in the rapidly developing countries – e.g. China or India in recent years. (Table 2, Appendix). [1]

As for the reasons behind that: generation rates are intertwined with the consumption rates and are mostly industrial manufacturing-driven, i.e. the more production takes place in a country, the higher the required electricity supply. Next in magnitude is the residential sector, i.e. the more population there is to use basic home appliances, street lighting and district heating, the higher the total consumption. (e.g. Chinese consumption rates for different sectors, fig. 51, Appendix). [2]

Obviously, immense numbers of terawatt-hours of electricity required by countless consumers are supposed to have sources. And, indeed, various methods to convert energy into versatile electricity have been discovered over the history of mankind - from harnessing the kinetic energy of motion with a generator to converting the energy of sunlight with solar panels. These methods in turn have evolved into different PP types employed to generate electricity on the commercial level. The plant types have the main structural differences mostly dependent on the type of energy source used: fossil (gas/coal), nuclear fuel, wind etc. [3,4]

Nevertheless, disregarding the type, these plants have one quality in common - nearly unfathomable level of sophistication. Countless elements are intertwined into a complex interdependent combination: heavy rotating machinery, multilevel monitoring and controlling electronics unified with computer networks, high pressure and high temperature withstanding routings and mechanisms. Sophisticated appliances might fail under constant heavy load due to various reasons, be it a manufacturing imperfection of even a single important element in the system, loads exceeded over nominal values or just plain pre-estimated wear, not to mention the human factor (poor maintenance or operation). Independently of the cause, final consequence is always the same – critical malfunction of a device, rendering it inoperable. Additionally, apart from a single breakdown the malfunctioning device may cause an outage of a branch of a system or an entire system (thus upsetting the stability of local electrical network), make the working environment hazardous for the operating personnel, incur heavy financial losses for the operating company or even lead to catastrophic events, if the PP in question is nuclear. [5]

Existence of various techniques makes it possible to prevent any of these consequences by addressing the core cause – the original malfunction itself. All such techniques are a part of an important subject of CM, role of which became prominent for the majority of energy companies since the beginning of 1990. CM can be divided into two major parts: offline – a machine is shut down for a scheduled thorough inspection or repair to be conducted, and online – a machine is running normally while being monitored. Further on, online methods are currently comprised of different techniques of monitoring each machine or part of a PP system with a myriad of various sensors dotting every important device. This sensor-based monitoring became incredibly reliable and irreplaceable with the advancement in technological development – the further the advancement, the more compact, accurate and cheap sensors become and thus the more ways to easily monitor a machine with a constant access to its exact current status without the need to shut it down or run the checks manually with an external apparatus. Furthermore, advancement of computer technologies also brought the possibility of synergy between computers and various sensor data that has never been available before, e.g. computers equipped with ML based software are able not only to monitor the current state of different parts of a system and alarm when something is wrong, but also can predict failures long before they happen by detecting early systematic deviations from normal measurement values. [6]

The main focus for this thesis is going to be the subjects of a generic thermal power plant (coal/gas-fired only, excluding nuclear PPs) processes and suitable predictive maintenance ML based software solutions. More precisely: basics of PP processes and their structure is going to be presented in the beginning to demonstrate the necessity and reasoning for CM and it is going to be followed by a brief discussion on the CM techniques (also often used in conjunction with ML methods) themselves, monitoring and control systems, as well as on the basics of ML. Next, a research is going to be conducted into the current state of the PM software market (on the global scale) with comparison and estimation of the trends for future developments. Solutions to be studied mostly belong to the "energy applications" group (i.e. designed for use on PPs), but some solutions are designed for industrial use (application on various factories). Nevertheless, they still are going to be analyzed and listed, for the technology applied is similar as is the functionality.

2. Thermodynamic processes.

Figure 1 Damavand CCGT plant, 3000MW, Iran [7]

As it has already been mentioned, an electricity generating plant in essence is a very sophisticated system with numerous interconnected multilevel main, supporting, failsafe and monitoring subsystems. Main purpose of such system is simple – to provide electricity to supply various industries as well as ordinary members of society, which often means that hundreds of MW need to be generated by each plant (far beyond 1000MW when needed in a heavily loaded part of an electrical network, fig. 1).

The core idea in any PP around the world is to transform one form of energy that humanity can't use directly, e.g. fuel combustion, sunlight or nuclear fission, into the other: harvestable, easily transportable, transformable and applicable for endless variety of needs, i.e. electricity. Although, the idea sounds rather simple, it is the various details and nuances in the actual implementation that make it complex in the end. For path from initial fuel to the final product - electricity, is a long one, with many obstacles present (i.e. various transitions). The main challenge in the design of a PP is that high power output requires bulky machines, dozen meters tall reservoirs (e.g. boiler), thick couplings and pipes to conduct the process of fuel transformation into electricity. Moreover, the process includes many stages (and sometimes also additional reheat cycles) and often more than one working fluid, as well as plethora of different machines working in tandem - this is overlooking various supporting and auxiliary systems and the economical side in general, since obviously enormous investments are involved in a venture of such scale. [8, 9]

The input in a thermal PP (in this thesis by "thermal PP" term is going to be meant coal-fired, GT and CCGT, thus excluding the nuclear normally also meant by the term) is the related fuel, that is delivered, fed and combusted in the suitable reservoir. The base process employed on a coal-fired plant is following: the energy freed in the combustion is then used to transform water (working fluid) into high pressure vapor that in turn expands in the turbine that makes it rotate. Turbine rotation is exactly the useful work that is being harnessed, since it is built on the same shaft as TG rotor, i.e. the direct connection to the generator makes rotation of the turbine generate electricity in the end. In case with a GT, the process normally revolves around gas (e.g. air) as a working fluid – after the combustion, the resultant high pressure and temperature flue gas expands in the turbine immediately after combustion chamber.

The exhaust gas after a GT is still hot enough to be useful, hence often used further to perform the same process of heating water into the state of superheated vapor as described earlier. (fig. 2) This type of PPs is called CCGT, the name comes from the fact that the plant combines two cycles in its operation enhancing overall efficiency up to approximately 60% from 40% of a simple coal-powered plant. [9]

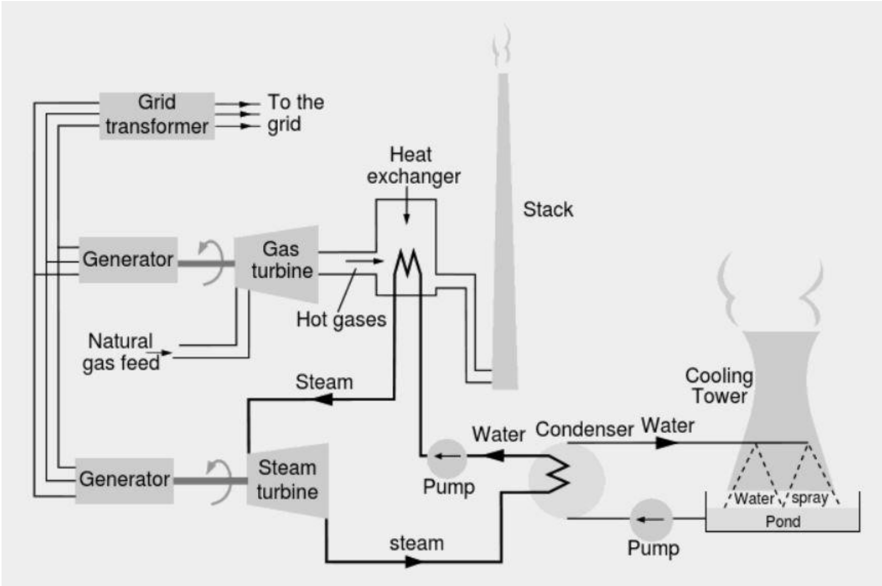

Figure 2 Simplified schematic of the process on a CCGT plant [9]

The following parts are going to delve deeper into the entire process from combustion to generation of electricity, with basic theory behind it explained. Main nodes of both thermodynamic (i.e. aforementioned cycles) and electrodynamic parts of the process are going to be described.

2.1. Enthalpy

The state parameters for working fluid in the system of a PP are easily determined with utilization of a rather simple thermodynamic concept: enthalpy.
By definition, enthalpy is a heat function depending on the state of a system (e.g. working fluid):

$$H = U + pV \qquad (1)$$

Where H is enthalpy, U is internal energy, p is pressure and V is volume.

This equation is best explained with an example system of a gas-filled cylinder with a piston. (fig. 3) Let us assume that gas within the cylinder is at pressure p and that the piston with an area A moves within the cylinder without friction.
If the system is considered with the piston affected by a force $F = pA$ that counterbalances the internal pressure of the gas, then the system can be considered “expanded”. Enthalpy of such system then would be equal to the sum of the gas internal energy U (energy contained within a system in the current state, i.e. at current temperature) and potential energy of the piston $E_{pot} = Fx = pAx = pV$ where x is the distance to the

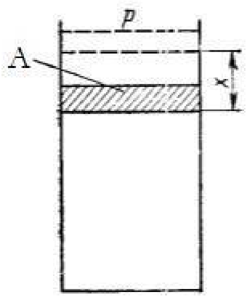

Figure 3 Piston in a cylinder [10]

point of equilibrium travelled by the piston when the force is applied.

Therefore, enthalpy is the sum of internal energy of a system and the work required to introduce an object of volume V into the system being at pressure p and in equilibrium with the object. Thus, enthalpy depends not only on temperature (via internal energy) but also on pressure, which makes it especially useful in the working fluid state calculations.

Total enthalpy of a complex system containing N independent parts would equal a sum of enthalpies of all parts (additive property): [10]

$$H_{tot} = \sum_{i=1}^{N} H_i = H_1 + H_2 + \cdots + H_N \qquad (2)$$

Furthermore, when the fluid is known, so-called "specific enthalpy" can be used, the enthalpy per unit mass, that is usually denoted with a lowercase h, yielding similar yet more versatile version of formula (1):

$$h = u + pv \qquad (3)$$

It is more versatile in the sense that it can be used to calculate changes in heat/work on the mass flow basis ($\dot{m}$, kg/s), when combined with the first law of thermodynamics[1], and depending on the type of energy primarily involved in the operation of a part (e.g. boiler, turbine, pump etc.) of the system in question,

Work:

$$\dot{W} = \dot{m} * w = \dot{m}\Delta h = \dot{m}(h_2 - h_1) \qquad (4)$$

or heat:

$$\dot{Q} = \dot{m} * q = \dot{m}\Delta h = \dot{m}(h_2 - h_1) \qquad (5)$$

In either case, the known enthalpy change with known mass flow yields the magnitude and direction of energy flow (e.g. power produced by a turbine or amount of heat flow consumed in the process of steam superheating) in the part of the process. Thus, making the flow rate the one of the most important quantities to be measured along with pressure and temperature.

Summarizing the aforementioned formulas and the concept itself: one can use changes in enthalpy levels to design or analyze thermodynamic systems of any complexity. Also, basic analysis can be performed even by hand, given the existence of vast amount of accurate data accumulated in the form of tables sorted by temperature and pressure of a fluid in question (e.g. VDI Heat Atlas [11]) and additional tools as e.g. temperature-specific entropy (Ts) diagram (Fig. 53, Appendix) with distinctive fluid state variations. In the end, these known enthalpy changes let one define the amounts of work/heat to be consumed or produced by any part of a thermodynamic system. [12, pp.62, 68-72]

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[1] thermodynamic variation of the law of conservation, stating that energy can on only be transformed but neither destroyed nor created: $\Delta U=Q-W$, i.e. change of internal energy of a system is equal to the difference between heat introduced into and work done by the system. [12, p.60]

2.2. Cycles

The basic theoretical postulates above serve as a good backbone for another concept, that is closer to the practical implementations in reality: thermodynamic cycles. While there is plenty of different cycles (apart from mentioned here, e.g. Otto and Diesel cycles employed in combustion engines), suitable for various uses, those affiliated with PP processes the most are going to be discussed.

2.2.1. Carnot

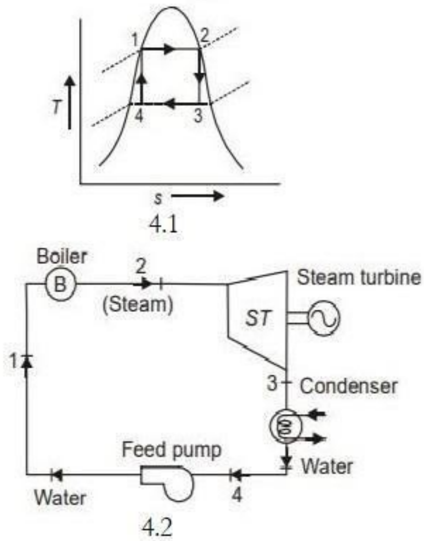

Figure 4 Carnot cycle, Ts diagram (4.1) and simplified schematic (4.2) [12]

The most basic cycle, which serves mostly as an idealistic one to compare the rest to: Carnot cycle (fig. 4). It is idealistic, because while it has the highest possible efficiency of all cycles, it includes conditions that are either impossible or just not feasible to implement. In the cycle 1-2 is isothermal[2] heating of the working fluid (feedwater) in the boiler, 2-3 is adiabatic[3] expansion in the turbine of a generator, 3-4 is isothermal condensation (steam-to-water) in the condenser and 4-1 is adiabatic compression via a pump. All of the processes in the cycle are also assumed to be reversible: nearly infinitely gradual i.e. excluding any rapid changes for the system to stay in the constant state of equilibrium, where real thermodynamic processes are often in equilibrium only at the endpoints [14, pp. 60-61]. Efficiency of the cycle is:

$$\eta = 1 - \frac{T_{min}}{T_{max}} \qquad (6)$$

Which basically means that efficiency is higher when the temperature difference is higher (between the minimum temperature in the cycle and the maximum). Also, it can be noted, that the lower temperature and pressure values are at the condenser, the more work is produced by the turbine during the process of expansion. While simple in theory, this cycle has severe limitations impossible to overcome in practice, main of which is the regions of operation of the cycle. Namely, the expansion 2-3 and the compression 4-1 that happen to be mostly in the "wet steam region"[4]. For both the turbine and the compressor (pump) it would be mechanically difficult to manage moist steam, for particles of liquid water would greatly reduce the lifespan of both due to damage incurred to moving parts given high levels of pressure and temperature. Not only that, but also idealistic processes would

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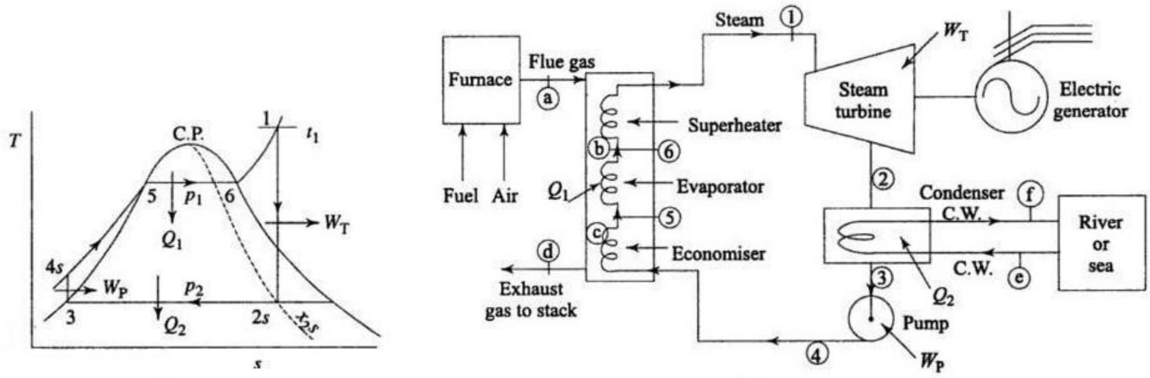
[2] water-to-steam transformation, no temperature change

[3] without heat transfer with outer environment, hence lossless, ideal process

[4] fig. 5.1, inner area inside the bell is the "wet steam region", fig. 54 (Appendix) – percentage of steam dryness, i.e. "quality of steam" can be seen.

require machines not feasible to build to achieve performance even somewhat close to the desired, e.g. 4-1 would be realized with enormous compressor (pump) that would virtually devour most of the energy produced by the turbine in 2-3. [12, pp. 251-253; 15, pp. 44-45]

2.2.2. Rankine



5.1 5.2

Figure 5 Rankine cycle TS diagram (5.1) and schematic (5.2) [15, p.41]

Because the Carnot cycle imposes challenges that are impossible to solve in reality, when steam is the working fluid in question, a modified version of the cycle is commonly employed on PPs – Rankine cycle (fig. 5). Main difference from Carnot is that previously purely idealistic assumptions have been altered to more realistic ones (fig. 5.1): heating 4-5-6-1 and condensation 2-3 are now isobaric (pressure is kept constant). Ideal Rankine model still contains adiabatic processes: expansion 1-2s and compression 3-4s (although now realistically irreversible). Nevertheless, given that these processes are taken to the "superheated steam" and "subcooled[5] liquid" regions respectively, it doesn't render them impossible for implementation, because in this cycle the turbine handles only dry[6] steam and the pump compresses only pure water, and both are possible to design to be durable and reliable. The only difference in reality from theoretical "adiabatic" in this case is that both processes are slightly less efficient: less work $W_{\square}$ produced by the turbine and more work $W_{\square}$ consumed by the pump. Additionally, boiler now contains several heat exchangers, each with its own separate function to transfer the working fluid from one state to another: Superheater, Evaporator and Economizer (to be described in the later chapter).

The heat Q_1 is introduced into the exchangers via flue gas from burning the fuel (e.g. coal powder) in the furnace, that usually is also a part of a boiler. The rest of main elements of the cycle is identical to those in the Carnot cycle and only the points of operations in each node are different with highest temperature of up to 565ºC (limited only by metallurgical considerations, i.e. infeasibility to use stronger but too exotic and expensive alloys). [12, pp.253-255; 14, pp.39-49]

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[5] i.e. under the boiling point.

[6] must be above 85% dry, if less: condensation on the turbine blades will cause increased wear due to formation of droplets that damage the turbine at high rotation rates.

2.2.3. Brayton

When natural gas[7] is employed as a primary fuel to drive a power plant (or a gas-powered part thereof), another cycle is used: Brayton cycle. It differs from the aforementioned cycles mainly in terms of working fluid - in this case it is air (or another suitable gas if the cycle is closed). Thus, the entire process and machinery is somewhat different (fig. 6).

