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# Predictive pumping based on sensor data and weather forecast

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***Abstract*—In energy production, peat extraction has a significant role in Finland. However, protection of nature has become more and more important globally. How do we solve this conflict of interests respecting both views? In peat production, one important phase is to drain peat bog so that peat production becomes available. This means that we have control over how we can lead water away from peat bog to nature without water contamination with solid and other harmful substances. In this paper we describe a novel method how fouling of water bodies from peat bog can be controlled more efficiently by using weather forecast to predict rainfall and thus, minimize the effluents to nature.**

***Keywords—Internet of Things, open data, predictive control, rain prediction***

## I. INTRODUCTION

Today, nature protection has become a more and more important issue. All technology solutions to help avoid nature resource overconsumption are welcome.

In Finnish peatlands the peat production area is approximately 68,000 hectares. In 2016, there were 45,000 hectares of energy peat production and 5,000 hectares of peatland in the production of environmental peat. During the 2000s, the production of energy peat has averaged about 400 megawatt hours per hectare. The total output of energy peat has varied from 8 terawatt hours to 35 terawatt hours in the 2000s [1].

Peat production is seasonal. The peat season is in normal years from mid-May to early September. The average summer lasts 40-50 days, when production is possible. The production is also weather dependent, and the yield per hectare varies both at the annual and regional levels [1].

Views on the harmfulness of peat production on watercourses are based on obsolete data and beliefs about peat production. These beliefs are bolstered by the fact that peat production has been accused of water contamination [1].

The central part in avoiding fouling of water bodies is predictable control of runoff water. An important role in this process is the ability to filter in significant quantities solid and other harmful substances before water accesses water bodies. The present method in Finland is based on pumping of the water from drainage reservoirs (pump pool) to filtering field by measuring the water height in reservoirs.

In this research paper, we introduce a novel method to powerfully filter solid and other substances from water. Our solution is based on using IoT technology with weather forecast and rainfall measurement locally in peat bog. It stabilizes the flow of water from the drainage reservoirs significantly and thus notably reduces the load on the peat production area.

## II. COMBINING SENSOR DATA AND WEATHER FORECASTS IN IOT SYSTEM

There are some experiments of using weather forecasts for prediction in the IoT systems, for example in different agricultural systems and applications. Reference [2] proposes a smart water dripping system for the farmers to irrigate the farms efficiently. It is mainly based on local sensors like soil temperature, moisture and pH. The systems also collect the weather forecast information from websites and use its information to decide if the watering is needed. Due to possible forecast inaccuracy, the system gives for the operator possibility to manually override the system suggestion [2].

A farming automation system for plants watering which uses the weather prediction based on fuzzy logic algorithm has been introduced in [3]. The system is based on sensor data and forecast from the weather service provider. The system uses fuzzy logic algorithm to calculate if the plant should be watered. Sensor data includes the soil moisture data and rain sensor data. Weather prediction data is collected from two different weather service providers (WSP Open Weather and Weather Underground) [3].

Rainfall forecasts have been used in cyber physical systems for predicting and preventing flood hazards. Yang et al. [4] have used an ensemble numerical prediction system to get more reliable rainfall forecast. The ensemble numerical system used is based on 20 ensemble units. These ensemble units are various numerical weather prediction models with different configurations. The system is based on worldwide observation data of weather parameters. This data is obtained from various sources like satellites, atmospheric sounding devices, buoys, aviation routine weather reports, ships, and other sources. The ensemble system provides a 72-hour rainfall forecast every six hours with 5 km spatial resolution. Then the statistical artificial neural network method has been used to combine the 20 ensemble rainfall forecasts to improved 24-hour forecast. To further improve the short-term rainfall forecasts the real-time radar data has been included for the model [4].

Weather forecasts together with local weather data have been used to forecast crop frost. If the frost occurs in the growth season, the economic losses can be very significant for the farmers. The weather forecast accuracy to predict actual temperatures in the field has been researched by using several regression techniques. According to the different regression techniques used, it is not possible to predict the actual temperature in the field from the weather forecast with the accuracy needed for predicting the frost. More advanced and complex techniques have been proposed to be tested like genetic algorithm and neural network [5].

