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Understanding Former Drive Load in Paper Machines by Using Big Data Techniques

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ABSTRACT

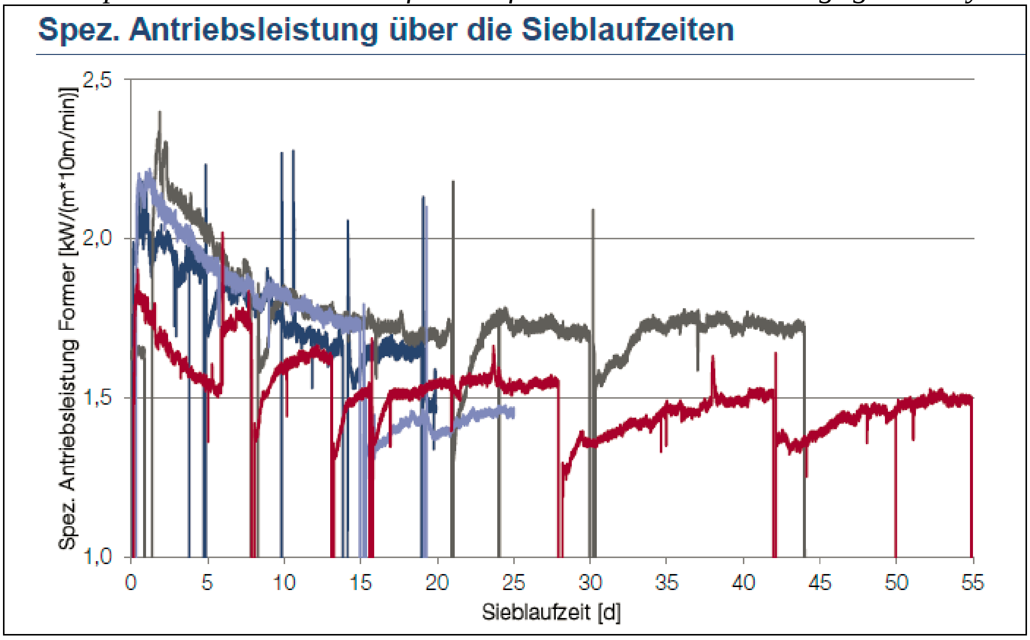
Identifying saving potentials to optimize energy consumption (Hing, 2010) of a paper machine forming section in a systematic way requires detailed knowledge about exactly where the energy is consumed, that means converted into heat by friction between the moving forming fabric and static elements of the former. Since this is a large amount of energy in the order of megawatts that can be done by measuring temperature, consumption of energy leads to increased temperature of for example suction bars. Unfortunately it is difficult to measure these small temperature differences at these positions directly because of the unfriendly environment in a paper machine. One could mount a number of temperature sensors at different elements of the former but that would be very cost intensive. Compared with that, measuring wastewater temperature is simple and cheap but this temperature is influenced by many parameters of which energy consumption by friction of the fabric is only one. Using big data techniques, especially analyzing temperature differences in wastewater over an extended period of time, allows to better understand energy consumption in paper machine forming sections. This information can be used to optimize vacuum settings for the different suction boxes which leads to lower wear of forming fabrics and reduced former drive load.

Keywords: Big Data, Paper Industry, Energy Optimization.