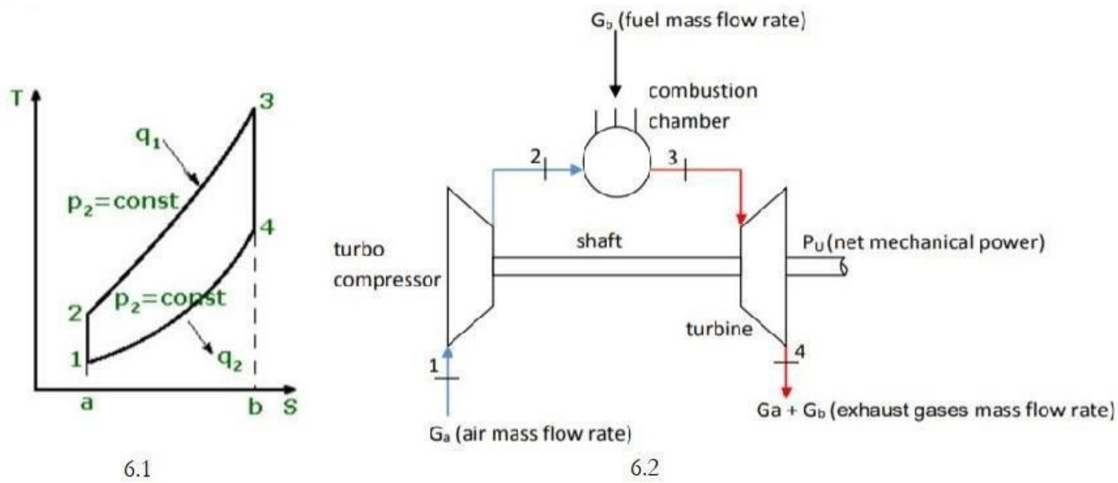

Figure 6 Brayton cycle TS diagram (6.1) [16] and schematic of an open cycle (6.2) [17]

In this case, both the compression and expansion (fig.6, 1-2 and 3-4 respectively) occur via compressor and turbine both installed on the same shaft. Former compresses air supplied from outside of the plant (open cycle), whereas latter performs the same function as in the cycles mentioned before – does the useful work on the generator that is attached to the shaft and also driving the compressor. In the ideal case: both compression 1-2 and expansion 3-4 processes are adiabatic, whilst heat addition (combustion, q_1) 2-3 and rejection (exhaust, q_2) 4-1 are isobaric (fig. 6.1). Between the compressor and the turbine resides the combustion chamber, where introduced natural gas burns with compressed air producing chemically transformed air, i.e. flue gas. This product of combustion at high pressure and temperature proceeds then to the turbine where it expands rotating the shaft and thus producing the actual work that is harnessed. After the turbine, exhaust is either sent directly into a stack where it escapes into the atmosphere (simple case, open cycle), or used once more to provide heat for a part of a plant working with steam as a working fluid (i.e. steam turbine generator, CCGT case) and only then proceeds into a stack. Another solution based on Brayton cycle is a closed cycle (fig. 7): air or other suitable gas is circulating in the closed system comprised of compressor, heat exchanger (combined with combustion chamber for instance), turbine and another heat exchanger (refrigerator). Combustion (or any other process with sufficiently high heat output) introduces heat to the compressed working fluid via heat exchanger without chemically altering it; after the turbine, the fluid is cooled down and fed into the compressor and the cycle is repeated. [16, 17]

[7] methane, CH_4

Closed cycle is not employed in reality due to technical constraints imposed by the need of enormous heat exchangers ("refrigerator" unit also requiring vast mass flow of coolant) and overall high pressure in the system making it infeasible to design such a plant. [8, pp.268-271] Although, according to [18], closed cycle GT plants have future not only in the form of small experimental 2MW plants but can actually find a niche as a supplementary efficiency-increasing solution, complementing e.g. nuclear PPs, concentrated solar and other electricity generating facilities with a high temperature source of waste heat.

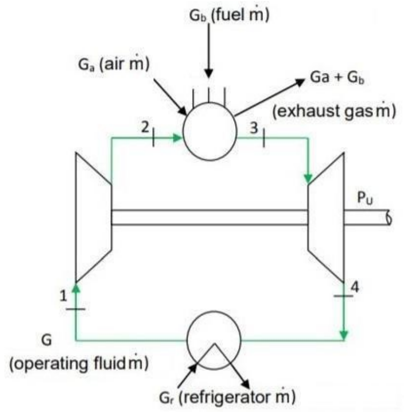

Figure 7 closed Brayton cycle [17]

2.2.4. Cycle improvements

Lastly, one could also describe two additional cycles when discussing primary thermodynamic cycles: Reheat and Regeneration. Both are more or less sub-cycles (or cycle modifications) that can be a part of either Rankine or Brayton cycle implementation. In case with Reheat, primary boiler pressure is increased along with the temperature, and additional turbine with additional heat exchanger in the boiler are added. After expansion in the HP turbine 2-3, cooled and lower pressure steam is reintroduced into the boiler via the additional reheat exchanger 3-4, after which this steam rotates the LP turbine 4-5 and, in the end, passes through the same alterations as in a normal Rankine cycle 5-6-1-2 (fig.8). Usually, not more than 2 reheat stages are implemented, for complexity of the system grows rapidly (fig.9) while marginal efficiency improvement (according to [19] providing up to 49% efficiency in the dual reheat case, which is still lower than with a CCGT layout) is not enough to justify. [12, pp.259-260].

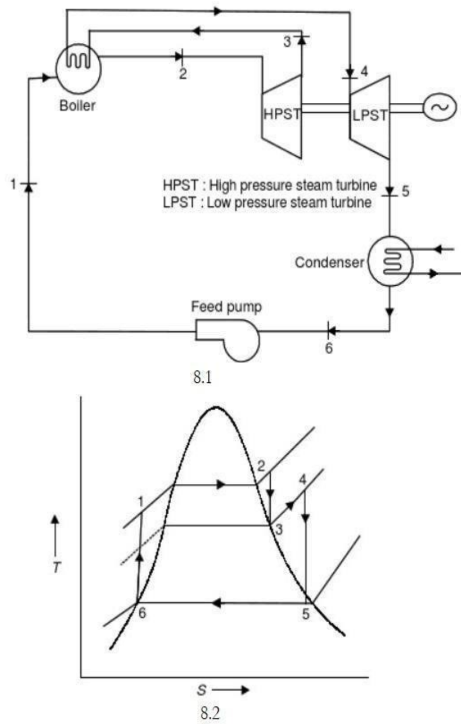

Figure 8 Reheat cycle schematic (8.1) and Ts diagram (8.2) [12, pp.259-260]

As for the Regeneration cycle, it is another modification of the traditional cycle employed to reduce the required heat addition in the boiler via preheating the feed water by means of heat exchange with a part of steam exhaust of a turbine. [12, pp. 260-262] It is often used in conjunction with Reheat cycle as can be seen on the example schematic on fig. 9, since the operating temperatures are higher, thus higher is the temperature of a turbine exhaust, which makes it feasible to redirect part of it to heat the feedwater. Additionally, efficiency of a regeneration system of a power plant can be slightly improved (by ~0.6%) via installation of absorption heat pumps between the condenser and the LP heat exchangers, thus using some of the heat rejection in the condensation stage for heating the feedwater, as illustrated in [20, 21].

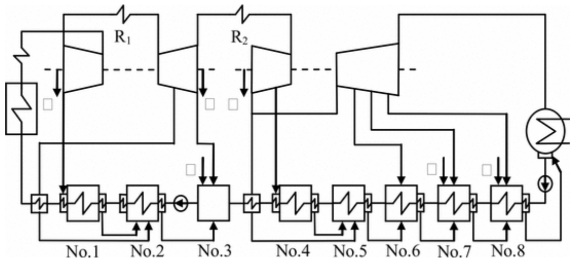

Figure 9 Standard double reheat layout [19]

Reheat and Regeneration cycles are both applicable also to GTs with Brayton cycle, with an addition of a process known as Intercooling (fig. 10). Not necessarily employed simultaneously, each improves efficiency of a gas-powered turbine, requiring different modifications of the system. Reheat cycle assumes that there are two turbines and two combustion chambers – one between the compressor and HP turbine and the other between the HP and LP turbines. It provides supplementary heat addition (fig. 10, 7-8) for the second turbine stage at lower pressure. Regeneration cycle on the other hand, includes a heat exchanger that transfers part of the exhaust heat to preheat compressed air before the combustion. (fig. 10, 4-5 and 9-10) to reduce the amount of heat required to be added in the combustion chambers. Intercooler in turn needs two compressor stages to perform heat rejection during compression of intake air (fig. 10, 2-3) to reduce the work needed to be consumed by the process. [12, pp. 245-255] Each of these modifications provide a marginal (1-6%) improvement amplifying overall efficiency up to 40% at the expense of a more complex structure of otherwise simple and compact cycle. [22]

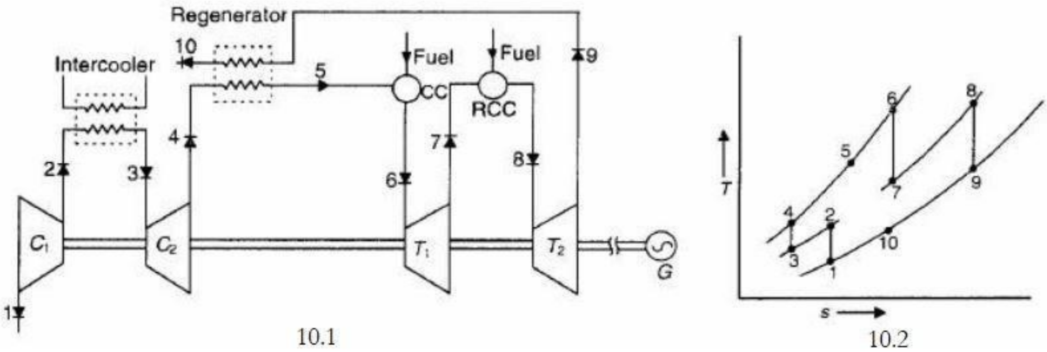

Figure 10 schematic of a GT with regeneration, reheat and intercooling (10.1) and Ts diagram (10.2) [12, p.355]

Next, the actual implementation of the cycles commonly applied on thermal power stations is going to be discussed.

2.3. Boiler

Perhaps, it is best to start thermodynamic machinery description with the largest and crucial part of all thermal power plants, part where water gets heated (and sometimes also reheated) into steam that is then utilized to harvest the energy. Several main types of boilers are going to be discussed in this part: typical pulverized coal fired boiler, Heat Recovery Steam Generator (HRSG) and Circulating Fluidized Bed (CFB) boiler. A boiler in general contains several heat exchangers within for different purposes as well as the furnace where the fuel is burnt, if the unit is coal-fired. In any case, a boiler applied on a typical PP is an enormous structure of approximately a dozen meters tall, that contains following common elements:

- Economizer: water preheater, heats it up to the boiling point for the pressure level, i.e. to saturated state
- Evaporator: turns the saturated water into saturated (dry) steam
- Superheater: heats steam further to increase overall efficiency and exclude possibility of condensate formation in the turbine during expansion
- Air preheater: heats air to be used e.g. in the furnace during combustion

All the parts listed are heat exchanger types comprised of an array of pipes for the fluid to pass through. There is not necessarily only one heat exchanger of each type – especially if the plant in question includes steam turbines of different pressure levels. In this case, there can be several superheaters/reheaters to reach the desired temperature levels. [23, pp.105-108] Usually, also a steam drum is present in the closest vicinity of the boiler: it is responsible for water/steam separation and it links together all the stages of the fluid. Preheated water is fed into the drum, from there it passes into the evaporator via downcomer pipes or directly into a heat exchanger and the resultant steam is circulated back into the drum being heated in the process. As steam is recirculated, it gets separated from water either by force of gravity (water remains in the lower part of the drum) or via system of scrubbers (more compact and able to obtain steam as dry as less than 1 ppm of solid content). Boilers that don't contain a steam drum are called once-through: they have economizer, evaporator and superheater connected in series as one. It is the only boiler type viable for supercritical pressure (Fig 54, Appendix) operation. [24, p.31,52; 25 p.99]

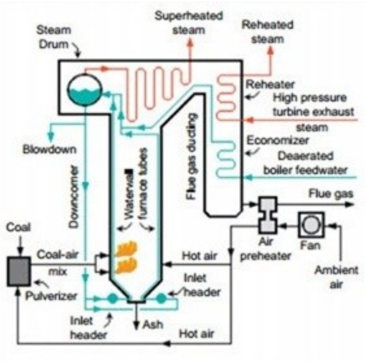

Figure 11 Generic pulverized coal-fired boiler [26]

The pulverized coal fired boilers have a furnace as the primary source of heat generation. It takes a vast portion of the boiler internal volume and has numerous burners with lighters installed in the middle that ignite the coal powder/air mixture introduced into the combustion chamber. From the chamber, flue gas is directed towards all the heat exchangers mentioned above and proceeds out of the boiler to a flue gas purification section. [25, p.139]

CFB boilers differ mainly in the structure of the furnace: lower part is now filled with a layer of solid particles (commonly limestone, $CaCO_3$) of relatively small size. These particles are lifted along with fuel particles by the hot combustion air supplied from the nozzles located in the bottom of the boiler. Flue gas formed in the combustion then passes through normal heat exchangers and additionally a classification stage with cyclone in between to separate unburnt particles and return them back to the combustion chamber. (fig.11) This approach enables solid non-pulverized (crushed to sizes of 2-25mm) coal fuel to be used, at the same time absorbing most sulfur content in the flue gas (approximately 90%). Also, a lower quality fuel can be used (e.g. lignite, the lower energy content cheaper coal) but at the expense of more logistics related difficulties caused by the vast amount of fuel needed to be supplied on a daily basis. This boiler has simplified flue gas purification requirements (only fly ash removal is needed) and therefore the system is more compact, but at the same time it has more complex structure of the boiler compartment, has to withstand more stress during operation and needs more electricity for the more powerful fan to fluidize the bed. [24, pp 99-108, 27]

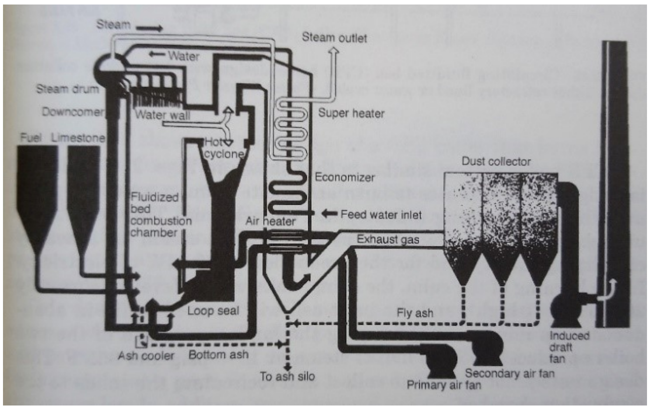

Figure 12 A CFB based system (Foster Wheeler Pyropower, Inc.) [24]

HRSGs on the other hand are installations that are used as to recover the outlet heat of a GT in CCGT plants. Structurally, it is similar to the standard boiler type, with the only difference of lacking a combustion chamber – air enters the boiler already combusted in the form of hot flue gas. This type of boiler can also contain heat exchangers for more than one pressure level and reheat stage to increase the overall efficiency. [23, p.192-194]

2.4. Turbine

In this part, another vital element of a thermodynamic cycle of a PP is going to be discussed: the turbine, also called a prime mover, responsible for production of useful work transformed into electricity. Basically, turbines exist in the two main forms: impulse and reaction. (Fig. 13, 1 = nozzles, 2 = turbine, 3 = fluid stream, 4 = direction of turbine motion) The impulse type employs nozzles as a part of immobile housing of the turbine - these nozzles direct streams of working fluid onto the blades the turbine is comprised of thus giving it the impulse and setting it in motion. The reaction type on the other hand has nozzles as a part of the turbine itself, i.e. mounted on the rotor and creating rotation through reaction force (or "thrust"). In case with PP turbines, the main difference is in terms of the shape of

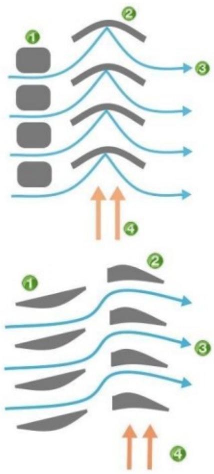

Figure 13 Turbine types: impulse (upper) and reaction (lower) [28]

the turbine blades: impulse turbines have the "bucket" shaped blades directed towards static nozzles. Actual change of pressure, i.e. fluid expansion, occurs only where it leaves the static nozzle in this case, the blades are rotated by the impulse translated from velocity of fluid particles affecting the blade surface. Reaction turbines have the blades shaped more closely to nozzles and the stream is directed via static vanes installed just before the turbine, the fluid creates reaction force through the converging nozzle-shaped blades and the fluid expansion occurs at the rotating blades as the fluid passes through. Nevertheless, in reality such strict division is somewhat absent, since reaction-based force still takes place in the motion of an impulse turbine although low in magnitude, and vice versa: there is some impulse-based interaction in a reaction turbine as well. Moreover, PP turbines contain a plethora of turbine stages, often with a mixture of both blade types to reach maximum efficiency. [28]

2.4.1. Steam

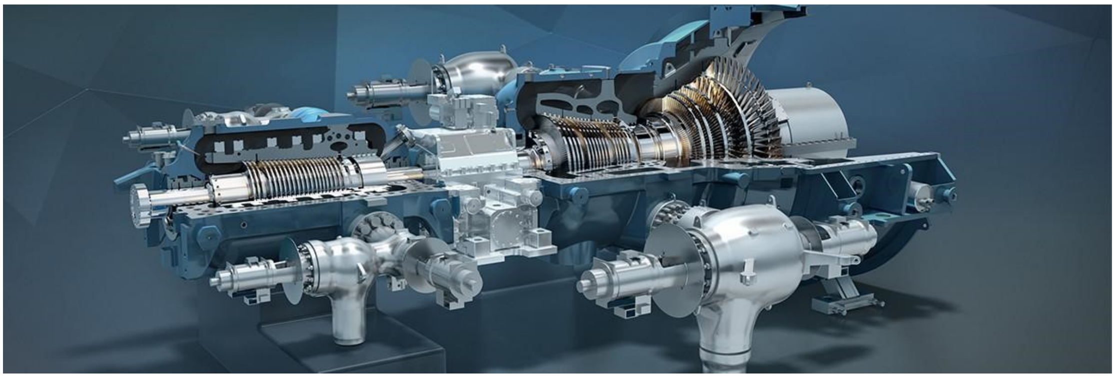

Figure 14 GE STF-D200, up to 300MW of output power. HP, IP and LP (left to right) turbine stages are clearly visible. Courtesy of GE

Steam turbines are divided into extraction (condensing) and back-pressure turbines (non-condensing). The former is used mainly on PPs with a sole purpose of electricity generation, in this case steam exits the turbine as exhausted (pressure below atmospheric) and cooled as possible and then condensed immediately with a large supply of external cooling water. The latter, back-pressure turbines, are in turn used on more multifunctional plants where heat co-generation is as important as electricity generation, for steam processed in the turbine returns with enough energy content to use it for district heat production. [29]

2.4.2. Gas

GTs are usually considered to be comprised of several modules (not limited to 1 per type): GT itself, combustion chamber and compressor. Since all of these modules are contained within the common casing and around the common shaft (sometimes twin- or triple-spool shaft when several pressure level turbines and compressors are present), the entire system is regarded to as GT for simplicity. This also explains why simple Brayton cycle GT installations are so compact – all the main nodes of the cycle are within the same shell just a few dozen meters long and few meters tall (excluding the air intake filtration module), especially opposed to innumerous variety of heavy spacious auxiliary machinery in the coal-fired plants. Also, there is no need for complex flue gas filtration system, since there are no solid particles in the gas. (fig. 15). [30]

Basic GT installation archetypes are: [31]

- heavy duty - high power output (above 100MW), rugged design for PP applications
- industrial - medium power (4-70MW), rugged design for supplementary power generation applications
- aero-derivative – medium power, light design based on aeronautical GT designs, for applications in remote areas with the requirement of easy transportation of the unit

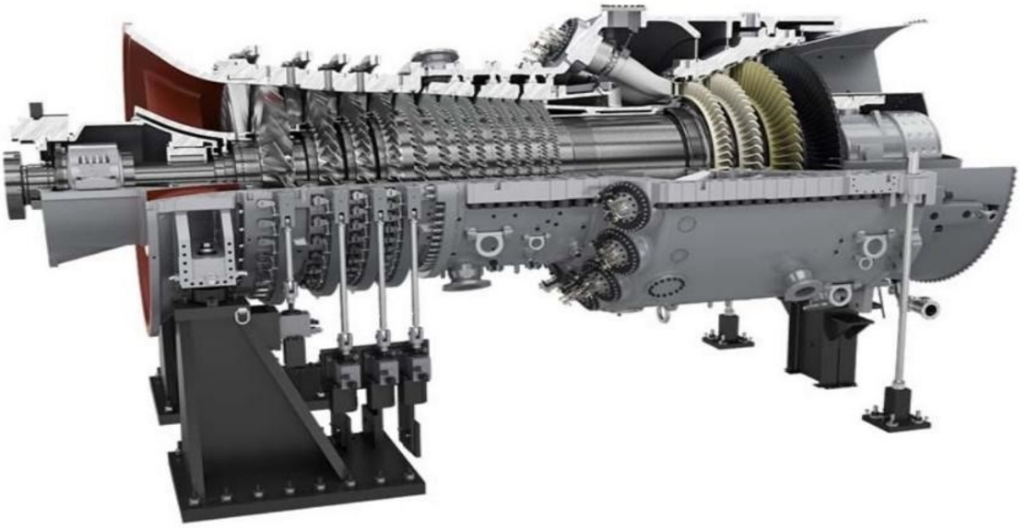

Figure 15 SGT-8000H heavy duty GT, 450MW of rated power output and efficiency of 61% in CCGT, compressor turbine stages with 4 variable vane stages can be seen on the left, 4 GT stages are on the right and combustion system in between. Courtesy of SIEMENS AG