Weather forecasts have been also used for predicting the heat load for family houses [6][7]. Heating systems based on hot water circulation have the disadvantage and challenge of the long response time. It cannot react quickly enough for the outside temperature changes. By using the weather forecast as one input, it is possible to react proactively to weather changes and it can improve the comfort and reduce energy consumption.

Weather and especially rainfall forecasting is a challenging task locally. There is a lot of research done in that field. There are several methods to weather forecast. One of the most used methodologies is complex time series [8][9]. One of best-known methods for time series analysis are Exponential Smoothing [10] and Autoregressive Integrated Moving Average (ARIMA) [11].

Prediction of rainfall is a rather complex physical phenomenon. For this reason, methods such as machine learning are used today. Examples of such methods are among others Artificial Neural Network ($ANN$) [12], k-closest neighbor ($knn$) regression [13], Radial Basis Support Vector Regression ($RBSVR$) both separately and in combination as a hybrid model [14].

## III. SMART PUMPING SYSTEM

Water treatment in the peat production area is a very important and challenging task. For production, the peat needs to be dry. Water is flowing via ditches to the separated reservoirs. From the reservoirs, the water is pumped to the filtering field where the vegetation and soil is filtering the water. Water is filtered through the field that restrains the solids and nutrients before the water is flowing to the watercourses [15].

The filtration through the filtering field is more effective if the pumping and water flow through the field is as constant as possible. In traditional pumping systems, the pumping starts when the water level is high in pump pool and stops when the water level is rather low. The pumping takes place in constant speed. Therefore, the pumping and water flow is not smooth but occurs more in bursts.

With the frequency converter, it is possible to even out the pumping by slowing down the pumping speed as the water level in the pool is lowering. This is a very simple and effective method to even out the water flow through the field. It is also possible to program to the frequency converter a ramp-up time for soft starting and to lower the starting burst in water flow.

The next step to even out the pumping even more is to use the predictive pumping. When the weather forecast is predicting rain or if the rain has already started, but the water is still flowing to the pool, it could be possible to start pumping while the level in the pool has not yet reached the pumping level. This way the pool could buffer more water and the pumping of the raining water would take more time and the filtering field should filter the water more effectively.

There is a delay in water flow from the peat production area to the reservoirs. The field from which the raining water is flowed via ditches to the pool can be several tens of hectares. The flowing speed depends on, for example how dry the soil is. Dry soil can absorb more water thus lowering and slowing the water flowing to the pool.

This paper presents the implementation of the smart pumping control and the algorithm for the predictive pumping. The predictive pumping is based on the weather forecast for the area and the local weather station data together with the actual water level in the pump pool.

The construction of the IoT pump control can be seen in Fig 1. The decision is made in the ThingsBoard.io Open Source IoT platform, which is located in the cloud server. The data gathered to the IoT platform are the weather forecast (rainfall prediction from open data) data, local weather station data and the actual water level information.

The water level in the pump pool is measured with the hydrostatic level transmitter (water level transmitter). Its output signal is 2-wire 4-20 mA traditional current loop, which is widely used in automation technology due to its immunity for electromagnetic disturbance. The current loop level is converted to the digital I2C-bus with separate converter and connected to the Raspberry PI Linux computer. The Raspberry PI sends the water level data to the IoT platform (cloud) via 3G/4G cellular network.

The other data inputs for the IoT platform are local weather forecast (from Finnish Meteorological Institute) and data from local weather station located in close proximity to the pump station and peat production area.

The Finnish Meteorological Institute (FMI) offers several different data sets as Open Data. FMI offers weather forecast for 17,000 places in Finland. Weather forecast in open data is updated four times a day, thus every 6 hours. The rainfall forecast for the closest offered place from the peat production area was the main focus in this case [16].

The local weather station is located in close proximity of the pump station. Weather station sends the data to the cloud server (weatherlink) via cellular network and the data is obtained from there via interface to the IoT platform. The main factor gained from the local weather data in the predictive algorithm is the rain during the last hour. Water rained during last hour is still partly flowing to the reservoir, thus it does not immediately raise the water level in the reservoir.