Introduction

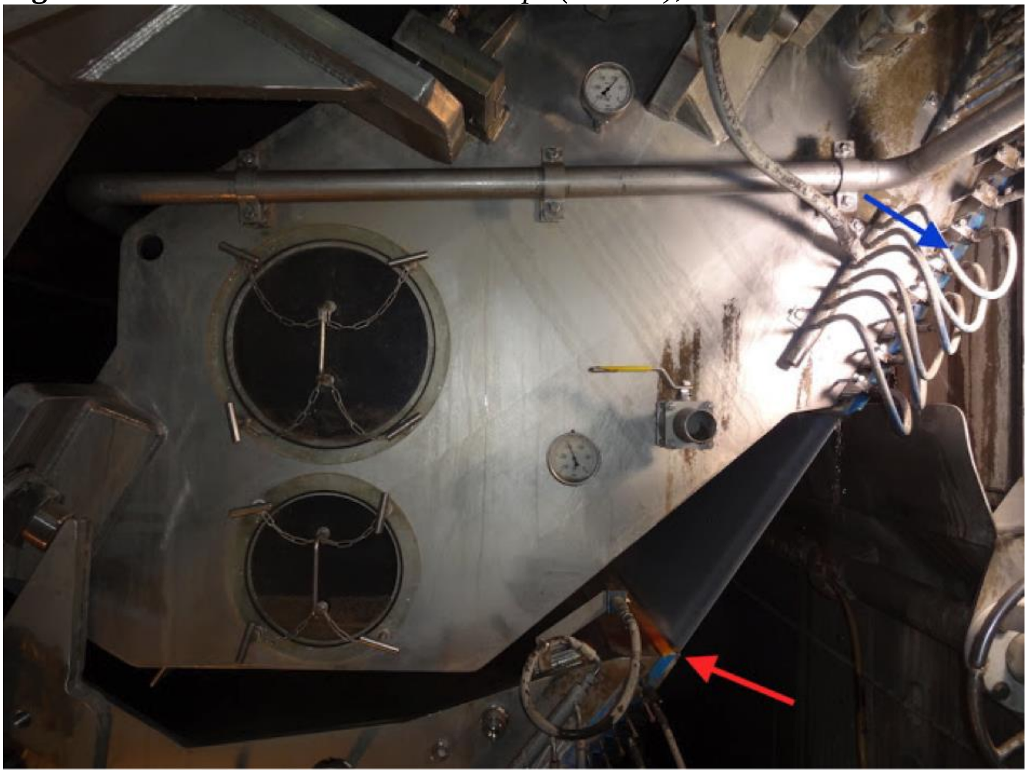
A paper machine produces sheet paper from stock containing 98 – 99% water and 1 -2% fibres. The first step in paper production is sheet forming which is done in the former section. The suspension is brought on the forming fabric, which is a textile structure with the task to dewater, to retain the fibres and to transport the wet sheet to the press section. This happens by gravity and centrifugal force in the first place, most of the remaining water is sucked out of the paper pulp with suction boxes (see Figure 2). These boxes have a slight vacuum inside and slots, where the water is sucked through. The forming fabric with the paper to be is pulled over the suction boxes with a big enough tension, so that it does not hang through the slots. But the pressure difference between the inside of the suction boxes and the surrounding air (typically in the order of 0.1 to 0.3 bar) generates a force that presses the fabric on the ceramic strips which form the slots and tries to brake the fabric. The braking force of the vacuum and the friction between the fabric and the ceramic strips on top of the suction boxes is responsible for a large part of the energy required to run the forming section. And since paper machines are large, this is much energy, typically between 1.300 and 4.000 kW for a state of the art machine. Depending on the fabric used and the parameters of the machine the amount of energy required varies much more than current knowledge about the friction processes can explain (Figure 1), these variations might be so large, that in certain situations the machine has to stop because the drives cannot deliver enough power.

Figure 1. *Exemplary Power Consumption. As can be seen, the Power Consumption Varies over the Lifetime of the Fabric in a Non-negligible Way*



This is one of the reasons, why it is important to understand, exactly how and where the energy is consumed, that means, where and why the friction between fabric and suction box is higher than expected.

Figure 2. *Suction Box with Ceramic Strips (Arrows), Side View*



Temperature measurements are one way to find out exactly where energy is consumed, the friction as the cause of the energy consumption converts most of the mechanical energy into heat. The precision of the measurement will be better, if the measured temperature difference is larger and the changes are faster, that means, it is better to measure as close as possible to the point, where the friction happens. There have been attempts to measure the temperature directly in the ceramic strips on top of the suction box, see Figure 3. But this approach has two problems: First, these parts are under heavy thermal and mechanical stress, this limits the lifetime of a sensor in or directly at the strip. Second, there are many of them, in the scenario described below, some 60 strips, each of them at 6.40 m length would have to be equipped with sensors – and this is a machine with only 3 suction boxes. Such strips are commercially available, but the cost would be in the order of some hundred thousands of euros which limits practical use to very special cases.