2.5. Condenser and water processing

Another pivotal change of the state of the working fluid in a steam based thermal power plant occurs in an appliance called a "Condenser". In essence, it is a large heat exchanger located in the nearest vicinity from the steam turbine, its role is basically to be the cooling node of as low pressure and temperature as possible. The pressure is kept at levels far below atmospheric (at tenths to hundredths of a bar, where normal atmospheric pressure is around 1 bar) that allows for more steam heat (energy) to be converted into useful work. The temperature on the other hand is held at the point where it causes the turbine outlet steam to condense into water in the condenser for a condensate extraction pump to be able to process it further. Cooling water is supplied either from a nearby (either natural or artificial) water reservoir or a cooling tower. In each case the water heated in the process is cooled down via evaporation in the lake/tower and recirculated back into the condenser. Structurally, it is comprised of a large outer shell, that has an array of tubes built in through which the cooling water circulates supplied from outside. The exhaust steam from the turbine passes through these tubes and has the temperature dropped enough to start to condense. Condensate in turn is gathered at the lowest point of the condenser, i.e. "hot well", where it is suctioned by a condensate extraction pump to be processed further and in the end to be returned to the boiler. (Fig. 16) The top side of the shell of the condenser includes apart from the turbine exhaust steam intake also a vacuum steam ejector system intake, responsible for the low pressure in this part of the system. [25, pp.223-225]

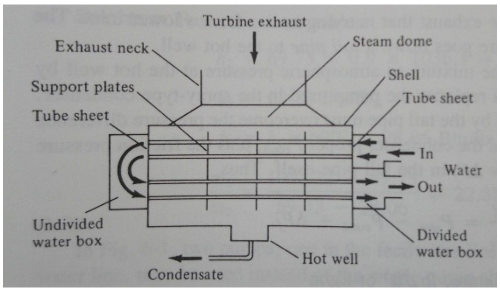

Figure 16 Condenser schematic [25, p.224]

Condensate extracted from the condenser proceeds to the feedwater tank, that can also be combined with a deaerator. The main purpose of the device is to remove oxygen and other gases (e.g. carbon dioxide) from the condensate, preheat water before the boiler (e.g. using heat from steam between HP and IP). This, as well as additional forms of treatment, are performed to condition the water before it gets processed in the boiler to avoid damage caused by impurities in the working fluid and reach optimal operating point. Additionally, for the same reasons, water in the cycle is constantly monitored in a local laboratory and when it is required to add water, the water from outside gets processed through multiple filtering/conditioning stages before the feedwater tank. [25, p.224,240]

2.6. Flue gas purification

Exhaust gas purification is conducted in the manner suitable for fuel combustion technique applied on the station: pulverized coal boilers require both fly ash removal and desulphurization stages, CFB boilers need only fly ash removal, GTs in turn need nothing except accurate combustion control and steam injection for NOx[8] emission reduction.

2.6.1. Fly ash

Both pulverized coal-fired and CFB boilers have one purification requirement in common - the flue gas has solid particles to be removed before it can be either processed further (at desulphurization facility, pulverized coal) or directly fed into the stack (CFB). These filtering devices can be split into two major categories: Electrostatic precipitators (electrical filter) and Baghouses (cloth filter).
The first type uses a phenomenon of static electricity where the basic idea is "opposite charges get attracted to each other". This idea is realized with two electrodes that produce high-voltage electric field (Fig. 17). First electrode is

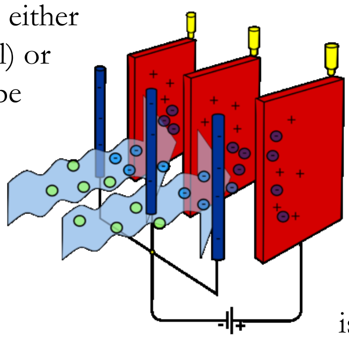

Figure 17 ESP filter principle [32]

[8] nitrogen oxides, NO_1 and NO_2, the toxic components of exhaust gas

negatively charged, and it passes this charge onto the solid particles in the flue gas introduced into the filter. Then, the gas with negatively charged particles gets in between of surfaces of the positively charged electrode that electrostatically attracts the solid particles of fly ash. The electrode is to be cleaned at known intervals for the ash to get detached, e.g. with vibration, to be then collected at the bottom of the structure and in the end - disposed of. Electrodes can be of different shapes, be it plates or thin vertical rods. This type of filter can be 99% efficient at securing fly ash content in the flue gas, although approximately 2-4% of electrical output of a PP might be used to energize it. [32]

The other type of such filter, the "Bag filter", employs numerous long bags made from high temperature withstanding fabric (Fig. 18). These bags are hanged within the body of the filter (several meters tall) on the cage-like frames and a fan forces the flue gas to pass through the bags, leaving most solid particles stuck in the fabric. Akin to the electrodes of the previously described filter type, the bags require periodic cleaning by various methods: with vibration ("shaker"), air flow being momentarily reversed ("reverse air"), or with compressed air jets ("pulse jet"). The type of cleaning defines some slight structural differences, e.g. first two types are built in separate compartments because the cleaning sequence requires the flow of flue gas to be stopped, hence the compartments get cleaned in turns, whilst the pulse jet baghouse can operate during cleaning without stopping any compartments.

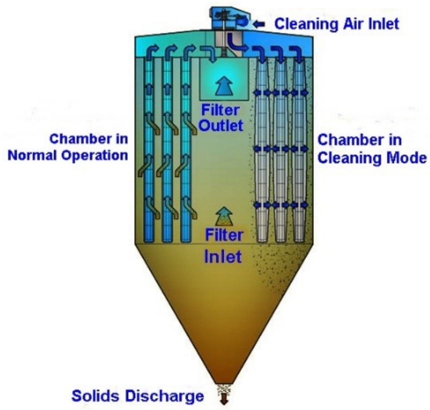

Figure 18 Bag filter schematics [33]

In the end, bag filters don't need same high-power supply as electrostatic precipitators, also they are more compact, nevertheless, the filtering cloth of the bags deteriorate over use and thus bags require replacement roughly every 15 months. Because of this the electrostatic precipitators are mainly used in larger coal-fired PPs, where there is flue gas flow vast enough to justify the high electricity consumption. Baghouses on the other hand are normally employed on smaller facilities where there is either no electricity production or relatively low levels thereof, making it reasonable to use a more maintenance-demanding solution whilst saving in the energy consumption department. [33, 34]

2.6.2. Desulphurization

Flue gas of a coal-fired PP normally contains significant amount of sulfuric chemical compounds (and other pollutants), amongst which SO_2 is the main culprit in acid rains and overall toxic pollution. Therefore, there is a necessity of sulfur dioxide removal from exhaust and with this idea in mind various techniques are applied. In a CFB boiler SO_2 is captured and removed during combustion process in a reaction with the limestone, while the more common pulverized coal PP requires a separate facility for this with the main part of it being the scrubber. There are many different types of scrubbers, but this subchapter will be focused only on the most common ones: wet and spray dry scrubbers.

Wet scrubbers are the most commonly employed technology capable of SO2 removal - they can be further classified into limestone-based ones and the seawater scrubbers. Limestone scrubbers have the best efficiency of SO2 removal at 95-99%, they operate by introducing a mix of limestone and water into the same chamber with flue gas, forcing it to flow through the mix. The purified gas is directed to a stack and the main byproduct of the reaction is gypsum that is widely used in construction. This is one of the more expensive solutions both due to high capital cost (complex additional facility requires large investments) and high operating cost. (Fig. 19)

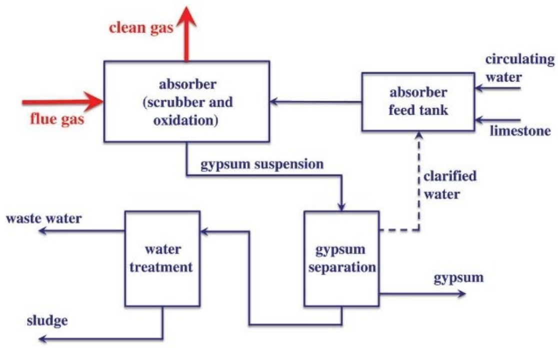

Figure 19 Wet scrubbing facility schematics [35]

Spray dry scrubbers in turn, have a maximum SO2 removal efficiency of 90%, also the acceptable flue gas flow is limited thus requiring several modules in case of a large PP. Akin to wet scrubbers, lime-based absorbent is used, that is sprayed in the form of finely ground suspension into the absorber compartment. Also, precipitators have to be used after and sometimes before the scrubbing for the main byproduct of the process is basically the fly ash. Normally, the baghouse type precipitators are used due to the fact that part of unreacted absorbent with remaining SO2 in the gas gets additionally mixed in the filter fabric (which is impossible in case with electrostatic filter), increasing overall efficiency by as high as 20%. Nevertheless, this type of scrubbers is significantly more simple, compact and cheap than the previous type of flue gas filtration, that makes it a viable option for smaller facilities. [35]

2.7. Fuel supply and conditioning

Most demanding in this department amongst the discussed types of PPs are definitely the coal-fired stations: the coal needs to be transported to the plant - normally by a truck, or by railroad if such type of transportation is available, in enormous quantities. Then it is relocated into the coal silo where it is stored with some excess for gradual and constant fuel supply for the plant. From there it proceeds through some more transportation and preparation stages before getting actually combusted to provide heat into the cycle. To be discussed in this chapter: coal transportation across the station and conditioning before being supplied to the boiler furnace.

2.7.1. Conveyors

One of the main means of coal transportation within the plant for extended distances (above 50m) is a belt conveyor (Fig. 20), that is simple in terms of its operation, reliable and easy to maintain. It consists of the rubber belt with a metal fabric core that is looped around numerous pulleys which enable the belt to roll. One of the pulleys is powered by an electrical motor, others remain passive. Normally, conveyor belts are not designed to be completely shielded from all directions to provide easier maintenance access, at the same time this open design imposes a hazard of accidental interaction with the moving parts. Hence, an emergency stoppage thread is stretched along the hazardous end of the operating machinery.

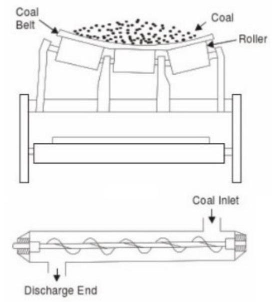

Figure 20 Belt (upper) and auger (lower) type conveyors [8, pp.146-147]

Screw (auger) conveyors (Fig. 20) on the other hand are most suitable in short distance (less than 50m) applications to transport solid matter of varying degrees of fineness from powder/ash to relatively coarse coal. The main element of such apparatus is a rotating spiral-shaped core that has the spiral surface pushing the matter needed to be transported usually in a horizontal or slightly inclined direction. The spiral is also energized by an electric motor and has a completely closed design since the main element rotates within a tube.

Additionally, exist the bucket type elevators where numerous buckets are connected by chain and driven by an electric motor on one end. Equivalently structured elevators are used e.g. for sludge transportation or vertical coal transportation in confined spaces. (Fig. 21). [8, pp. 146-147]

Figure 21 Sludge removal elevator, Suomenojan PP.

2.7.2. Coal processing

First, the raw coal is normally crushed into smaller pieces by a crusher (unless the coal is delivered already preprocessed) – a crude mechanism driven by an electrical motor, for equalizing and reducing the size of particles transported further on. Then, coal mills (also "pulverizers") are used to grind coal further into dried homogenous powder that is used as a main fuel on a pulverized coal fired PPs (otherwise, the crushed coal can be supplied to a CFB boiler directly). Basically, the overall structure of PP coal pulverizers is somewhat reminiscent of a CFB boiler, with only difference that the hot air[9]

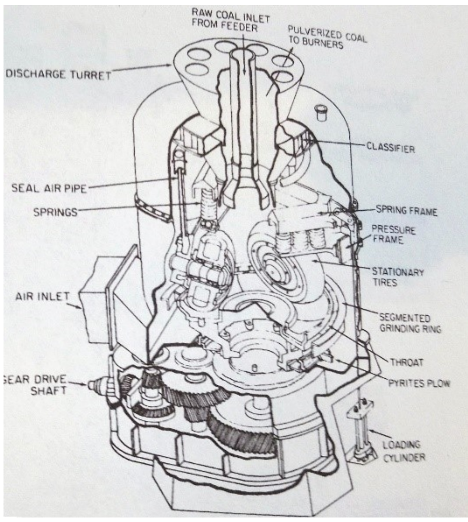

Figure 22 Coal mill [24, p.267]

[9] (boiler primary air kept at 100°C to dry the coal from any possible moisture content)

supplied to the bottom of a mill fluidizes coal only for the classification purpose. Such approach allows the fine enough powder to be separated from yet coarse coal that needs to be ground more. Other than air circulation system, the mill consists of the coal supply channel from the top of the mill, that leads directly to the surface where it is ground by rolling elements (Fig. 22), the hot air lifts the ground coal and then it passes through rotating separator screen if the powder is fine enough, if not, it is returned back to the rolling elements. The power for grinding (as for the hot air circulation fans) elements is supplied by electrical motors of suitable output, which are normally connected through a reduction gear to provide higher torque (i.e. force applied to the rotating axis) at the expense of rotational speed. [36; 24, p.265-268]

2.8. Fluid control

Working fluid be it air, water or steam also needs control and direction for a cycle to perform well. Primary fluid control machinery and mechanisms are going to be described in this chapter.

2.8.1. Pumps and fans

Pressure of a working fluid is reached via pumps (for liquid fluid) or compressors (gaseous), while having the similar purpose, both differ greatly in the structure department. Fans on the other hand are used to create an airflow, where pressure induced is of lesser importance, but not the volume of air that needs to be displaced, e.g. boiler furnace air supply. Compressor basics have already been described in the GT section above, whilst the pump and fan principles for the majority of PP applications are going to be described in this section. Both fans and pumps employed on power plants are usually of centrifugal type, hence both have similar structure overall. Rotating impeller (visually reminding a turbine) is secluded in a volute casing that directs the flow of the fluid. (Fig. 23) The impeller is rotated by an electrical motor, either directly or through a clutch with a gearbox if the nominal rpm of the motor is different from the rpm required in the mechanical appliance. In the centrifugal type suction of fluid happens in the middle of the impeller and is directed by the casing outwards through the single opening into a pipe (water) or diffusor (air). Also, in centrifugal pumps several stages are employed, when high pressure levels of water are required, e.g. boiler feedwater. [37; 24, pp. 479-491]

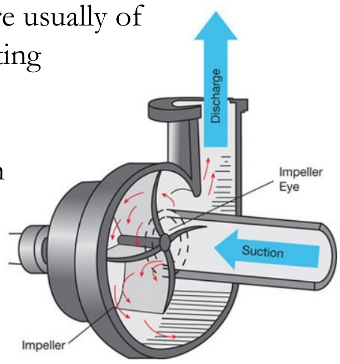

Figure 23 Centrifugal pump [37]

2.8.2. Valves

Another type of fluid flow control devices are the valves. This kind of machinery is used neither to create the flow nor to enhance (where pumps and fans are used), but rather to alter it. In other words, to open an additional flow route, to cease flow or decrease it in a controlled manner via “throttling effect” (reducing the area through which a fluid can pass thus also reducing the flow rate). Thus, it is possible not only to cut the fluid off from admission into a part of a system, but also to redirect it, for when piping is designed accordingly, a valve can:

- open a controllable bypass path around a part of a system that needs to be either temporarily disconnected or its through-flow to be reduced
- prevent a backflow (water) that would damage a centrifugal pump (non-return valve or check valve)
- open a controllable recirculation path that would e.g. once again prevent centrifugal pump damage in case of the need to reduce the flow rate after the pump output, since they are also very susceptible to flow rates below nominal. (Fig. 24)

Depending on the function and placement, valves vary across the range from being slow-acting and precise, hand or actuator (e.g. electrical motor) driven heavy duty mechanisms as in case with district heating water routes to light quick (quarter-turn) hand-operated valves.
Structurally, all valves have some form of a mobile obstacle that is capable of completely obstructing the flow-through. This obstacle can be a shifting/rotating plate (gate/butterfly types respectively), moving plug (globe type) or a screw (needle type). [24, pp. 380-386]

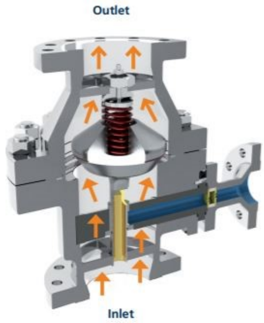

Figure 24 Automatic recirculation valve, courtesy of SchuF Group.

3. Electrodynamic processes

Various electrical machinery and subsystems are just as important, for it is the electricity that needs to be produced in the end (apart from heat) by generators, it is electrical motors that drive numerous mechanical rotating nodes in every cycle (fans, pumps and actuators, to name the few). Not to mention different automated control measures that are possible only with the application of electrically powered circuits. This part is going to discuss the electrodynamic basics that is employed in the operation of the systems mentioned above, as well as main electrical machinery types.

3.1. Basics

First of all, electrical current[10] can be of two types: alternating and direct, i.e. AC or DC. AC is oscillating in the wave-like manner with constant fixed period and cycle, while DC on the other hand remains on a constant level. Also, AC can be supplied in the form of three-phase current, where the three phases are delayed from each other by 1/3 of a full cycle (Fig. 25) – this allows for more efficient long-distance transmission and industrial applications. Any current produces magnetic field around the conductor and it is also possible to create current by magnetic field, as stated by the Faraday's law of induction. The law of induction is the cornerstone mechanism behind electrical machinery operation. Some theory in the simplest mathematical form:

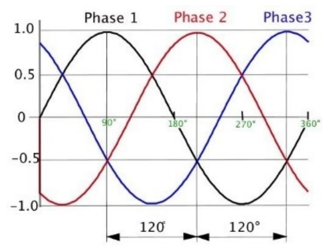

Figure 25 three-phase current. [38]

$$\Phi = \int BdA \;\; \leftrightarrow \;\; \text{EMF} = -\frac{d\Phi}{dt} \quad (7)$$

Where Φ is a magnetic flux of a magnetic field, B is a density of the magnetic flux, A is an area of a contour through which the magnetic field is passing, and EMF here is basically the electricity (voltage) produced by the change of flux. So, summarizing these formulas in other words – generated EMF is proportional to the rate of change of the magnetic flux (or vice versa – rate of change of the flux is proportional to the EMF supplied). [39, pp. 13-17]

Motors and generators consist of two key elements: rotor, the rotating part and stator, the stationary one. If electricity generation by a TG is taken as an example of (7): the rotor is supplied magnetizing DC current[11] to produce a constant magnetic field, the change of flux of the field is realized via rotation of the rotor and electricity is then generated in the stator in the form of alternating three-phase current. There is a predefined rotation rate of a TG for the generated current to be of required (by widely accepted standard) frequency for the entire network and appliances connected to operate as designed:

[10] a directed voltage-induced "flow" of free electrons that are in abundance in conducting materials, especially metals

[11] the process called "excitation"

$$n = \frac{f}{p} * 60 = \frac{50Hz}{1} * 60 \frac{s}{min} = 3000rpm \quad (8)$$

where f is the network (and stator current) frequency, normally 50Hz (Hz = 1/s) in Europe, p is the amount of magnetic pole pairs of the rotor, normally for TGs it equals 1 (2 poles) and the fraction is then multiplied by 60 to convert 1/s to 1/min = rpm.
The same theory can be applied to a common electrical motor, only the other way around: the stator is supplied AC current, that causes the magnetized rotor to spin, where amount of pole pairs and the frequency of supplied current define the speed of rotation. The dual-application nature of the induction law also yields the capability of a motor to be a generator and vice versa.