The analytics from the obtained data is carried out on the IoT platform. According to the analytics, it creates the information for the current signal needed for guiding and controlling the frequency converter. This information is sent to the Raspberry PI via wireless 3G/4G connection and the Raspberry PI creates a new control signal with I2C/current (4-20 mA) converter. This current loop is connected to the frequency converter.

The flow meters are located after the filtering field. The flow meter data can be used to evaluate the smart pumping effectiveness to even out the water flow after the filtering field. It cannot be used for real time feedback to the pumping because there is a delay when the effect of pumping can be seen in water flow.

In a pilot case, the water level in the measuring well can vary from 0 meters to 3 meters. The frequency converter is programmed to keep the water level in 1.8 meters and the

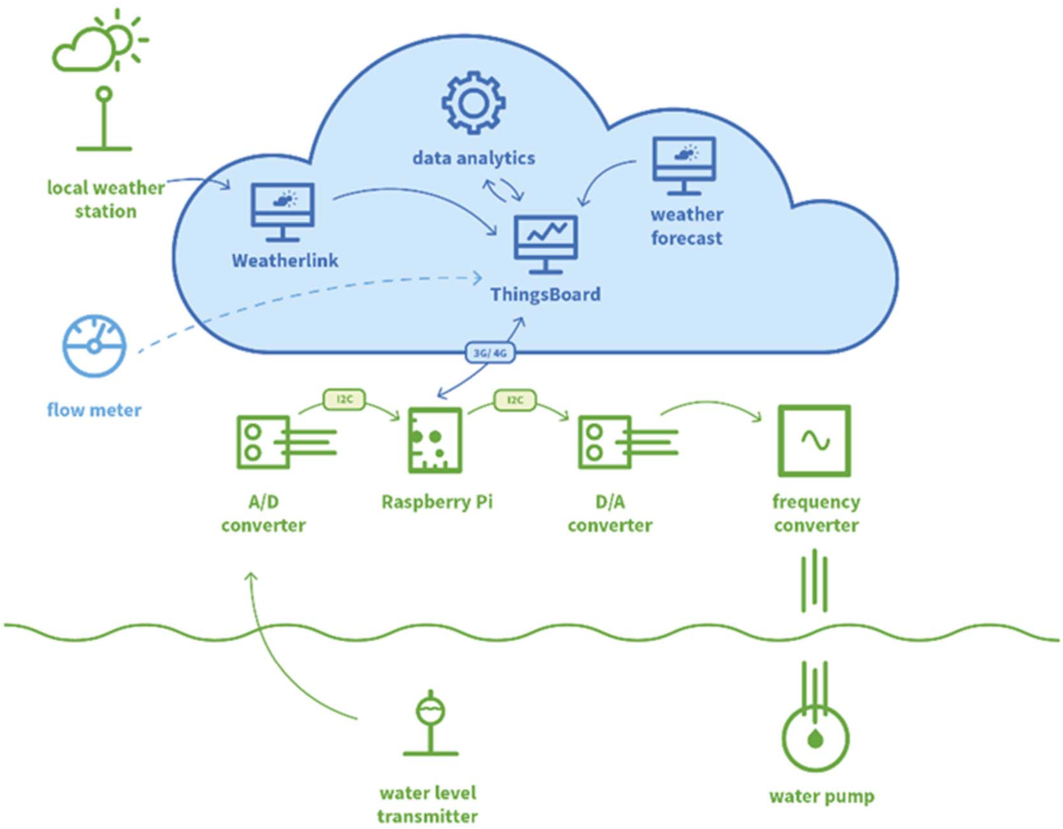


Fig. 1. The construction of the IoT pump control.

range is approximately between 1.8 m to 2.2 m. Thus, the pumping starts when the water level has reached the 2.2 meters. The pumping starts at nominal speed and it slows down stepless until the water level reaches 1.8 meters level.

The predictive pumping algorithm can start the pumping before the water level reaches the 2.2 meters level. Moreover, with predictive pumping the water level can be pumped down to 1.5 meters level to yield to raining water.