Figure 3. *Suction Box. On the Left Side the Ceramic Strips (Blue) and the Slots between them (Black) can be seen. For Size Comparison in the Middle a Colleague in the Suction Box Installing One of the Sensors*

On the other hand it is possible, to analyze energy flow on a very high, mill wide level, which can bring substantial savings but doesn't give enough information about the exact position, where energy is wasted, so it is not possible to optimize in all cases (Bakhtiari, 2015).

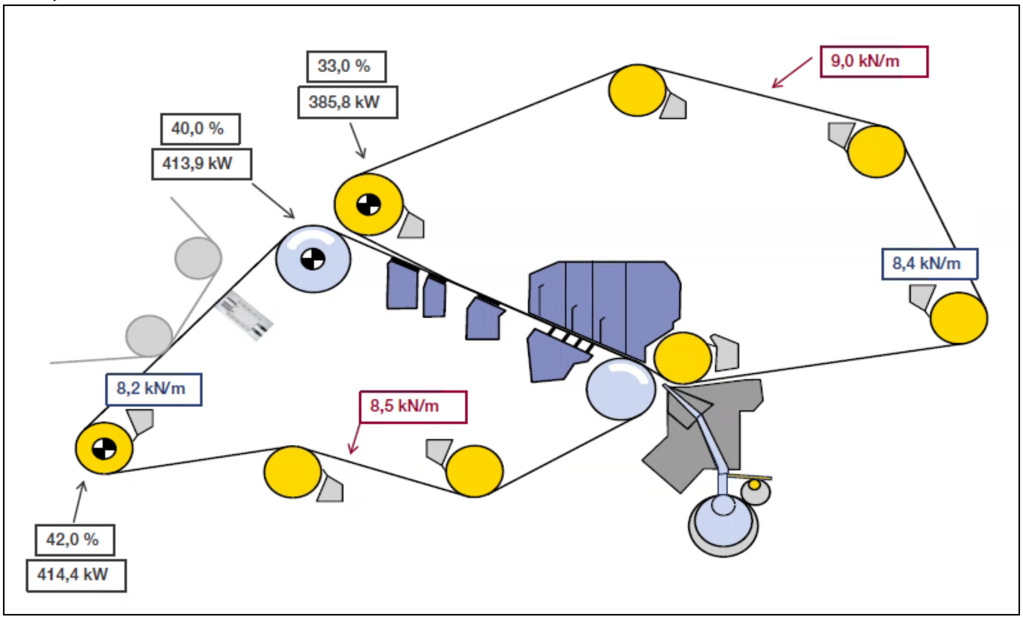
Big Data has common uses in process industry, for example for anomaly detection in complex processes (Windmann, 2015), which has some similarities to our problem. Because of this, we tried a big data approach by measuring the wastewater temperature at a few points, typically 5 to 10, in the former. A quick calculation shows, that for typical values (x l pro minute, y kW usw.) the temperature differences should be in the range of xx °C, which might be measurable, if the changes in ambient temperature are represented in the model used to compute the actual temperatures. Because there are many factors which might effect on the wastewater temperature in the order of the effects we are looking for, big data techniques were used to conduct the experiments (footnote: Experiments with paper machines tend to be pretty expensive and lengthy on the scale of many months, we tried to gather as many data as possible to get what we need in the first place).

Material and Methods

Temperature sensors (Analog devices ADT7410 attached to a 2x2cm PCB according to the recommendations of the manufacturer datasheet URL) were attached with thermal conductive paste to 8 wastewater pipes in total, see Figures 4 and 5.