The law of induction is applicable not only to motors and generators but also to an important part of electricity distribution and control – a transformer, which performs a function similar to a gearbox in a mechanical system. The main reason is the manipulation on electricity to achieve voltage and current levels[12] suitable to an application. Induction results in the simple relations between voltage, current and transformer structure (ideal case):

$$\frac{N_1}{N_2} = \frac{V_1}{V_2} = \frac{I_2}{I_1} \quad (9)$$

Where N_1 and N_2 are amount of turns around the core in each winding that are the main elements of the transformer, V and I are the related voltage and current values over the primary and secondary terminals. (Fig. 26) Since the transformer is immobile, the only way to provide changing magnetic field to induce voltage in the other winding is by using AC, hence transformers cannot manipulate DC. [39, pp. 33-36]

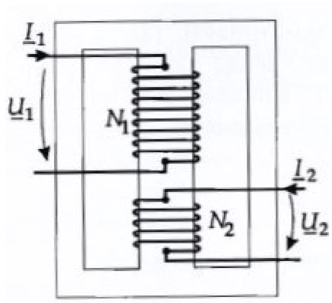

Figure 26 Transformer, simplified schematic, 1-phase [39, p. 51]

3.2. Generator/Motor

Electrical motors and TGs have similar overall structure, with TG differing mainly in terms of size and presence of additional cooling, monitoring and controlling elements. Therefore, it is logical to describe the more complex machine first, the TG.

TG is a large synchronous (i.e. has rotor and magnetic field rotating at the same rpm) machine, where high pressure vapor or flue gas is the main source for rotation of the turbine driving the machine of up to about 1500MVA rating. Despite that for the majority of electric motor applications Tesla's induction (asynchronous) motor is being used instead

[12] the levels of generated electricity (e.g. 10500V and 2584A by a 40MVA generator AEG KANIS) are too high to feed the local LV networks – need a voltage step-down. And at the same time the current is too high to effectively transmit electricity over distances due to "I^2R" losses in the conductors caused by metal resistance, dependent on current – need voltage step-up

of synchronous motors, synchronous generators are still universally used for electricity generation across the world.

Stator of a TG is made of steel laminated core that is uniformly slotted with open slots, which itself is the framework for the three-phase AC winding (armature winding, fig. 27). Laminations of the winding are insulated, and the thickness of insulation and the type of steel are chosen to make hysteresis losses and eddy current[13] as low as possible. Modern generators are usually equipped with a winding which is of double-layer lap type - shape reminiscent of a hexagonal lattice. [42]

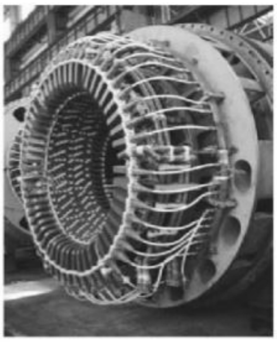

Figure 27 600MW TG stator winding with water-cooled windings [41, p. 21]

The majority of TGs is designed as two-pole, because higher rpm (at lower pole count, since according to (8): $n \sim 1/p$) allows for better turbine technical and economical characteristics, with the exception of slower four-pole TGs that are designed for some nuclear power plants. TG rotors are typically manufactured out of solid high-quality steel forging, the diameter of an active part of the rotor can't exceed 1.2-1.5m because of mechanical loads caused by great centrifugal force at the usual rate of rotation of 3000 rpm (8). That is why the rotor of a high-power rating machine is designed to be rather long, where its length is limited by flexibility and deflection of the rotor. The magnitude of vibration during rotation is connected to these characteristics too, thus the longest possible length of the rotor to be reliable is approximately 8.5m. So, in the end, maximum dimensions of the rotor are limited by capabilities of modern metallurgy. Winding of a TG rotor (field winding, fig. 28) is made in the form of concentric coils and is fixed in slots with non-magnetic metal (duralumin etc.) wedges, which have enough durability and able to withstand quite large centrifugal forces. [43, pp. 83-90; 44]

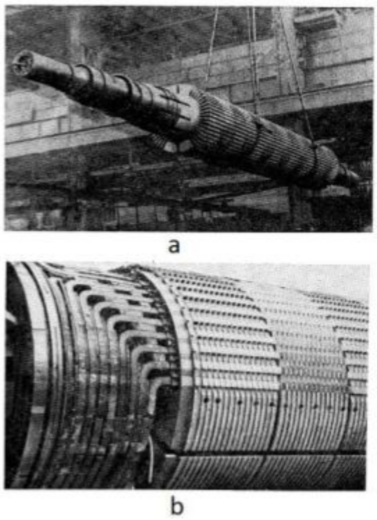

Figure 28 a. Not yet wound 320MW TG rotor, b. Same rotor with winding in place

As already mentioned in connection to (7), DC current needs to be supplied to the rotor for the TG to actually generate electricity. It can be supplied from one of few sources:

- DC power generator installed on the same shaft with TG
- External rectifier that uses a part of the stator output current (solid-state, i.e. without moving parts)
- Brushless excitation with rectifying system mounted on the shaft next to the rotor

[13] hysteresis losses are caused by specific behavior of magnetic parameters of ferromagnetic materials (e.g. iron) during current fluctuations (Fig 53, Appendix), eddy current losses - by parasitic current in unwanted direction present e.g. in large conductors

First two sources require a commutator in the form of slip rings and carbon brushes, the last one just has simply more complex structure with the purpose to eliminate the necessity of a commutator. [41,42]

The cooling system is also a very important element of any large generator, because overheating is a big problem in a several meters long constantly working rapid rotation machine. In TGs of various power-output ratings different types of cooling are used: in low power smaller (less than 30MW) generators it is a closed air cooling system; in larger more powerful generators hydrogen is used instead of air as a more efficient solution, it is over-pressurized by about 0.05 atm to prevent air from getting inside the hull and forming a dangerous mix. In generators of more than 150MW output hydrogen in the system is over-pressurized to 3-5 atm, and in all aforementioned cases multi-flow radial cooling is used, basically a direct cooling of rotor where air or hydrogen is in the closed loop with cooling chamber and it passes stator core and the gap between stator and rotor. In larger more than 300MW more efficient methods are applied – direct cooling of winding conductors with water or hydrogen via the use of hollowed conductors or conductors with ventilation channels respectively. [44]

On the other hand, structure of a traditional motor is much simpler, even when it performs e.g. a demanding function of driving a powerful district heating pump. If TGs are usually synchronous machines, apparatuses devised with a motoring function in mind, on the contrary often are asynchronous, i.e. have a rotor spinning at the slightly slower rate than the "synchronous speed" – stator magnetic field rotation rate (and when generating, rotor is rotating slightly faster than the field induced in the stator). These motors are called "induction motors" and this type is mostly represented with "squirrel-cage" rotor type motors, when industrial application is in question. "Induction" part comes from the fact that the rotor current is induced by the stator via electromagnetic induction[14] rather than from direct feeding from elsewhere: this means that there is no necessity for commutation with slip rings and brushes, thus simplifying construction. "Squirrel cage" is a suitable name due to the rotor core structure, that is basically a short-circuited cage frame installed on the shaft (with laminated steel in the frame). Overall structure provides admirable reliability and easy maintenance, thus making this type of motor a welcome choice for driving the majority of mechanisms around a PP of variable sizes, e.g. fans, motors, pumps transportation conveyors etc. The cooling requirements are quite simpler than those of a TG, usually realized with a fan attached to the opposite end of the motor shaft to direct the air flow onto the hull. Same as monitoring devices - normally only a temperature sensor is present by default on larger machines. [41, 42]

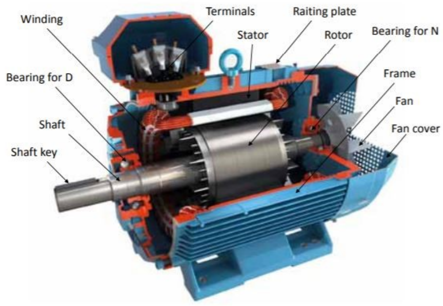

Figure 29 A cross-section of a typical induction motor, courtesy of ABB

[14] current is induced via this difference between the mechanical rpm of the rotor and rpm of the stator field, i.e. this difference (called "slip") is present also during steady state operation – for it satisfies the change of flux condition of the induction law.

3.3. Transformation

The necessity of transforming electrical current comes from the fact of greatly differing levels of the voltage/current on the generator output, magnitudes required for efficient transmission and for application at the consumer end. Also, real-time flexible conversion of supplied electricity by a frequency converter allows for efficient speed control in the AC motoring applications (e.g. district heat pumping) where it might be useful. This subchapter will have discussed these two electricity transformation methods.

3.3.1. Transformer

There are two basic types of power transformers important on a PP: step-up, e.g. to change a relatively low voltage at the generator output into high voltage suitable for transmission (with levels up to 500kV depending on the distance of transmission); and step-down, e.g. to lower the voltage level to desired magnitude (down to a minimum of 230V for local applications such as lighting).

Figure 30 A modern LV/MV 3-phase transformer (up to 4MVA), Siemens GEAFOL Neo, courtesy of Siemens AG

Aforementioned basic transformer structure remains unchanged disregarding the magnitude of the current handled by a unit: magnetic core with windings of particular number of turns (e.g. three-phase units typical for PPs and substations, fig. 30). Step-up and step-down functionality is defined only by the number of turns in primary and secondary windings (also possible a tertiary and more windings if there are more than one level of output voltage). The core is made from high-grade iron (also laminated just as motor/generator stator core) or a more advanced alloy, depending on the application and requirements, windings are normally copper. Usually, internals are submerged in oil, for it provides cooling while being dielectric (non-conducting). Heat dissipation is important in transformer operation, since approximately 2.5-5% of power transformed is wasted as heat (caused by hysteresis and eddy current losses in the core, and copper losses in the windings[15]) which can be significant considering over 100000kVA rating devices. System components differ relatively to the power rating of the transformer apart from the size, though:

- power inputs: terminals that connect the transformer to busbars or cables have different isolative solutions applied to - ceramic, oil, polymer, SF_6 (hexafluoride) etc.
- cooling: radiator, forced air ventilation, circulation of oil etc.
- control mechanisms: voltage reduction via variation of the number of turns used in a winding

[15]copper losses – the same as losses in conductors, caused by the resistance of metal, hence also called “I^2R losses” being practically the power wasted on heating the conductor.

- additional equipment: gas relay (malfunction causes gas to form from degrading oil, the relay shuts down the faulty machine in case there is this gas detected), temperature indicator, oil level indicator etc.

[41,42,35]

3.3.2. Frequency converter

Often also called "Variable Frequency Drive" (VFD), this type of device mainly serves as an accurate speed controller, as it has already been mentioned. Apart from the simple function of variating rpm of a motor, it has other useful functions:

- gradual smooth starting and controlled braking, contrary to the full-blown on/off that loads a motor significantly reducing its lifespan
- efficient power supply at other than nominal speeds, granting economic benefit during operation if compared to operation without VFD
- speed stabilization during load fluctuations
- drive diagnostics (also the motor and its power feed diagnostics) and flexible adjustments

Structurally, a variable frequency controller consists of several major parts: a rectifier, DC bus and a Pulse Width Modulation (PWM)-controlled inverter. Rectifier, normally in the form of diode/thyristor (electronic components allowing current to pass only in one direction) bridge that converts AC to DC with some ripple present. DC bus contains additional components to eliminate ripple, thus provides filtering function. PWM-section of the converter is normally a transistor-based[16] bridge that produces pulses of required frequency and magnitude thus producing fully controlled AC current that in turn drives the motor. All of this is complemented by sophisticated electronic measurement and control devices that are responsible for the converter output control, taking into account feedback from the motor itself and the preset program or command fed.

The output control schemes are following:

- Scalar control: V/Hz, "Volts per Hertz", simple linear frequency control suitable for non-demanding applications where some inaccuracy is acceptable
- Vector control: provides control over magnetization current in the rotor thus yielding very accurate rpm regulation, albeit requiring sophisticated hardware and software. Can be used with sensors for improved accuracy.
- Direct Torque Control, another type of efficient vector control with torque control in mind, slightly more simple and quicker to respond, although less accurate if used sensor-less (without rpm measurement)

[43, 44]

Figure 31 ABB ACS550, modern compact wall-mounted VFD for drive control of up to 315kW, courtesy of ABB

[16] transistors are switch-type components that have the current pass-through on/off function controlled by applying low voltage over its terminals

4. Condition monitoring and automation

All of the previous chapters described the structure, main components and basic theory behind PP operation. One could notice - it is not necessarily each component is the culprit of overall complexity and fault sensitivity, but all of the components required to be working constantly and in tandem at high loads. Just one malfunction in any of the main sections of a cycle and the entire system needs to be abruptly disabled both for the safety of environment and operating personnel, as well as for preservation of the cycle elements still retaining integrity and functionality. With this in mind, majority of the vital components is duplicated for failsafe and load equalizing reasons – feedwater pump, district heating pump, air and flue gas fans, piping etc. Whilst more expensive, large and sophisticated components (e.g. boiler) are not duplicated, but there are often additional TG units (or entire cycles) built for a PP to have some extra capacity: these normally can have load transferred to them in case of emergency so that the PP is never rendered completely powerless
Next are going to be discussed: vulnerabilities, the most common and effective methods to monitor them and prevent malfunctions, as well as automation systems allowing for user-friendly monitoring over an entire power plant from one place.

4.1. Weaknesses

This chapter will include common malfunctions for each node in the cycle. Most parts share similar vulnerabilities based on the structural rigidity depending on the strength of material used, where the most differences come from the type of stress that given part has to withstand. Some weaknesses for majority of functionally similar nodes are basically the same:

- excessive thermal and mechanical stress of heat exchangers – the effect can be reduced with higher quality materials and accurate control
- corrosion of heat exchangers due to impurity of water – prevented by water chemistry processing (control and filtering), higher quality materials and coatings [49]
- bearing wear of rotating machinery of any size and function – lessened by oil supply systems and timely maintenance.
- any other sort of pre-estimated end of lifecycle/functional effectiveness, e.g. clogging (BH) or electrode wear (ESP) in filtering devices – solved by timely maintenance or replacement

The more specific common vulnerabilities/malfunctions and their solutions are going to be briefly discussed further in this chapter.

Any type of boiler being a vast structure made of metal, is mainly susceptible to the damage of the material that internals are comprised of. Apart from the obvious thermal stress from high temperatures and pressures, there is also a common problem of ash fouling/slagging in coal-fired units, caused by fly ash getting collected on the surfaces of heat exchangers. Thus, ash reduces the efficiency of heat transfer requiring in the end to run the boiler at higher temperatures to upkeep the performance of a PP. For this reason, the sooth blowers (producing jets of steam on all levels of heat exchanger piping) are employed to overcome this problem. The problem can be detected by lowered heat output of the boiler. [50]

Steam or gas turbine, as a delicately shaped element comprised of slim parts (blades) operating in aggressive high-temperature environment, is prone to "creep" or gradual deformation due to material fatigue. This phenomenon is common for both steam and GT turbines and requires advanced alloys - the more advanced the higher the operating temperature is. Prediction of the creep happening can be realized not only with direct calculation of power outputs (where lowered performance at normal parameters would indicate ongoing damaging), but also with mathematical modelling (ML methods: inaccurate linear creep/damage prediction, more accurate non-linear or an ANN method). [51, 52]

Performance of a coal mill can suffer from a variety of factors combined: high moisture content in the coal, rapid load changes and high coal demand by the process. This might cause some quantity of coal dust to remain moist and begin to accumulate within the mill that in the end might lead to this excess of accumulated fuel to abruptly get into the furnace thus possibly causing an overheat. This can be prevented by more sophisticated control with an assistance of predictive mathematical modelling. [53]

Pumps on the other hand have a purely hydraulics-related issue, common for hydraulic machinery overall: cavitation. This phenomenon occurs when the local pressure of the working liquid becomes lower than the pressure of the liquid in vaporous form at current temperature. This causes vaporous bubbles to form at the location of the pressure drop, that in turn cause pump performance decrease, increased impeller deterioration and increase vibrations that affect the deterioration rate of both pump shaft bearings and bearings of the motor that drives the pump. This can be prevented by correct piping construction on the suction side of the pump, ensuring stable high pressure. [54]

For TGs, according to statistical data presented in [55], primary causes of generator stoppages starting from most common: damaging of shaft oil seals, weakening of mounts of frontal parts of stator winding, fluffing of stator end core packages and few others, significantly less common. Although, the shaft seal related problems are much more common than stator-related ones, it is the stator malfunctions that cause the most down-time or overall power generation deficiencies. Additionally, there are malfunctions which are unlikely but could lead to catastrophic failures in case they happen: fissures in the main shaft, fissures in the rotor banding parts and significant hydrogen leak, all of which lead to total TG destruction with fire or even explosion if not addressed rapidly enough. The only solution to these possible problems is thorough monitoring and predictive maintenance.

The primary weakness of a transformer is the insulation of its windings due to constant electrical and thermal stress - their deterioration leads to short circuits and severe damage with performance drop. For this reason, the most important transformers may not only their I/O electrical parameters monitored but also the composition of the gas produced by the oil heated to temperatures beyond nominal. The gas analysis can also be bolstered with an AI technique (ANN) as presented in [56] to point at the type of fault present within (overheating, arcing, etc.) by detecting particular chemicals in the gas associated with known fault.

4.2. Monitoring techniques

Nevertheless, most of these primary failsafe measures do not remove the necessity of monitoring the status of each component and working fluids. Such monitoring is realized with the help of countless sensors of various types installed in important spots, often duplicated so that the more important the measurement is, the more duplicates are installed, e.g. TGs having numerous temperature and pressure sensors at each step to provide the most accurate and backed-up measurement possible.

Figure 32 GT flue gas temperature measurement (wired sensors can be seen mounted radially on the outer rim), Suomenojan PP

Perhaps, temperature measurement is the most useful, versatile and thus common, for it can quickly indicate overheat or other deviation from normal operating temperature due to wear or even electrical malfunction/overload. Temperature is measured off basically every but the smallest machines (coolant bulk temperature, hull temperature), mechanisms (e.g. bearings) and piping sections (to monitor the working fluid). In a more important machinery, there can be numerous temperature sensors measuring basically the same temperature, e.g. GT exhaust temperature (Fig. 32). [57]

When working fluid is in question, an equally important status parameter is the pressure. Often located after pumps, along the piping, in a manner that there are numerous measurements in the same part of the cycle. Just as temperature sensors, they are used to monitor pressure of all fluids in all parts of the cycle: steam, feedwater, district heat water, coolants, lubricants, intake air and flue gas. Pressure levels can indicate the health of pumps and integrity state of the piping, and can be used for other calculations.
Another fluid related measurement is the flow rate monitoring in the feedwater, coolant water and fuel supply department. As it has already been mentioned in the beginning of the theoretical chapters, flow rate is a crucial quantity, that can be used to instantly define the heat transfer between two known points, knowing other parameters (pressure and temperature). [58]

Another technique employed on modern PPs is monitoring the chemical compositions of substances. This is done to ensure the quality of the feedwater supply, i.e. absence of unwanted particles in the fluid from various parts of the cycle that might cause erosion of heat exchanger conductive surfaces. Additionally, TG lubrication oil can be monitored for presence of debris (signs of bearing deterioration) or signs of thermal decomposition due to overheating. Also, coolant gas in a TG can be monitored for traces of thermal deterioration of insulation (pyrolysis). [59, 60]

For all rotating machines, vibration of known estimated magnitude is a normal companion during operation. Nevertheless, anomalies in vibration patterns can indicate a wide variety of problems starting with trivial bearing wear and up to rotor insulation faults causing imbalance in the magnetic field and thus noticeably increasing vibration of the shaft at nominal speeds. Pattern deviations can be only detected either through thorough offline analysis, or online via a computer complemented with ML algorithm-based software that can quickly process large amounts of data and compare them with previously recorded trends of vibration at normal operation.
When a vital mechanical appliance is in question (e.g. feedwater pump), monitoring a lubricant (oil) level in the system is also commonly applied. This is useful along with vibration monitoring, because it allows to detect a lubrication system general malfunction before it causes a significant temperature increase in the bearings when they already started to deteriorate. [41, p.159, pp. 177-181]

Figure 33 Search coil installation [61].