Figure 4. *Temperature Sensors (Blue Arrows) and Sensor Node (Red Arrow)*

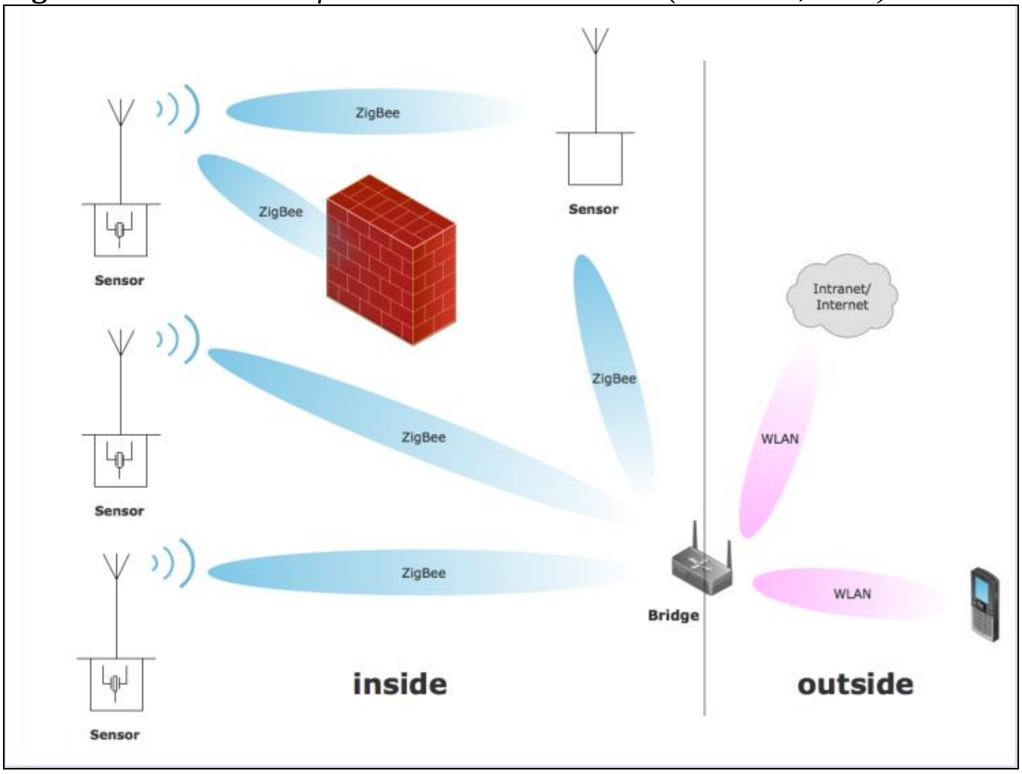
Figure 5. *Positions (Numbers in Red) of the Sensors. 1 = Skimmer, (2,3,4) = Top Wire Suction Box Zone (1,2,3), 5 = Wet Cleaner, 6 = Separating Suction Box, 7 = Flat Suction Box*



The temperature was measured every 60 seconds. In settings like these, using sensors wired with cable, the installation cost for cabling can make a project very expensive (distances might be long and the environment is very unfriendly, see for example (Haenisch, 2015). Therefore using battery powered sensors and wireless data transmission is an enabler for projects like this. Data was transmitted wireless via a ZigBee network to the base station where the values were collected. The architecture of the system is shown in figure 6. Details of the system are described in (Haenisch, 2014). The temperatures were sampled for a total of xx months and evaluated offline with apache spark[1].

[1]The performance of the initial R-version running on a single machine was considered to slow, so the programs were rewritten in python using spark.

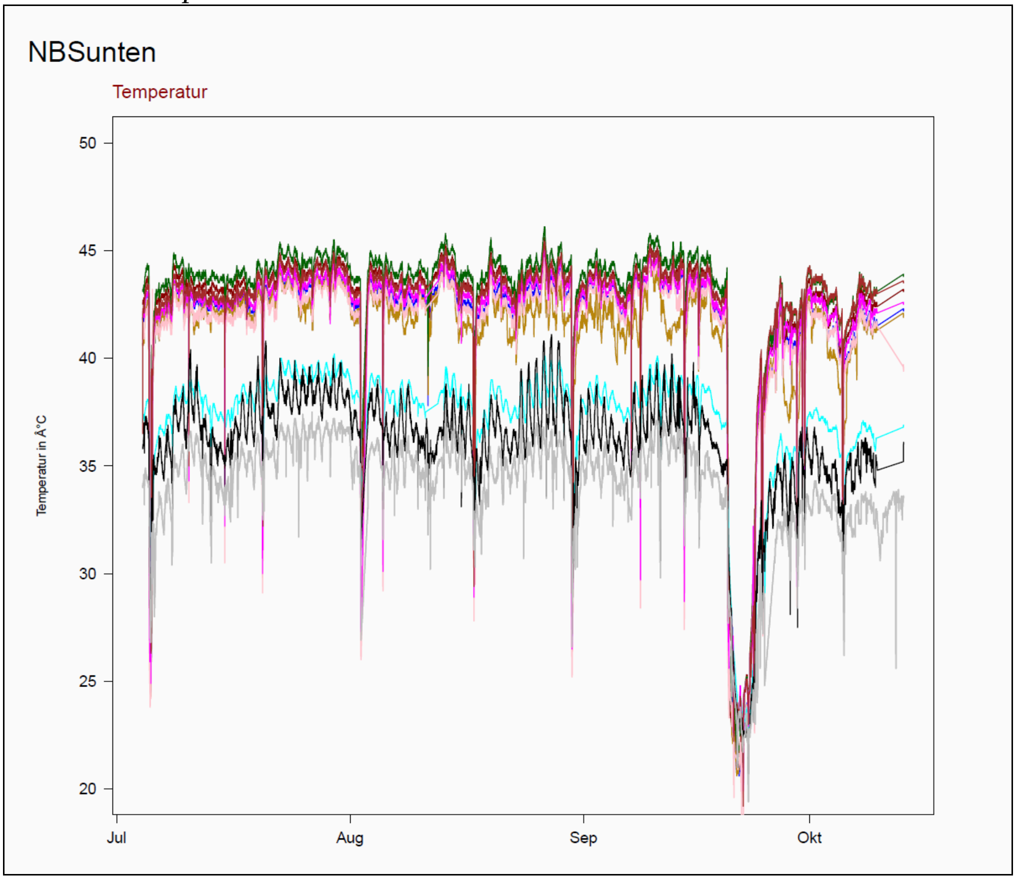
Figure 6. *Architecture of the Sensor Network Used (Haenisch, 2014)*