If one to view effective TG electrical CM techniques directly related to the rotor, the first to mention would be a search coil. This is a type of magnetic flux measuring sensor, installed in the air gap between rotor and stator (Fig. 33). Data received from it is analyzed to detect abnormal fluctuations that would indicate the oncoming rotor winding insulation failure. [61]
The other types of TG electrical CM is directed more towards indication of stator insulation integrity problems. The operation of this type of sensors is aimed at detection of partial discharge (PD) – phenomenon occurring when there is a small cavity inside the insulation material (e.g. air bubble) or just the first signs of insulation wear begin to manifest. This phenomenon can be detected as a short pulse in the stator output, that can be indicated by different types of sensors (measuring charge in the capacitors installed on the stator output, or antenna-like RF sensors) whose data is read with the aid of a ML technique or by using mathematical manipulations to filter the noise out. [6; 41, pp. 238-240]

4.3. Automation

Each of the aforementioned measurement techniques is represented by a number of sensors – ranging from just a few (e.g. PD detection) in one location up to hundreds (e.g. temperature and pressure) across an entire PP. Overall, this is already an immense number of signals not to mention also signals from actuated control valves (position data), switches and machinery statuses and control signals. All of these signals require a common location where they are received, organized and used to analyze and control.

4.3.1. Hardware and software

In terms of hardware, the location where all the analysis data arrives from a myriad of sensors and actuators is a cross-connection relay room containing numerous "closets" that in turn contain I/O modules that send and receive these signals. Signals from sensors located in the vicinity from one another (e.g. from the same apparatus) are normally carried within a single cable containing several conductor pairs with a grounding conductor/shielding for interference protection. Cable is connected to cross-connection slots where each conductor pair or cable is then connected to a suitable I/O unit to perform in turn the send/receive/interpret signal functions, where modular structure allows for easy access in case of need of modification or repair. These units can be either PLCs (programmable signal communication unit, versatile modules) or RTUs (preconfigured communication units, e.g. Modbus RTU), depending on the application and requirement. I/O modules are then connected to CPUs and other controller units that organize the data and transmit it to servers, from where it becomes available on monitoring and control computers. (Fig. 34)

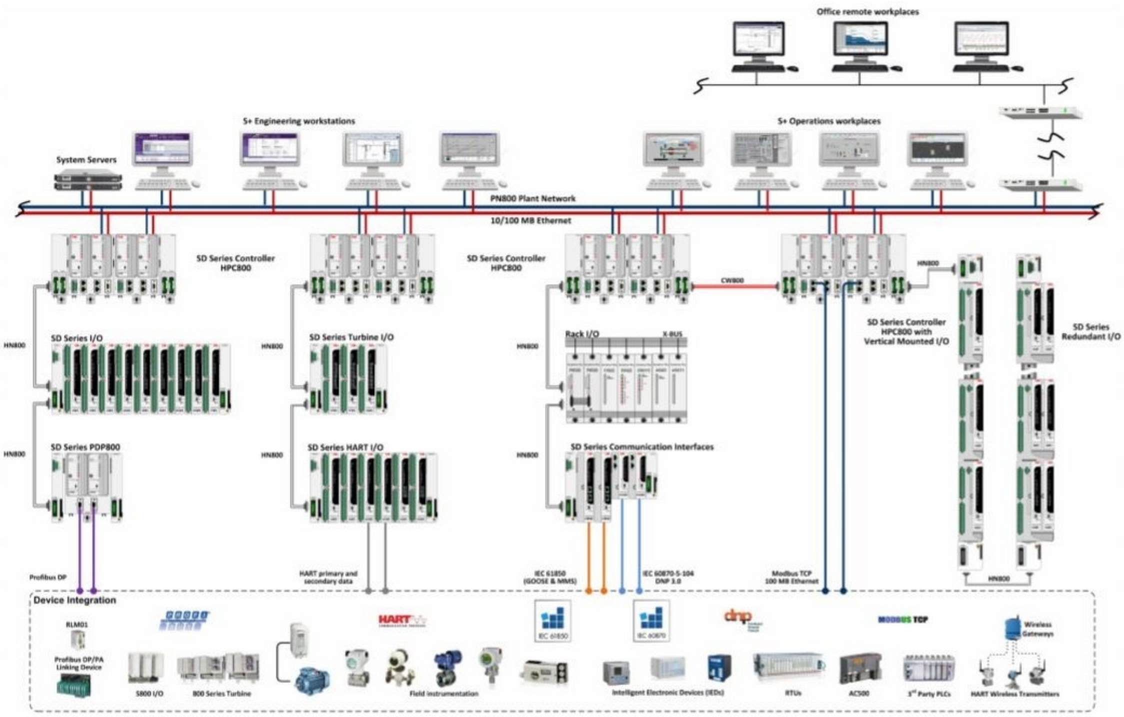

Figure 34 Example of automation communication hardware arrangement, ABB Symphony Plus

In terms of software, there are 2 main layers to operate and monitor the system: visual and actual programming. Visual layer is where all the data and available triggers (actuators) are displayed on the schematic drawing of the process (Fig.35). From this schematic the plant is actually monitored, controlled and it even enables some malfunctions to be superficially analyzed. As for the programming layer, it is used to define connections between particular nodes (to program e.g. one action to affect several actuators) in the background: their addresses (I/O ports) and labels.

Additionally, all the data is archived and stored within a relational database (usually in some form of SQL[17]-based language) on a local or remote server as timeseries. This allows remote access to data other than real-time using specific software tool or service, such as a data historian (e.g. Schneider Electric Wonderware, Siemens SIMATIC Process Historian, GE Historian and many others). Historian services often offer connectivity to third-party database solutions and provide user-friendly access to the data stored for analysis. Some solutions are hybrid, i.e. having both the database and historian functionality offered as a suite, e.g. OSIsoft® PI System®.

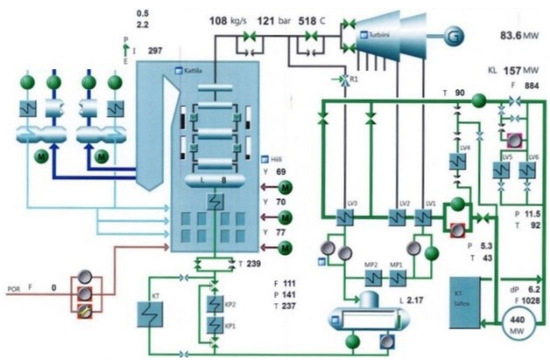

Figure 35 Example of an automation system UI: boiler, DH and steam TG, Suomenojan PP (Metso DNA system)

All of the aforementioned levels (sensor/machine → I/O → database/historian → interface) comprise the SCADA and DCS architectures. SCADA stands for "Supervisory Control And Data Acquisition", whilst "DCS" stands for "Distributed Control System". Both used to be distinctively separated in the past - DCS is the lower-level local control network (sensor/machine → I/O → interface, local with elaborate control, e.g. boiler initialization sequence) under control of higher-scale SCADA (DCS data → database/historian → interface, with remote access capabilities). With DCS, as more process-oriented system, having more functionality for direct local control, while SCADA, as more data-oriented hierarchy, having broader functionality for remote data access. Currently, both types have evolved and intertwined to the point where they became very similar in terms of functionality, e.g. remote networking capabilities that used to be part of the SCADA are now accessible directly for DCS level devices via internet protocols (e.g. Modbus TCP). [62]
Additionally, an OPC UA (Open Platform Communications Unified Architecture) specification provides means for unification of all automation systems and data access/transmission in terms of standards and protocols applied on all levels (from local PLC level to cloud-based servers). This specification is supported by all vendors of industrial hardware/software and thus, an OPC server installed in-situ, can become a binding link for any hardware with any third-party cloud[18]-based software that does not support some of the local PP data standards (e.g. database) directly. [63]

4.3.2. Data transmission protocols

Measurement and control data needs to be transmitted and accessed both locally (within the station) and remotely (anywhere, e.g. cloud services). This can be achieved only by

[17] SQL - Structured Query Language that databases are built upon, some larger companies like Microsoft or Oracle have their own variations of SQL or other similar query language
[18] Cloud services are usually provided (by software giants like Google, Amazon, Microsoft et al.) in the form of flexible server clusters with remotely accessible "virtual machines" – computers with scalable computational power and data capacity with required software installed.

adopting widely spread transmission protocols that allow data transmission between different devices produced by different manufacturers. These protocols are numerous, both proprietary and open, for local network and distant long transmission via internet, few of the most common of each type are going to be briefly described.

There are different sets of commonly used protocols depending on the type of transmission, but first, some of the most common protocols that local measurement and control signal transmission can be realized with: [64]

- DC 4-20mA analog signal, "current loop" - perhaps, the most simple and widespread type of sensor connection, that is realized by using one pair of conductors. Sensor either adjusts resistance according to measurement value, thus altering the current in the energized loop (passive sensor, loop energized @24VDC) or forms the current signal (active, i.e. with external voltage supply) itself.
- HART (Highway Addressable Remote Transducer) protocol – physically akin to the previous connection, only now implying additional capability of signal frequency modulation of the current signal with modulating fluctuations of 0.5mA in magnitude, (when several devices are connected in "Multi-drop" mode, current becomes locked at 4mA), available to the sensor/device, thus allowing several devices installed on one line and signal becoming in essence digital. In the digital mode, devices in the network obey the master/slave[19](single device connection allows also continuous signal broadcasting) communication order. Protocol (just as other smart digital protocols) allows for error checking - in case of weak/distorted transmission errors are detected, and "resend" operation is imposed.
- Modbus is another master/slave series communication protocol widely used for connecting many devices with PLCs, differs from HART in the fact that analog inputs are separate (and converted) with transmission between slave and master being purely digital. Simple overall, versatile (supporting single- and multi-pair twisted pair shielded cables) and robust, albeit relatively slow compared to more modern protocols. Original Modbus (not the modern Modbus TCP internet-adapted variation), supports only one master device and very strict master/slave order – slaves cannot inform/interrupt master device even in case of malfunction or other exceptional state.
- Profibus (PROcess FIeld BUS) – protocol similar to Modbus (digital, master/slave, widely available), but more modern (original Modbus has been developed in the 1970s, Profibus has been devised in the 1990s), supporting much higher transmission rates, multiple master devices and is suitable for use in hazardous (e.g. explosive) environments. It supports only the multi-pair shielded or optical cables, has more complex hierarchy both physically and communication-wise than the Modbus.

[19] communication order, where "Slave" devices are polled by the "Master" unit, i.e. slave sends data only when requested by the master.

Remote communication protocols used for data transfer across long distances, e.g. via internet, are usually built onto the TCP/IP - Transmission Control Protocol/Internet Protocol - two layers of protocols commonly used for all kinds of networking and distant data transmission. TCP/IP protocols basically organize transmission in a vast worldwide network that is internet. Additionally, in the era of cloud-computing when local data is often continuously sent to remote servers, there is a need to provide secure encrypted (Fig. 36) connection to avoid unwanted access especially when a functionality of remote control is present. With this in mind, several security transmission protocols are used for industrial data-transfer, the two most common ones being:

- SSL (Socket Security Layer) and TSL (Transport Layer Security) that has evolved from it, are widely used key-exchange protocol that excludes unauthorized access and ensures integrity of data transferred. The data is encrypted, and encryption keys are automatically generated every connection, the encryption algorithm and keys are defined before any portion of data is sent. Whenever the secure connection is requested from a server supporting SSL/TLS, a digital certificate signed by a certificate authority is sent, that ensures the genuineness of the server and the encryption method. [65]
- SSH (Secure Shell) is another secure protocol, similar to SSL/TLS, with main difference being expanded functionality, e.g. capability of direct remote control over the server via login. There are no certificates of SSH verifying such connections. [66]

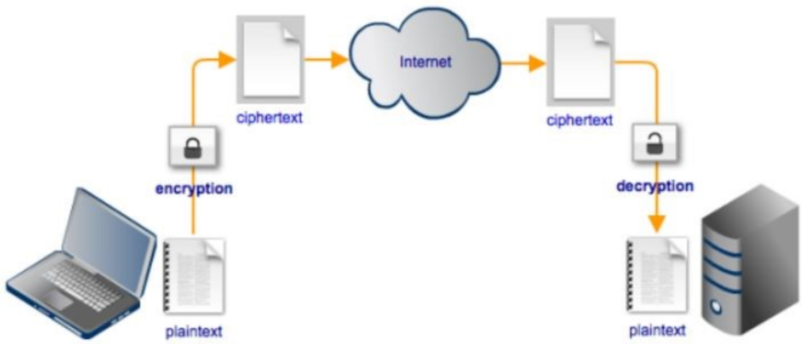

Figure 36 Basic schematic of a secure internet connection [66]

5. Machine learning

Today, when computer and information technologies have evolved to the point that we can simulate entire virtual worlds on a single compact machine and then send the data to another machine within adequate time frame. Definitely, such computational power and network bandwidth can be of most usefulness in the field of electricity generation (and industrial applications overall) with vast arrays of signals required to be processed continuously. Moreover, the need especially persists since standard automation systems use human personnel to operate and monitor processes – whilst there is no problem with operating a plant, continuously monitoring thousands signals from a myriad of sensors is physically impossible no matter how large the number of personnel is. Also, value limits at which a signal makes the automation to produce an alarm are usually set in the nearly-critical region, for otherwise alarms would flood the control monitors at each minor fluctuation. This meaning that often when the automation system has produced an alarm, it is possible that significant damage has already been done.

This is where advanced computer technologies bolstered by AI methods and Internet of Things[20] solutions have become extremely useful. Whilst the subject of AI is rather broad, including e.g. image recognition, voice processing and other forms of imitation of human intelligence, a separate form of machine intelligence is discussed in regard to predictive maintenance: machine learning. ML enables a computer to be capable of data analysis and decision making based on learned data examples, e.g. whether a slight departure from normal readings is a momentary consequence of another change in a process, a single chaotic fluctuation in the sensor data (either can be ignored) or it is a systematic deviation signaling of oncoming failure that needs to be reported urgently.

Not only does this approach allow to warn in advance about a deviation that might have gone unnoticed otherwise, but it also does so for a constant flow of intertwined data that would be impossible to process in this manner with any other method efficiently. This constant vast flow of various sensor readings is commonly addressed to as "big data". The concept of big data has imposed challenges that would have been impossible to overcome in the past: amount of data needed to be gathered, transmitted and processed is enormous. In case with PPs the data requires entire server networks for it to be successfully manipulated even now, while in the past there was no feasible solution for this at all.

Vast computational power is required because AI techniques used for analyzing the data in essence are mathematical models consisting of myriads of interconnected mathematical functions. These functions are able to classify the input data or use it to predict expected values, correlate values to each other and detect abnormalities. But to do this efficiently, such model needs to be "trained", or in other words needs to optimize itself (or "learn") using an example set of data, in order to accurately detect the "abnormal" values. The area of ML optimization is actually the one where the main differences and challenges lie, and it is going to be discussed in this chapter along with the basics of learning algorithms.
[67; 68, pp. 2-5]

[20] new trend in the current age of smart computerized devices meaning the network of such devices communicating with each other and user, locally and over internet. [67]

5.1. Regression

Perhaps, regression type of ML algorithms is the best to begin delving into the subject. Main purpose of regression algorithms is to form a mathematical function that is able to forecast output from input fed into the function. The simplest regression model is the linear regression, that mathematically is represented in the following form (common for all linear algorithms):

$\hat{y} = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} + b$ (10)

Where $\hat{y}$ is the estimated output, $\boldsymbol{x} = [x_1, x_2, \ldots, x_n]$ is the input vector (set of input values), b is bias (increasing accuracy if linearity is not in line with the coordinate origin) and $\boldsymbol{w}^{\mathrm{T}} = [w_1, w_2, \ldots, w_n]$ is the transposed[21] weight vector. Weight is the concept common for all similar-purpose ML algorithms, that is the target for training. Training process defines the weight values that are used afterwards to predict output based on input and is done by feeding in the training datasets of both input and output values ($\boldsymbol{x}^{\mathbf{train}}, \mathrm{y}^{\mathrm{train}}$) – this is also a definition of supervised[22] algorithm.

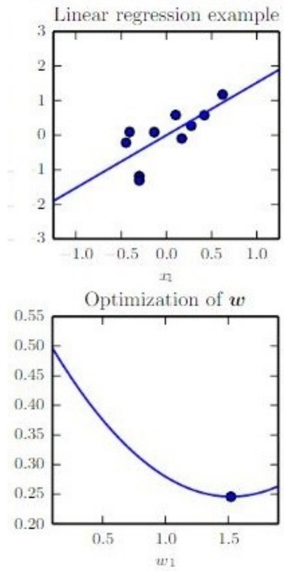

Figure 37 Linear regression (upper) and MSE optimization (lower) [68, p. 107]

Performance of this simple model can be increased via analyzing the Mean Squared Error (MSE) between *m* estimated and actual output value pairs in a *test* subset:

$\mathrm{MSE}_{\mathrm{test}} = \frac{1}{\mathrm{m}}\sum_i^n\left(\hat{y}_i{}^{\mathrm{test}} - y_i{}^{\mathrm{test}}\right)^2$ (11)

MSE is also used to define the most appropriate weight in linear regression in the simplest ML method – vector $\boldsymbol{w}$ producing the lowest MSE ((11), only from “train” dataset) is the most optimal (Fig.37):

$\nabla_{\boldsymbol{w}} MSE_{train} = 0 \rightarrow \boldsymbol{w} = \left(\boldsymbol{X}^{(train)T}\boldsymbol{X}^{train}\right)^{-1}\boldsymbol{X}^{(train)T}\boldsymbol{y}^{train}$ (12)

This operation, in the end, is computationally basically the simple $\mathbf{w} = \frac{\boldsymbol{y}^{train}}{\boldsymbol{x}^{train}}$, where $\boldsymbol{X}^{train}$ is the complete training input matrix (all the input vectors) and $\boldsymbol{y}^{train}$ is the training output vector. Overall, this method while simple, can prove rather inaccurate (as an example of method efficiency – around 30% error for linear regression in a PM experiment conducted in [69]), rending it useless in demanding non-linear tasks on its own without modifications or supporting algorithms.
[68, pp. 105-108; 69]

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21 transpose is vector/matrix related manipulation where rows become columns and vice versa, usually for multiplication purposes – turning product of 2 vectors/matrices of suitable size into a single value/vector/matrix depending on the order of the calculation and target of a transpose

22 supervised, i.e. an algorithm is given not only the inputs (“features”) but also the correct outputs (“labels”) associated with them. In unsupervised training, algorithm is provided only with inputs.