Results

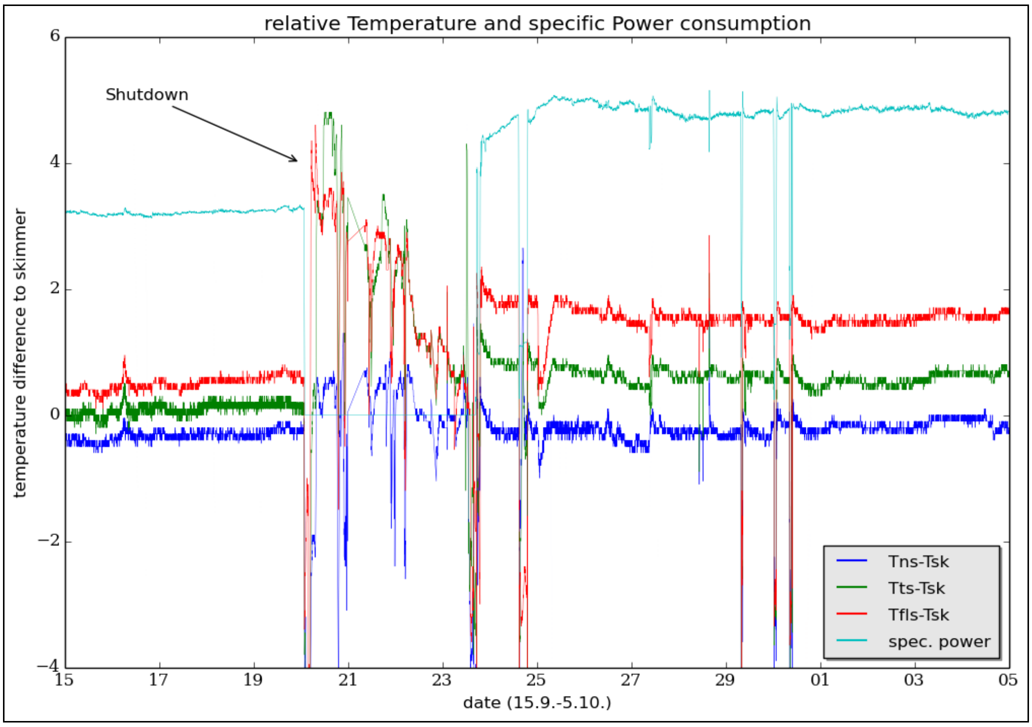
From the data it is obvious, that the temperature measured by the different sensors are correlated but depend on external effects like ambient temperature (see Figure 7).

Figure 7. *Data from the Different Sensors. The Lower Traces are Ambient Temperatures at Different Positions, the Upper Traces Temperatures at the Wastewater Pipes*



In part, this depends on the temperature of the ambient air, in part on the temperature of the water used to disperse the paper fibers and so on. Only some of these values are known (you never have enough sensors …). For an initial evaluation, this effect was factored out by building the difference of the temperatures measured at the different positions to the first suction box (the skimmer, number 1 in Figure 5). This suction box is at a position directly behind where the fiber suspension hits the fabric. Because of this geometry, the wastewater temperature of this suction box is a good approximation of the temperature of the stock. Results are shown in Figure 8.

Figure 8. *Temperature Differences for the Interesting Time Window around the Change of Forming Fabric around the 24. In the Period between the 20. At the 24. The Machine was Shut down for Maintenance. The Temperature Differences are shown in Degree, the Specific Power Consumption (Blue Green) in Arbitrary Units*



With the new fabric installed, the power level is clearly higher than before (here some 2 points on the scale on the left). Of course this simple correlation model cannot explain all effects like the dip at the 25, but is sufficient to show, that the method works. As can be seen in Figure 7, the temperature difference is larger for the sensors (that is the suction boxes) which are located at a later point in the former: The blue curve corresponds to number 5, the green trace to number 6 and the red trace to number 7 in Figure 5. This is consistent with the theory (and other results to be published in XXX in YYY 2018) that the initial dewatering of the fabric installed during the shutdown shown in Figure 7 is higher than that of the fabric used in the preceding period: If the initial dewatering is higher than expected, the suction boxes at the end of the process will run dry, leading to higher friction leading to higher temperature that is higher energy consumption at this point.

Several other interesting insights were found, for example pipes, which were not operational or others, that transported water but were considered dead by the operator. Such unexpected insights are common to projects like ours, see for example (Auschitzky, 2014).

Discussion

While the data collected in this project is not sufficient to analyze the details of the investigated process by finding enough correlations between the different parameters influencing the wastewater temperature like environmental temperature, pulp temperature, pulp density etc. to allow the development of a detailed model of the energy consumption in the forming section, it has enough details to find interesting results about the process, here the distribution of the energy consumption between the suction boxes. This allows to optimize the process and thereby the energy consumption. So the main contribution of this case study is to show, that even with a small data set (and a low financial effort) interesting results for the process owner can be found.

Conclusions

It is possible to analyze energy consumption in a paper machine former section by measuring the temperatures of wastewater. This allows to get insight into process mechanisms (here: friction at suction boxes) and increase the efficiency. The same techniques could be applied to other sections, esp. press.

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