5.2. Classification and kernel trick

Another important task of AI based algorithms is to produce automatic classification (labeling) of the input data (e.g. this approach used in image recognition), one of the primary methods devised with this function in mind is the Supported Vector Machine. Akin to the simplest ML technique, the linear regression, SVM at its core is linear, only the idea behind the linearity is different. All the input values are separated (labeled) into two groups during training, e.g. A and B, with corresponding to simple output values 1 and -1:

$$y_i^{train} = \begin{cases} 1, \text{if } x_i^{train} \in \text{A} \\ -1, \text{if } x_i^{train} \in \text{B} \end{cases} \quad (13)$$

Then, the imaginary line (as (10)) is drawn between the groups and the margin is maximized between the nearest values from the different groups to provide better accuracy and the vectors from the imaginary line to boundary x values are the support vectors (Fig. 38):

$$\text{w} = \sum_i^n \alpha_i x_i y_i \quad (14)$$

$$L_D = \sum_i^n \alpha_i - \frac{1}{2}\sum_i^n \sum_j^n \alpha_i \alpha_j y_i y_j x_i x_j^T \quad (15)$$

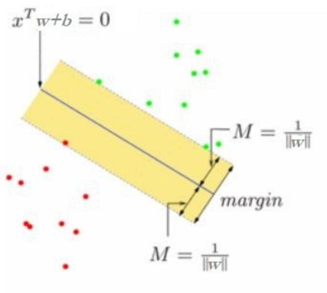

Figure 38 a graphical representation of the SVM algorithm [70]

Often, the bias term is dropped from calculations because data is assumed to be zero mean. α_i is coefficient, that is 0 for the points beyond margin (and in correct class boundary), is linear to the estimated output function and it is the value that is subject to optimization. Margin M is maximized via maximizing L_D, that represents (after some mathematical manipulations) the difference between the sum of all boundary coefficients and sums of products of those coefficients and respective datapoints. [70; 68, pp. 139-141]

When training is complete, the new input values can be accordingly defined to one of the preset classes. Additionally, SVM can be applied for regression analysis because of the functional similarity to linear regression model. There, the margin boundary maximization feature can be used to adjust "fitting" of the model to data (margins are adjusted to have the datapoints within, not without as in classification SVM). [71]

Some data might follow a non-linear pattern, following which can be more useful than following a straight line. There is a technique employed to adjust a model to this known non-linear behavior, called the Kernel trick. It is based on the idea that a linear function of an algorithm can be represented by a sum of dot products[23] of example input values. This allows replacing the actual input values in the main function (classifier function) with a kernel function that represents a dot product of the trained and unlabeled feature functions and alters (15) as followed:

[23] dot product for ordinary real numbers would be a normal product and in terms of vectors, it would be a sum of products, e.g. $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^{\mathrm{T}}\mathbf{y} = \sum_i^n x_i y_i$

$x \rightarrow \mathrm{h(x)}$
$\mathrm{K}(\ x_i, x_j\ )\ =\ \langle \mathrm{h(x_i)}, \mathrm{h}(\mathrm{x_j}) \rangle$
$L_D = \sum_i^n \alpha_i - \frac{1}{2}\sum_i^n \sum_j^n \alpha_i \alpha_j y_i\, y_j \mathrm{K}(\mathrm{x_i}, \mathrm{x_j})$ (16)

Where $K(x_i, x_j)$ is a kernel function, the most applied type being the radial basis function (or Gaussian kernel):
$K(x_i, x_j) = e^{-\frac{\left\|x_i - x_j\right\|^2}{\sigma^2}}$, with σ as a tuning parameter.

The kernel trick is especially important because it can be applied to any simple linear method (e.g. linear regression) to fit the data better and thus to dramatically increase accuracy for either classification or regression. Also, it doesn't increase the computational difficulty of the algorithm, which is important in case with complex datasets. Overall, SVM can be applied for maintenance-related tasks even on its own for a less demanding task: particular part of machinery can be continuously analyzed to be classified as "normal" or "abnormal" to evaluate the condition of the given part, as suggested in [70].
[68, pp139-141]

5.3. Clustering and unsupervised learning

If supervised ML models are trained via known input values with known labels (output values), unsupervised algorithms imply only availability of the input data. This type can be useful when there is a need to define the structure of the dataset without labeling, i.e. to cluster the input data into groups based on the similarity of features. This approach is logically called "Clustering" and is suitable for preliminary data analysis with the purpose of pre-processing to learn basic correlation between an array of input features.

One of the main techniques in this type of algorithms is k-means clustering. It can be represented as a k-dimensional vector $\boldsymbol{h} =\ [h_1, h_2, \dots, h_k]$ that contains information on whether or not input datapoint x_i belongs (thus $h_i\ = 1$) to a cluster or not (i.e. 0). Furthermore, there is assumed an equal amount of cluster centroid vectors $[\boldsymbol{\mu_1}, \boldsymbol{\mu_2}, \dots, \boldsymbol{\mu_k}]$ that describe the middle point related to the cluster of datapoints. Vicinity of a datapoint can be defined e.g. via calculation of average distance with shortest defining the cluster the datapoint belongs to.

Principal component analysis (PCA) on the other hand is a clustering related algorithm that is based on dimensionality reduction via mathematical transformation. First, a manipulation called Singular Value Decomposition (SVD) is applied to the dataset, that in essence is a matrix transformation used here to obtain the principal components:
$\mathbf{X} = \mathbf{U\Sigma W}^{\mathrm{T}}$, where $\mathbf{U}$, $\mathbf{\Sigma}$ and $\mathbf{W}$ are the singular vector matrices of different compositions.

The main goal is to perform transformation $\mathrm{z} = \mathbf{W}^{\mathrm{T}}\boldsymbol{x}$, where values z are mutually independent, and to produce matrix $\mathbf{Z}$ of lesser dimension, absent of linear correlations, that aims at hidden factor of data variation removal.

Both methods can be used in conjunction for data structuring, or each can bolster some other algorithm. According to [72], k-means clustering with prior PCA can be effectively used for abnormal behavior detection. A state-of-the-art method of advanced Kernel Spectral Clustering method has been devised in [73] based on spectral analysis of vibration data from accelerometers – it allows for predicting deterioration of various parts of modelled machinery, also with including the possibility of adjustment for either soft clustering (overlapping clusters) that could point at "probability of maintenance", whilst hard clustering (clusters are strictly separated) can determine data anomalies and thus malfunctions.
[68, pp. 145-148]

5.4. Artificial neural network

One of main AI model types for complex applications is called "Artificial Neural Network" – it is a combined method capable to be devised for both classification and regression purposes, with linear or non-linear data behavior. It usually doesn't require a supporting algorithm for increased functionality and/or accuracy, as often is the case with simpler models required to operate complex data. The name implies that it has a sequential layered model structure that is reminiscent of that of a human brain (Fig. 39).

Each "neuron" in the model, i.e. a mathematical function, is connected to other ones with a weight value, that defines how closely input values are connected to each node of next layer in a chain fashion (e.g. 3-layer function):

$$\mathbf{f}(\mathbf{x}) = \mathbf{f}^{(1)}\left(\mathbf{f}^{(2)}\left(\mathbf{f}^{(3)}(\mathbf{x})\right)\right)$$
$$\mathbf{y} = \mathbf{f}(\mathbf{x}; \boldsymbol{\theta})$$

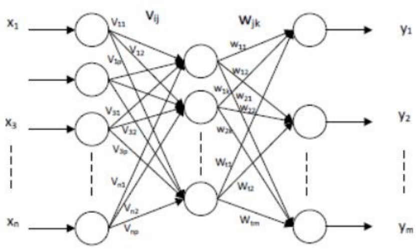
Figure 39 simple graphical representation of ANN [74]

Where $\boldsymbol{\theta}$ is the set of parameters defining model behavior, that includes weight and possible bias (e.g. if linear behavior is considered: $\mathbf{f}(\mathbf{x}; \boldsymbol{\theta}) = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} + b$)

There can be a plethora of layers: input, output and numerous "hidden layers" in between - in this case an ANN is called "Deep feedforward network", and this is one of the most useful types for commercial applications. Hidden layers are exactly the bulk of the entire ANN model defining the relation between the input and output data and correlation thereof. "Deep" in the name comes from the "depth" of the model, i.e. numerous layers it consists of (generally, more than 3), feedforward stands for the direction of propagation of the calculation to produce output values.

This model can be trained in a number of ways, the more basic (yet still noticeably more elaborate than previous ML techniques for simpler models) one is following. Firstly, initial values x_i are fed into the ANN to receive some output values $\hat{y}_i$. This output is used to calculate the error (e.g. MSE) between the model estimated output values $\hat{y}_i$ and the desired (known) output y_i. Afterwards, the known output $\mathbf{y}$ is fed into the network in the opposite direction (back-propagation) to define the gradient of the cost function (i.e. derivative or change rate of error function against the known x_i) that is used in optimizing the weight values in the way that the gradient is at minimum (Stochastic gradient descent algorithm), thus producing output estimation with the lowest error possible.

All in all, this approach can be used to define connections between input values and predict/determine possible output values. ANN models can be very complex, at the same time, increased complexity grants more flexibility and accuracy for the end result. They can be employed across variety of applications: from image and pattern recognition to steam turbine monitoring or general PP performance monitoring.
[74; 75; 68, pp. 164-174]

6. "Industry 4.0"

The idea of programmable computers with some sort of intelligence is older than 150 years (Ada Lovelace) and the AI techniques have been in development for many decades as well. Today, the technological advancement reached the point where it is feasible to widely apply various forms of AI not only for experimental purposes on supercomputers (e.g. IBM Deep Blue c.1997) but for basically any application where quick computerized analytical decision could be useful: from a simple image processing on a smartphone to the aforementioned industrial sensor data flow analysis. [68, pp. 1-2]

With this purpose in mind, numerous ML based big data analysis systems have already been developed, offered and deployed worldwide. Usually, these solutions are more than just software: they include a business model that in turn contains numerous aspects related to implementation of the software in question for a customer in a mutually profitable manner. Business model most notably includes:

- strategy - the purpose of the solution and goals of the company
- value statement - both for the customer and the company
- operating model – a bridging component between the purpose and implementation
- implementation – from commissioning to day-to-day use

[76, 77]

The latter two points are the most important in regard to this thesis for they contain the main differences in the "Industry 4.0" solutions, or in other words in smart AI based IoT automation designed to be used practically everywhere from manufacturing plants to PPs and smart grids[24]. Overall, the main technological aspects in terms of product structure, operating model, implementation, main technology used in such solutions are to be analyzed for the sake of comparison in the following sections.

6.1. Maintpartner INtelligence® (Remote Access Tool)

The first PM solution to be listed is the INtelligence of Maintpartner Oy, a Finnish maintenance company headquartered in Helsinki. The INtelligence team running the solution is responsible for realization of distribution, deployment and active application of the AI based software with Remote Access Tool (RAT, fig. 40) being a visual interface. Whilst the software updates/tweaks and data processing are provided by partner companies.

[24] likely the future of current electrical grids, where even private consumer can not only consume electricity, but also generate on their own e.g. with a solar panel and feed it into AI-controlled smart grid that is able to quickly adjust load balance and isolate anomalies. [78]

INtelligence represents an entire package of services provided to a customer where at the core is an industrial signal processing software suitable for both industrial (i.e. manufacturing) and energy applications. The package includes:

- ML analysis software with the cloud service that provides worldwide availability of the process analysis
- data integration with support of various protocols and databases (e.g. SFTP, OPC UA, SQL etc.)
- continuous support after deployment

  Additionally:

- a separate module for optimization via mathematically calculated optimal points of operation for maximum efficiency
- a web-based app is currently in development – for secure access to the data from any device connected to the internet

Figure 40 UI of Remote Access Tool

The operating model is following:

1) Process model definition, data overview, data connection establishing (2-4 weeks)
2) Data de-noising, unsupervised ML, model tuning (1-2 weeks)
3) Model validation and retuning, local RAT users training (1-2 months)
4) Model handed over to the customer, nevertheless its performance still monitored, model training continues (1-2 months)
5) "Software as a service" (SaaS, subscription business model) with updates, INtelligence team support, monthly review (continuous operation)

Technically speaking, general modelling is executed by the software based on the initial list of sensors (their position identification) provided by the customer. Software then defines automatically correlations between signals and their grouping. On this basis and with the data being fed from these sensors (possible to access the data via local automation system database directly), INtelligence is able to estimate the signal value via sophisticated calculations later on.
The training of a model starts with clustering of the data to group the sensors more closely to each other in the model. Next, more algorithms (e.g. kernel regression among others) are engaged in succession: they define the correlation patterns between the signals in the cluster, making it possible to estimate what the combination of all signals (their outputs) should be during normal run (or any other mode of operation learned by the system). This makes the solution computationally heavy, demanding a server cluster for its smooth operation, yet at the same granting relative independence from personnel – there are no features/labels that need to be gathered/chosen manually – only history data is required for training. The directly supervised part is initiated after the training is complete: during this stage, the team contacts operating personnel on the customer's site nearly on the daily basis to ensure correct model adjustments. As soon as there is significant[25] deviation emerges in the signal combination, program produces an alarm, then it is a task of an operator (INtelligence team member or local user later on) to evaluate the alarm and determine whether if it is correct or incorrect. When alarm is rated as either, the software makes adjustment to the dataset used for next retraining that is initiated in case of change of mode of operation or model expectation inaccuracies caused by other reasons – retraining is done during any stage of operation as the need arises. After the majority of adjustments have been completed, the predictive maintenance solution is fully commissioned to a customer with an ongoing support. In the RAT, all the sensor data is accessible and displayed in the form of timeseries (both in real time and history). Models are organized in a pie chart manner, representing data grouping that was determined during initial training of the model. [79]

6.2. NEC SIAT (Invariant Analyzer)

A technique similar in the main idea behind operation: System Invariant Analysis Technology employed by Tokyo based Japanese NEC (Nippon Electric Corporation). Just as the previous example, the operation of this method is based on the ML based constant sensor data analysis with the purpose of anomaly detection.
Whilst there is no mobile app separately announced, a photo of a tablet with analyzer UI is displayed on NEC

Figure 41 Invariant Analyzer UI on a tablet [81]

[25] significance, i.e. alarm boundaries, is defined by the software itself, although an operator can alter this in case of need

web-site (Fig.41). From UI it can be noted that the software also has a capability of presenting a model in the form of schematic of actual PP/factory with signal marked onto. Additionally, a separate cybersecurity solution is offered as a means to defend against external attacks, detect unauthorized network access etc. [81, 82]

NEC working in conjunction with its partner, another Japanese company - Sumitomo Corporation, provide this service in the following manner:

1. Verification of the target systems and data collection (1-3 weeks)
2. Invariant analysis (measurement relationship determination) period (6 weeks) with few overlapping stages:
    a. Data preprocessing (2-3 weeks)
    b. Active communication with a customer (4 weeks)
    c. In the end - the report with a briefing section (3 weeks, starting before the end of invariant analysis)

Data collection (as well as first meetings) and communication with a customer is realized by both NEC and Sumitomo, whilst data processing and analysis with report is executed by NEC only. This process is a sort of a preparation before the full continuous deployment on a plant: accuracy and effectiveness of the approach on the given site are verified. Additionally, NEC requires a timeseries of target systems data of at least one year for the creation of the invariant model. For detection of anomalies there has to be a timeseries with an anomaly example and normal run timeseries prior to the anomaly, thus making the algorithm supervised, for it needs clear separation between normal and anomaly data.
As it is implied in the name of the technology, it learns and later analyzes relationships between input data that are invariant (unchanging) during normal operation. When the invariance is broken, the method allows to point at the source data relationship change and alarm users via the Invariant Analyzer software interface. It allows timeseries data (anomaly score) to be analyzed at a glance displaying the percentage of deviation. Also, two options of analysis are available: quick but more simplified local analysis in-situ (directly from DCS data) and a more delayed but complex and deep cloud analysis (from historian/database). [80]

6.3. Avantis® PRiSM (Predictive Asset Analytics)

Avantis is a package that includes several services and software solutions. The core of this package – PRiSM was developed by the American software company InStep (Chicago, US) that is now a part of multinational corporation Schneider Electric (Rueil-Malmaison, France). [84]

The AI analysis software itself can be complemented with additional solutions that can be integrated with PRiSM (Fig. 42) and used for easier access and control over the data. Notably, amongst the array of applications is the Performance Optimization Services (process optimization by Schneider Electric experts) and Wonderware® series of products that include: SmartGlance mobile app that makes it possible to access the real-time plant data via a smartphone or a tablet from anywhere, and eDNA solution that stores, displays and analyzes measurement data and allows easy access to it (historian). Also, a software developer kit (SDK) with an open application programming interface are available for Wonderware SCADA interface, meaning that it is possible for a customer to develop applications on their own. In terms of cybersecurity, additional to security data transmission protocols, authentication and access control standard across all manufacturers, there is also a separate cybersecurity solution for e.g. network intrusion detection. [85, 86]

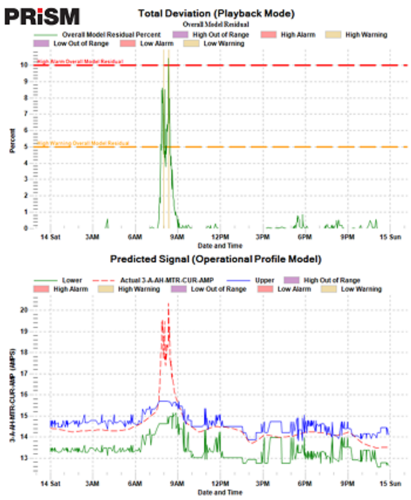

Figure 42 PRiSM UI [84]

The general operational model for the primary implementation is following:

1. Automation and sensor data connection establishing phase (to DCS, SCADA, smart sensors etc.)
2. Data processing and product information collection
3. Analysis via machine learning and fault diagnostics
4. Online application with collaboration of local personnel and Avantis team

The operation of the data analyzing software is based on the OPTiCS algorithm with Advanced Pattern Recognition. Overall, the algorithm (or combination thereof, according to US patent No. 9,379,951 B2, "Method and apparatus for detection of anomalies in integrated parameter systems" that belongs to the company) is based on the historical data analysis that is used to build a model via data feature selection (classification into "normal" and "abnormal" subsets) with clustering of the selected data set to structure the data according with similarities within the subset. Then, the resultant model is tested and tuned with cross-validation (self-checking of the model) of the data and can be used for monitoring. During the continuous phase, the new data is analyzed via calculation of the proximity to "normal" or "abnormal" operation mode clusters, alarming when the input data is considered "abnormal". [83]

6.4. Uptake™

The solution "Uptake", offered by American Uptake Technologies (Chicago, US) is another ML based monitoring platform. It has slightly different history of applications from the point of focus of this thesis, namely the industrial heavy-duty fleets of construction machines (tractors, bulldozers etc.) and city transport, wind turbines and oil/gas gathering industry facilities, and for energy sector it is developed mostly with smart grids in mind. Yet this means only that so far, the solution has been employed on smaller models largely identical to each other rather than interconnected variable models of a PP. Still, the idea is the same and the overall structure as well – the system gathers data from numerous sensors, relays it to the main platform server, where it is processed and then can be viewed by user. Additionally, it has an emphasis on cybersecurity, being able to analyze also possible network trespassing and unauthorized access. Also, it is capable of taking into consideration additional external variables that might affect performance – such as wind conditions for wind turbines. Overall, the analysis provided by the platform is aimed at easy visualization of state of machinery with hints at type of maintenance that needs to be conveyed and also the time when it could be critical to do. (Fig. 43)

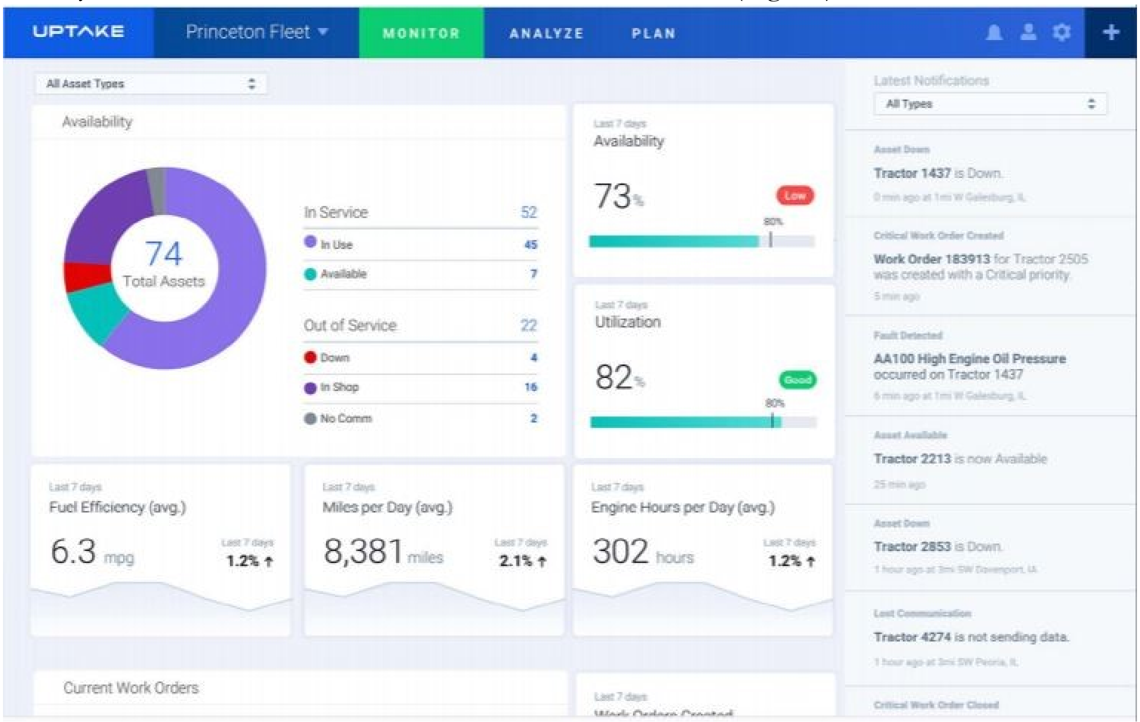

Figure 43 Uptake UI

Technically, determination of failures and applicable solutions heavily relies on models based on the result of so-called survival analysis, where likelihoods of particular failures and error codes (of on-board monitoring systems) are estimated and associated with particular variables. According to US patents No. 2018/0060703 A1 and No. 2016/0371584 A1 ("Detection of anomalies in multivariate data" and "Local asset analysis" respectively) that belong to Uptake LLC, the algorithm calculating the deviation of values at its core is based on a mathematical transformation of the input data, PCA, that reduces the dimensionality and input data type variability. Moreover, while compressing, it also forms the main components of the data, thus forming a cluster with general parameters describing the entire input subset. Next, the cluster is standardized using z-score[26], based on which the maximum variable is defined in the transformed data cluster for each input variable,

[26] i.e. with regard to standard (Gaussian) deviation

forming a threshold. These threshold values, calculated during training period, are stored and later allow for effective comparison of new real-time data, for noticeably differing data would also deviate beyond the threshold after transformation. After analyzing, the data is transformed back to original state to define the actual point of deviation if such took place. Additionally, likely is the use of an undisclosed ML learning algorithm for model updating/improvement.

6.5. Siemens Plant Monitor and MindSphere.

Next, the solutions offered by the German conglomerate Siemens AG (München, Germany) are going to be analyzed. The Plant Monitor (part of SPPA-D3000 lineup) is offered as a package of the predictive diagnosing software system and a technology server from the SPPA-T3000 automation control system (the Siemens-engineered DCS system) that is required for the Plant Monitor to run. It can be used even with any non-Siemens control system given that the data is transferred via OPC UA server and relayed to a separate T3000 server with the D3000 Plant Monitor (Fig. 44). Either way, client has access to all of the diagnostics, archiving and monitoring capabilities of the software (additional option – SPPA-P3000 optimization software). Akin to the solutions mentioned above, the implementation procedure is following:

- Preparation: model-based description of the processes based on archived data, measurement point (tag) collection and selection
- Training phase, that can last from days to weeks - the period is based on the magnitude of fluctuations in the trend data
- Retraining: model is readjusted in case of insufficiently long initial training phase, causing incorrect predictions
- Normal continuous monitoring

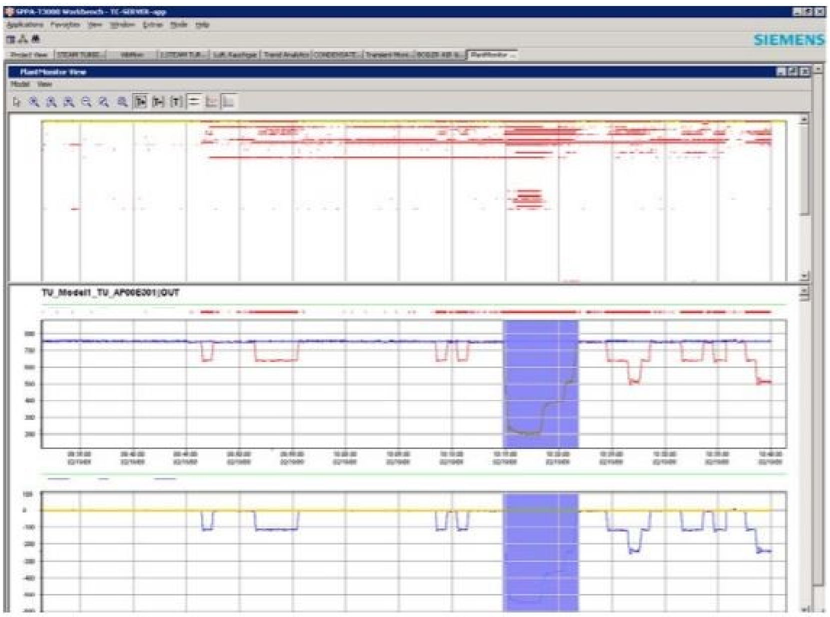

Figure 44 Plant Monitor UI opened inside T3000 app [87].

Technically, this diagnostics system uses a deep learning ANN algorithm (ANN is briefly mentioned in the technical description manual, also several ANN and deep learning patents are assigned to Siemens, [88]), likely modified with e.g. radial basis function for improved non-linear capabilities. The goal is exactly the same: to detect early deviations, only approach is different, since ANN is basically a complex model with interconnected hidden layers, where the previously described systems mainly used different algorithms in conjunction to form a model. Unlike most other systems, that are more of a "black box"[27] type, plant monitor actually requires tags to be chosen and selected, thus including some actual human-driven modelling. The training process can be easily adjusted any time with a possibility of choosing an exact training period, data sets and even removal of an already added abnormal data in the set. Similar flexibility is available also during operation, the model can be adjusted and retrained at any time, same variables can be used for several models and overall a model can be trained for modes of operation other than normal and make adjustments taking into account known aging of particular elements. [87]

While the Plant Monitor is mostly based on the older technology software that is in the possession of Siemens AG, there is a more modern solution available: MindSphere (Fig. 45, created in collaboration with SAP that is going to be discussed later in the chapter, [92]). It is a versatile IoT cloud platform suitable for various needs that includes different modules (MindSphere Apps, including third-party [90]), with offered open API for custom apps and extensive cybersecurity measures with additional data encryption, firewalls and virtual private network access (although, these are industry-standard measures, there is no separate network-security Mindsphere App mentioned). These modules provide a wide diversity of functionality, e.g. continuous access to online CM data anywhere via a smartphone app, with trend prediction and anomaly detection capabilities (likely also based on ANN) for separate signals. [89, 91]

Figure 45 Mindsphere UI as presented in the whitepaper, courtesy of Siemens AG.

6.6. GE SmartSignal and Predix

The SmartSignal is a software solution developed and offered by another large company, American General Electric (Boston, US). Currently, the software is closely tied to the GE Predix cloud platform, that is a data transmission, storage and management system with analytical functionality, similarly to the Siemens MindSphere. If used with Predix,

[27] a system where exact internal functions/technologies are beyond the scope of interest, and only I/O of the system is taken into consideration, thus assuming the system to be a plain black box with known inputs and outputs

SmartSignal is offered as a part of the Asset Performance Management (Fig. 46) package - the package that is responsible for analyzing and displaying measurements along with predicted values in the Predix platform. Predix is available with an SDK for custom app development, with an optimization package called Operations Performance Management (OPM) and in terms of cybersecurity, Predix is built around the standard practices of data encryption, security protocols, authentication control etc. If SmartSignal is employed separately – it is realized with supporting database server hardware in situ, although lacking the cloud-based easy access and data management functionality to some extent, as well as the integration with other GE Predix products (mostly revolving about process management and additional optimization functionality). [94, 95, 96]

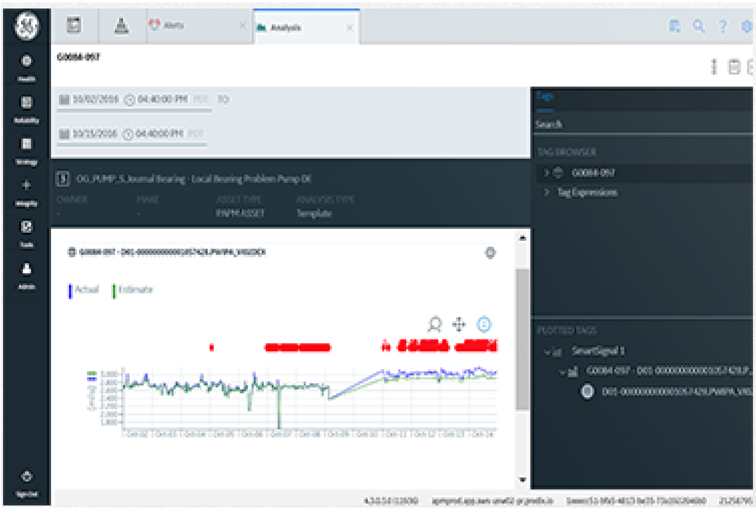

Figure 46 GE Predix APM UI, Courtesy of GE

In any case, SmartSignal is capable of processing signals incoming from database of any manufacturer supporting SQL or an OPC UA system. Overall reliability predictive functionality is based on the idea of determining the similarity of the current state of the model (i.e. a large machine with multitude of sensor data) to the previously determined one. The main learning algorithm used (according to US patent No. 7,509,235 B2 belonging to GE) is somewhat different in terms of the main idea: being dubbed "Evolutionary" or "genetic programming" for similarity to evolutionary processes in the nature. Input parameters are grouped into a set of "individuals", also called "chromosomes" or, in other words, vectors with weight and similarity data corresponding to a model. Chromosomes comprise "population" and the best gets selected in the population replacing the worst, i.e. less fitting model parameters akin to natural selection in the process of evolution. "Fitness" is defined during via classification into "true positive" or "false positive" by an additional fuzzified[28] model evaluation algorithm. This algorithm likely has kernel-based non-linear capabilities because of the gaussian basis function mentioned in the patent and also provides classification based on the weights between the input data calculated during initial clustering. Thus, the algorithm creates the model created

[28] Fuzzy meaning that traditional Boolean true/false are replaced with a wider variety of conditions, e.g. "completely true", "somewhat false", "quite true" etc.

via similarity-based clustering and then updates and improves it during numerous following iterations via self-analysis employing classification. [93]

6.7. ABB Ability™, IBM Watson and MS Azure

Similar to other corporations and conglomerates mentioned above, the multinational corporation ABB (Zürich, Switzerland) offers a rich series of products run by the name of “ABB Ability”. The product series unifies numerous applications and solutions suitable for different needs in different industries. To name the few ones developed for energy industry - system analysis and management solution Ellipse Asset Performance Management (APM), automation system Symphony Plus (unifying DCS and SCADA functionality), and Virtual Power Pools process optimization service (aimed mostly at power balance in the grid and system). [97]

Ellipse APM is the most important related to the focus of this thesis, for it provides the predictive information on the operating machinery. The main function of the package is to visualize in easily comprehensible form the current state of each machine with estimated malfunction probabilities and service intervals that are adjusted according to numerous parameters. As an example, the state of an HV transformer can be displayed in the form of Duval triangle (Fig. 47), that takes into consideration current chemical composition of the oil inside, as well as various other parameters (temperature, electrical inconsistencies etc.). [101] The triangle itself helps quickly see the state of transformer and probability of a failure of particular kind. Other equipment can also be monitored similarly, with maintenance suggestions, periods and overall health displayed for an operator to plan the maintenance accordingly. [97]

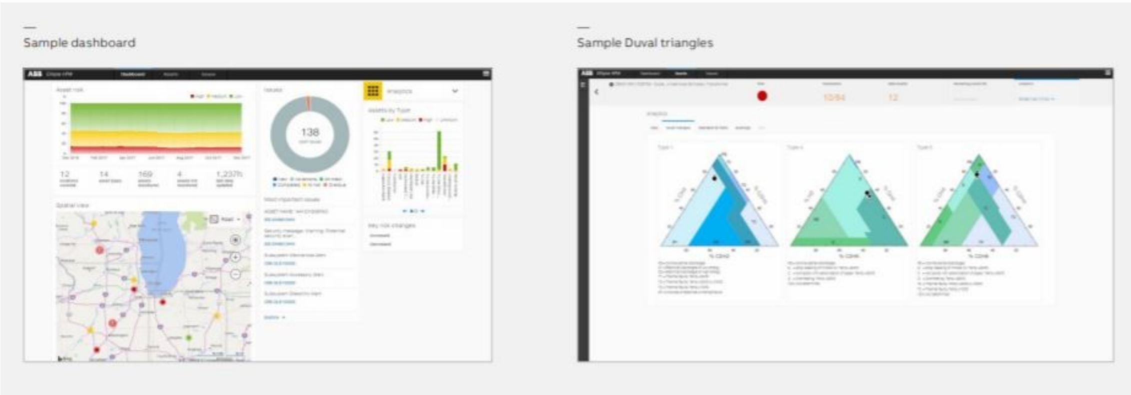

Figure 47 ABB Ellipse APM UI dashboard (left) and transformer Duval triangles (right), courtesy of ABB

Akin to Uptake, the approach is survival-based (US patents No. 9,665,843 B2, 2014/0365271 A1 and US2014/0156225 A1): the operation of the software revolves around the use of models estimating the lifecycle and probabilities of particular failures prior to estimated aging due to various factors. The models are developed with a machine learning technique(s) in mind, through the exact one used in Ellipse APM or e.g. in the marine ABB Ability Remote Diagnostic System (sea vessel CM solution with PM functionality) is undisclosed and the suitable patents are described in the way to support any of the openly available ML techniques (ANN, SVM, regression etc.).

Ellipse can be installed in situ, or in the cloud that is provided by Microsoft Azure service. Also, other cloud-dependent solutions of ABB are powered by the Azure platform. Moreover, another collaboration of ABB with IBM on the integration of the IBM Watson AI in ABB Ability, implies the wide adoption of it across many ABB solutions in the near future, e.g. for predictive maintenance, manufacturing defect detection and performance optimization. Thus, ABB has outsourced some of its services to third-party suppliers to focus more on the own product development and support, also making the overall solution structure somewhat simpler. As for the cyber security, it is mentioned extensively throughout various ABB product brochures, yet there appears to be no separate application/service for it, rather the security measures are built-in by default in the form of protocols and structure or in the form of additional network intrusion detection options for the Symphony Plus system. [98, 99, 100]

6.7.1. IBM Watson

Watson AI platform by American IBM (Armonk, US) is likely to be utilized to drive the AI based functionality of many ABB's applications. Watson is positioned as a flexible solution capable of fitting any need from arbitrary pattern recognition to predictive maintenance of any machine [102]. Whilst IBM has ready Watson IoT solution of their own, Watson can still be employed as a versatile platform for any need by any company or even a regular user - devised as an AI based algorithm for some particular function requiring machine analytical capabilities not available to a human mind.

IBM Watson is based on a concept of a supercomputer that evolved and was bolstered with additional functionality over decades. Initially, it was developed as an ANN-based question-and-answer machine to be used in a word analogy quiz television show called "Jeopardy!" against human players. [103] Later on, abilities of the AI algorithm proved to be so useful that gradually Watson has turned into a widely accessible pattern recognition cloud-based software platform with various preset applications added. Today, the advanced deep learning ANN algorithm of the AI solution is capable of, but not limited to: image pattern recognition (e.g. applicable for manufacturing defect detection) and regression analysis (useful in predictive maintenance) [104, 105]

6.7.2. Microsoft Azure

Azure by American Microsoft Corporation (Redmond, US) is a cloud platform widely used by various businesses across the globe. Offered on a Platform as a Service model (PaaS, platform subscription model) it is a flexible tool granting remote computing power in the form of cloud-based Windows or Linux virtual machines and access to them. Any kind of proprietary software (i.e. ABB Ability products in this case, or any other) can be deployed on Azure servers, hence some CM software offering companies like ABB rely upon Microsoft's services to provide cloud computing for own software solutions. [106]

Whilst offering a myriad of various cloud-related computing and networking services, Microsoft Azure platform also has analytics solution with ML capabilities of its own. It allows to use any algorithm suitable for one's needs (from linear regression and ANN to decision trees and many other techniques that have been left out of scope of this thesis) for any kind of data analysis. Moreover, Azure includes IoT package of applications called Azure IoT Suite, that has predictive maintenance preconfigured solution suitable for machinery monitoring and expected lifecycle analysis to be performed (although, showcased only with an example of an aircraft engine and the regression model derived from it). Also, this package also includes "Connected factory" solution, that allows for monitoring the state, performance and overall efficiency of a facility (showcased an example of a machinery part manufacturing plant). [107, 108]

6.8. C3 IoT Platform™

American C3 Inc. (Redwood City, US) offers a C3 Type System™, an abstract layer that unifies a cloud-based data storage and an analysis platform and numerous applications and services - the C3 IoT Platform. Overall, the product structure is clear and contains services/tools for various needs, distinctively divided into groups, e.g. C3 Predictive Maintenance™, C3 Sensor Health™, C3 Fraud Detection™ (finance application) and so forth. Any of these products can be evaluated in the form of a trial organized as a scalable 6 to 12 weeks long project (6-week long implementation as an example) costing $100000 to $500000 depending on the length and complexity:

1. "Discovery kick-off" along with design phase: week 1 and 2
2. Data integration phase: week 2 and 3
3. Analytics and machine learning (model training): weeks 2 to 5
4. Validation and tuning: weeks 4 to 6
5. UI configuration: week 5 and 6
6. Demo and review: week 6

After this trial, the product can be put to use immediately as a PaaS or/and SaaS (depending on the products chosen). Additionally, a team of up to 6 specialists from C3 IoT can be assigned to the facility for a period for up to 3 years to train 50 to 200 of the local personnel to be capable to develop and operate locally needed software solutions (ML/IoT) independently from C3, also providing an integrated development environment. [109]

The more related to the scope of this thesis products are going to be analyzed, namely the C3 Predictive Maintenance with the C3 IoT Platform (including C3 Data Lake cloud service). The cloud server functionality is based on the Amazon Web Services platform (according to the c.2017 product overview), and lately the company turned also to the aforementioned MS Azure service [110]. Apart from the cloud, IoT Platform package also contains different data processing solutions, e.g. an integrator for easy data mapping and transformation to other data systems via XML[29], a data explorer om the form of visual interface to analyze measurement data, an AI design tool for additional data manipulations,

[29] eXtensible Markup Language, a specific versatile data structure language, used e.g. in a configuration file parameter list

to name the few. The C3 Predictive Maintenance (Fig. 48) is based upon a combination of classification, regression and clustering algorithms (US patent No. 2017/0006135 A1), whilst another energy industry related solution, the C3 Energy Management uses regression analysis to perform energy consumption statistics and predictions (US patent No. 2016/0238640 A1). Additionally, C3 has a cybersecurity risk and vulnerability determination technology also based on ML, that can be used to indicate abnormal traffic or access to any part of a network, e.g. in a SCADA data acquisition system. (US patent No. 2016/0359895A1) [109]

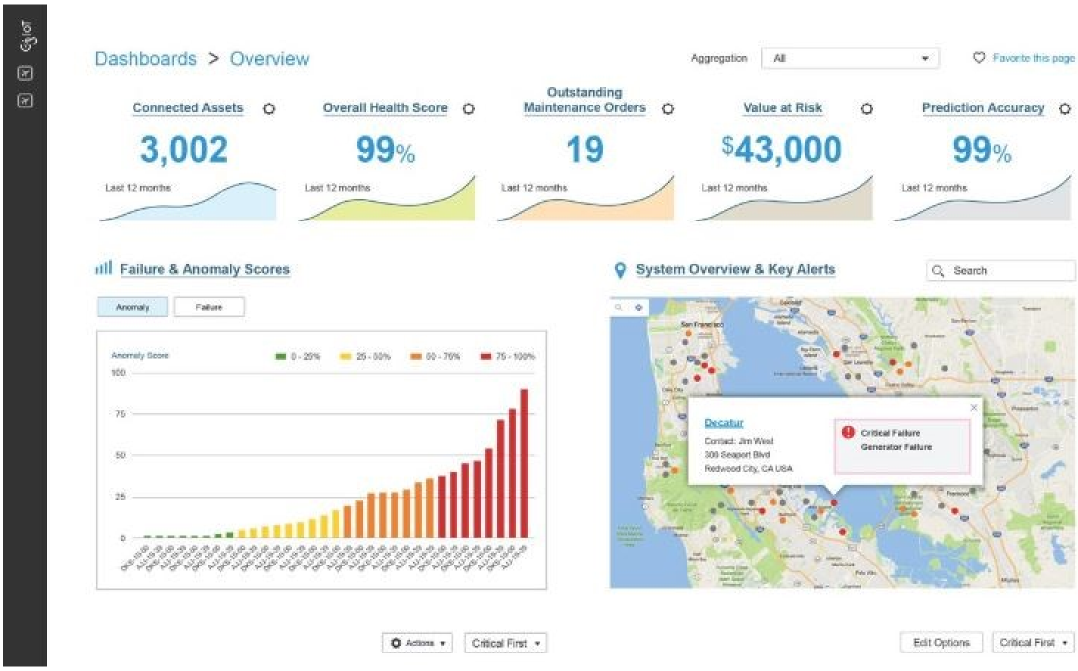

Figure 48 C3 IoT PM UI, courtesy of C3 Inc.

6.9. Seeq®

Another American company, Seeq Corporation (Seattle, US), offers a browser-based solution (written in HTML5 just as many modern web-applications e.g. YouTube). The cornerstone software is Seeq Workbench™ that is the visual interface used to access and analyze the data in a suitable manner. The solution has an emphasis on being lightweight, i.e. quickly deployable and accessible, being also versatile.

The product line is organized simply: apart from the Workbench™ (Fig. 49), there is a Seeq Server – a scalable server solution (i.e. comprised of one or a plurality of servers depending on the load and requirements) that provides the data integration, storage and processing functionality. Measurement data imported from a process data historian, even proprietary e.g. Schneider Electric Wonderware eDNA, OSIsoft PI System, a cloud database like Microsoft Azure, or directly from a local DCS via OPC UA. Also, software developer kits are available, making the solution open towards own software modifications conducted by a customer. Additional ongoing services provided by Seeq include support and additional software tweaks based on customer requirements. [111]

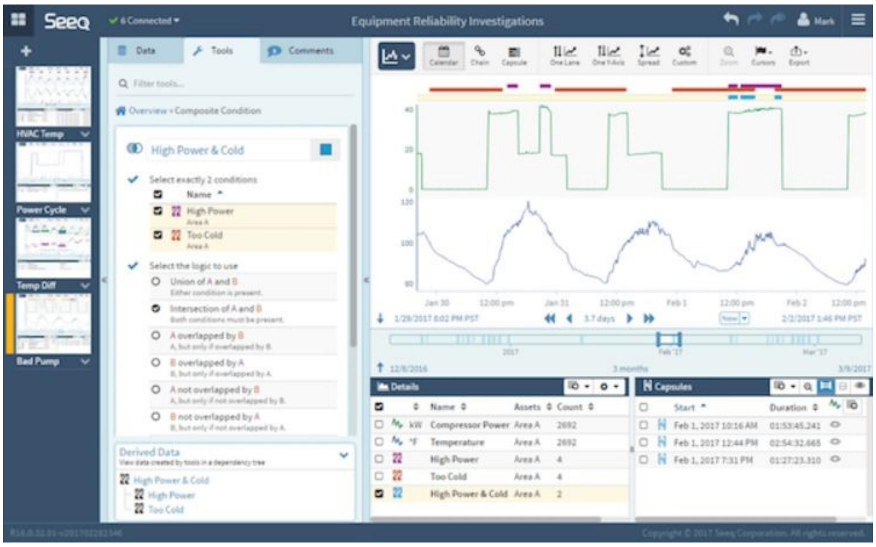

Figure 49 Seeq Workbench UI, courtesy of Seeq Corporation

In terms of the predictive functionality, the software includes numerous algorithms suitable for different approaches and data types. The ML techniques supported include pattern recognition and regression amongst else. Exact algorithms used, and training times of the models are undisclosed, but certainly they belong/similar to the widely known and used (not patented) techniques. Given the nature of the solution, i.e. the ability to connect to any data timeseries without importing, the analysis is likely fast but superficial and might be somewhat inaccurate in some circumstances. Additionally, the software has extensive 2-D visualization capabilities, applicable to any timeseries data in the form of scatter plots, histograms etc., also any portion of data can be easily exported in the form of a PowerPoint, Excel file or even as a direct internet link. [110]

6.10. SAP® PM and Service

A variety of all kinds of enterprise-oriented solutions are offered by a multinational software corporation SAP SE (Walldorf, Germany), amongst which is the SAP Leonardo line of solution packages. Whilst being suitable to a multitude of industries, Leonardo includes also the IoT functionality especially suitable for PP PM in the form of a built-in machine learning realized within the Predictive Maintenance and Service (Fig. 50) solution. Additionally, SAP offers additional security packages (e.g. Cloud App Security) and SDK packages for capability of designing own compatible applications to use with various services of the company.

Figure 50 SAP PM and Service UI, courtesy of SAP

Akin to other larger companies, SAP also offers a variety of services capable of working in tandem, to build a robust interconnected network of services:

- SAP Cloud Platform – cloud service that Leonardo is based on, running upon Amazon, MS Azure and Google Cloud
- SAP HANA - a database with built-in ML analytical functionality
- SAP Fiori – a mobile service with various apps for easy data access

[113, 114, 115]

SAP product structure is rather complex in that it has a myriad of services both aimed at enterprise application in general and suitable to industrial/utility applications. Some of these products enhance management and scheduling of all kinds of operations, others aim at change forecasting and data organization via ML algorithms on the software change and (e.g. applying methods such as ANN: US 2014/0201115 A1 or regression: US 2016/0062876 A1), additionally SAP possesses a patent engineered for parallel use of several ML models at once, that can be deployed for various applications (EP 3 029 614 A1). As a result, e.g. the SAP Predictive Maintenance and Service has the R packages with different anomaly detection algorithms (PCA, multivariate autoregression or SVM), lifecycle estimation or failure prediction via classification. [113]

7. Comparison and conclusion

The variety of PM solutions presented in the previous chapter makes it clear that both demand and development grow rapidly for such solutions at the moment. The core elements of a CM ML product are common for all the cases:

- a server (or likely a server cluster) either local or remote (cloud) to provide raw storage and computational power for the data and processing algorithm(s)
- the ML based software with a graphical user interface for convenient interaction with the data analyzed
- a database (historian), either separate (e.g. from local automation system) and/or on the remote servers
- a data integrator of sorts to transform data from original format to a CM software native format – can be contained within a database if the database type is fully supported, can be separate (e.g. OPC Server), and/or can be in the form of simple transitional software scripts on the AI analysis side.

Additionally, all solutions have support for widely accepted standards as OPC UA certification with included transmission protocols, all possess security-related features via secure transmission protocols and strict authentication control. The differences between all of the previously described solutions are going to be presented in the form of table:

	1. INtelligence	2. SIAT	3. PRiSM	4. Uptake	5. Siemens	6. GE	7. ABB	8. C3 IoT	9. Seeq	10. SAP
A family of products available	N	N	Y	N	Y	Y	Y	N	N	Y
Several algorithms employed	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
Deep learning ANN	N	N	N	N	Y	N	Y[30]	N	N	Y[31]
Lifecycle estimation (Asset health)	N	N	N	Y	N	Y	Y	N	N	Y
Tablet/phone application	N[32]	N	Y	N	Y[33]	Y[34]	N	N	N	Y
Custom applications (Open API)	N	N	Y	N	Y	Y	N[35]	Y	Y	Y
Additional security solution	N	Y	N	Y	N	N	Y[36]	Y	N	Y
Optimization option	Y	N	Y	N	Y	Y	Y[37]	N	N	N[38]

Table 1 Comparable feature overview for the solutions analyzed

[30] at the moment, the direct application for PP process analysis is undisclosed
[31] application of ANN is likely to be tangentially related to PP processes
[32] web-based application is planned for release in the future
[33] third party, access to the predictive analysis is unclear
[34] access only to process data, not the predictive analysis [116]
[35] mentioned for other product, unrelated to PPs
[36] exists as an additional network intrusion monitoring option for Symphony Plus
[37] more of a smart grid-oriented solution rather than PP performance optimizing one
[38] existing optimization solutions seem to be unrelated to PPs directly [117]

From the Table 1 it can be seen that the extent of functionality offered largely depends on the size and focus of a company. Large corporations (especially the enterprise software-oriented SAP) are capable of enormous investments in research and development of a myriad of software solutions simultaneously, having access to the long experience accumulated during their history, thousands of patents claimed via purchases of smaller companies or by own research specialists. Because of this, corporations have entire suites of solutions for various needs that can be ordered in the form of an entire array consisting of tightly interconnected services, e.g. AI analytics solution itself, a cloud service, a database-historian service, various asset management optimizing solutions with access to additional customizable applications etc. Smaller companies, on the contrary, focus on offering only the predictive maintenance and remote support services, yet still supporting primary third-party solutions (databases and cloud services).

As for the future of the AI market, one can say assuredly that it is going to expand more not only in the power generation industry, but rather in every possible industry around the world that has any sort of machinery-based processes and assets employed. It is the indisputable benefits of having abnormal deviations detected much prior to the point where they lead to critical malfunctions or even cause an alarm produced by the standard monitoring systems. Moreover, these benefits come at a very modest price (compared to operating costs and especially to multimillion losses caused by an unplanned stoppage of a crucial machine) of a service subscription monthly fees varying from several thousand up to several dozen thousand euros per month, depending on the complexity of the facility and amount of additional options (in case with an availability of suites and additional solutions, e.g. pricing of somewhat related product series from SAP [118] – basic limited package would cost 1500€/mon, whilst far more advanced one is already 15000€/mon). Such low pricing is easily justified by the fact that usually these AI solutions are normally run on a rented server cluster, thus often lacking any additional installations in situ - since the data analyzed comes from the monitoring systems originally installed when a PP was built, and UI software can reside within a laptop computer.

Furthermore, current developments in the field of augmented reality imply the next step for the industrial maintenance. Augmented reality is a form of projecting digital images onto a picture that a human user perceives, realized with the help of "smart glasses". There are the two largest and longest-running projects: Google Glass and Microsoft Hololens (Fig. 51). The Google Glass is based on the idea of having a small transparent screen installed on the right upper corner of the user's field of view without obstructing it. [119] On the other hand, MS Hololense is capable of 3D projections on the entire lower area of the field of view of a user, for it covers both eyes. [120] Both

Figure 51 Google Glass (upper, courtesy of Google Inc.), Microsoft Hololens (lower, courtesy of Microsoft) [119, 120]

products are finding their way into various industries (few examples):

- ABB is testing Hololens for maintenance, where projections display the status of machines in the user's line of sight [121]
- GE and Schneider Electric are using product named Skylight provided by Upskill company [122]. It is based on the Google Glass and is used to provide real-time instructions and hints for a worker to ease maintenance/installation/assembly, that are also capable of contacting an expert to provide real-time guidance
- Siemens is testing full-field of view AR glasses for remote expert services during GT maintenance, enabling an expert to see the worker's actions and to provide the worker with visual hints. [123]
- Additionally, Volvo and Ford motor companies are using (testing) Hololens to design cars [124, 125]

Given the complexity of PP systems, AR technologies can be also employed there with a great effectiveness providing support with hints, instruction videos and remote expert service. The full field of view type smart glasses akin to Hololens also could provide extensive information on structural condition/weaknesses based on 3D CAD blueprints and sensor data, by highlighting a part requiring attention. This could be bolstered even further with the data from predictive analytics software, with giving the AR glasses a capability to visually inform an engineer of oncoming failure in some particular part of the system pointing them directly to that part.

Even further in the future of industrial digitalization, one could easily imagine another technology stepping in: virtual reality. Unlike AR that has virtual images overlapped onto the real picture, VR has user completely immersed in the fully simulated environment. VR can be used also for remote expert services with expert being able to be virtually present on site, additionally granting and ability to research an object with thorough detail, be it a separate machine, system of processes or an entire facility. [126]

8. Appendix

	2012	2013	2014	2015	2016	Growth rate per y. 2016	2005-15	Share 2016
Total World	**22797.3**	**23402.9**	**23844.0**	**24215.5**	**24816.4**	**2.2%**	**2.8%**	**100.0%**
of which: OECD	10939.9	10929.3	10875.5	10911.5	**10939.2**	♦	0.2%	44.1%
Non-OECD	11857.4	12473.6	12968.5	13304.0	**13877.2**	4.0%	5.5%	55.9%
European Union #	3295.7	3267.3	3185.3	3234.3	**3247.3**	0.1%	-0.3%	13.1%
CIS	1523.7	1509.0	1515.3	1499.9	**1527.8**	1.6%	0.9%	6.2%

Table 2 Worldwide electricity generation, exempt [1]

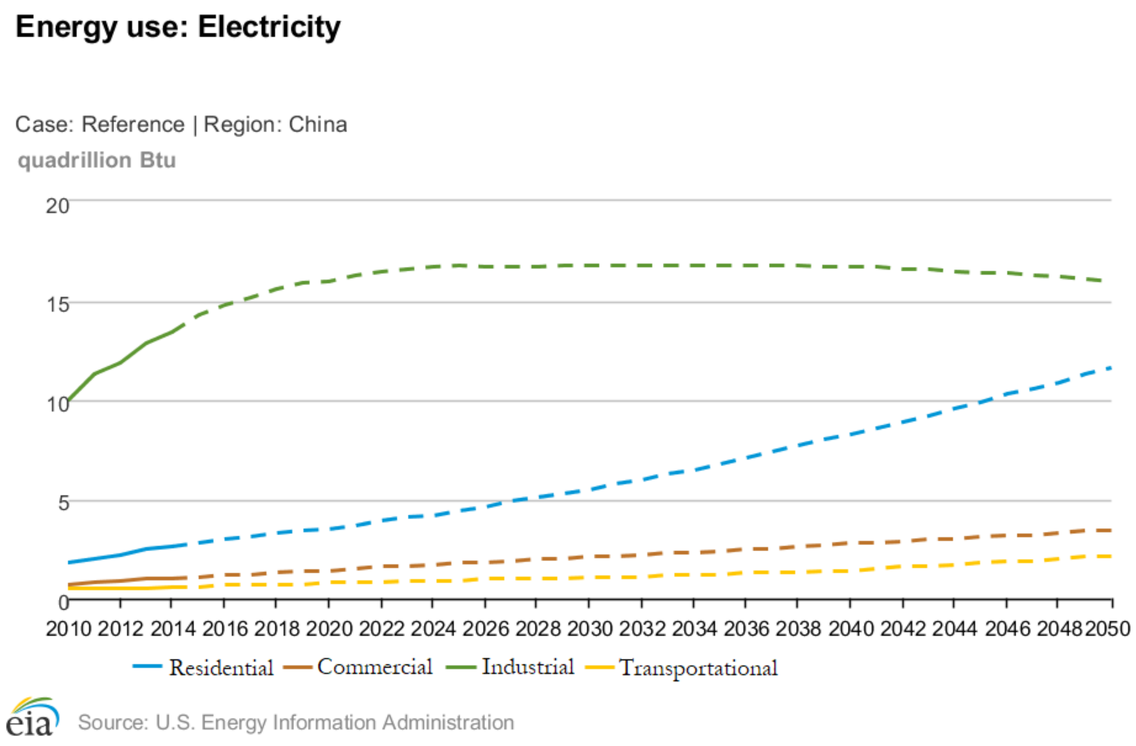

Figure 52 Electricity consumption in China (calculated and estimated) [2]

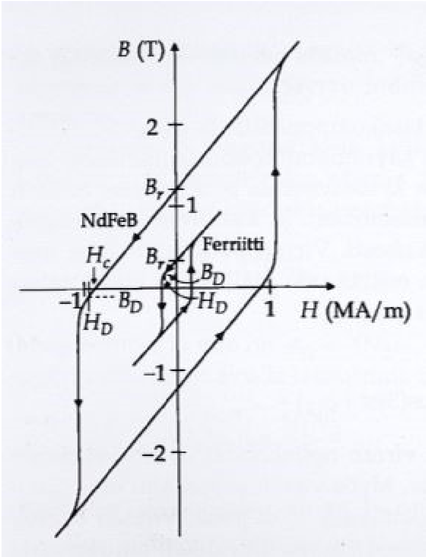

Figure 53 Hysteresis loop examples of ferrite (iron-based) and NdFeB (neodymium) magnets, displaying nonlinearity between magnetic field strength H and magnetic flux density B [39, p.20]

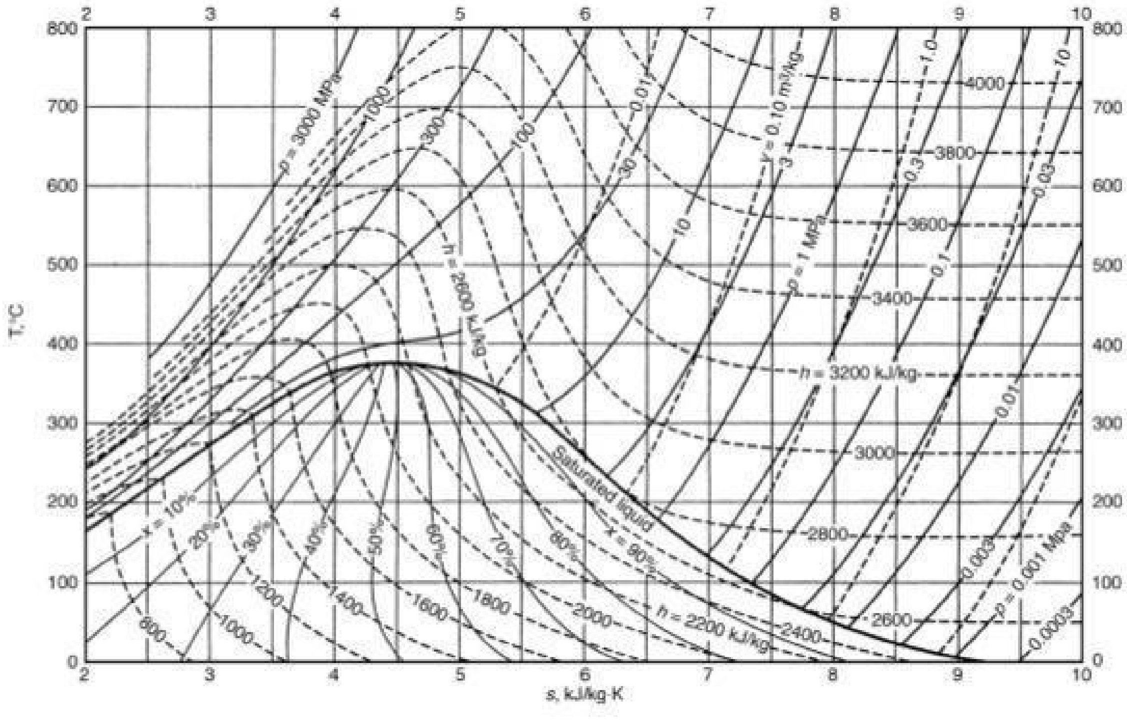

Figure 54 Example of a steam temperature-entropy diagram, beyond the right edge of the bell is the superheated dry steam region, left – liquid water, above the bell and upper right region is supercritical.

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