## IV. Predictive Pumping Algorithm Based on Sensor Data and Weather Forecast

The algorithm used in the IoT platform is creating the information for control signal needed. The first version of the pumping algorithm is rather simple but it will be developed further in the future.

The control algorithm inputs are:

- next hour rainfall forecast from FMI open data $R_1$ (mm).
- last hour accumulated rainfall from the local weather station $R_2$ (mm).
- actual water level in pump station $L_1$ (mA)

The control signal $L_2$ (mA) for the frequency converter is:

$$L_2(L_1, X_1, X_2) = \begin{cases} L_1, \text{when } L_1 < y \\ L_1 + X_1 + X_2, \text{ when } L_1 \geq y \end{cases} \quad (1)$$

$$L_1, L_2, y \in [4,20]$$

$$X_1, X_2 \in [0,16]$$

The $X_1$ (mA) is the effect of the rainfall forecast on the control signal:

$$X_1(R_1) = \begin{cases} 0, \text{when } R_1 < b \\ aR_1, \text{when } b \leq R_1 \leq c \\ d, \text{when } R_1 > c \end{cases} \quad (2)$$

$$R_1, a, b, c \in [0, \infty[$$

$$d \in [aR_1, 16]$$

Where $a$ is just a parameter to scale the control (slope) to the suitable level. The $b$ is the minimum predicted amount of rain to take account (for example 0.5 mm/h), $c$ is the limit for the predicted rain to be used for growing the $X_1$ (thus the rain prediction higher than $c$ is not raising the $X_1$ anymore), $d$ is the maximum for $X_1$ (for example 14 mA). Maximum value for $d$ is 16 mA but in real situation, it needs to be much lower.

The $X_2$ (mA) is the effect of the last hour accumulated rain measured in local weather station:

$$X_2(R_2) = \begin{cases} 0, \text{when } R_2 < f \\ eR_2, \text{when } f \leq R_2 \leq g \\ h, \text{when } R_2 > g \end{cases} \quad (3)$$

$$R_2, e, f, g \in [0, \infty[$$

$$h \in [eR_2, 16]$$

Where $e$ is the parameter to scale the control level. The $f$ is the minimum accumulated last hour rain to take into account (for example 0.5 mm/h), $g$ is the amount of accumulated rain during last hour to be used for increasing the $X_2$. The $h$ is the maximum for $X_2$.

The parameters used in this pilot case were $y$ = 12 mA, $a$ = 2, $b$ = 0.5 mm/h, $c$ = 7 mm/h, $d$ = 14 mA, $e$ = 2, $f$ = 0.5 mm/h, $g$ = 7 mm/h, $h$ = 14 mA.

Thus the algorithm for weather (rainfall) prediction effect $X_1$ was:

$$X_1(R_1) = \begin{cases} 0, \text{when } R_1 < 0.5 \\ 2R_1, \text{when } 0.5 \leq R_1 \leq 7 \\ 14, \text{when } R_1 > 7 \end{cases} \quad (4)$$

The effect of the local weather data:

$$X_2(R_2) = \begin{cases} 0, \text{when } R_2 < 0.5 \\ 2R_2, \text{when } 0.5 \leq R_2 \leq 7 \\ 14, \text{when } R_2 > 7 \end{cases} \quad (5)$$

Lastly, the final control signal for the frequency converter:

$$L_2(L_1, X_1, X_2) = \begin{cases} L_1, \text{when } L_1 < 12 \\ L_1 + X_1 + X_2, \text{ when } L_1 \geq 12 \end{cases} \quad (6)$$

The control chain in the IoT platform is presented in Fig 2. The Raspberry PI sends the water level transmitter data to the IoT platform. In the IoT platform, the effects of rainfall forecast and the last hour accumulated rain are calculated and added to the water level data if the water level is over a certain threshold level. This data is sent to the Raspberry PI in the field. If the water level is not over the threshold, the water level data is returned back to the Raspberry PI unchanged.

## V. Results

The predictive pumping system has been in use during autumn 2018 for few months. Due to exceptional rain conditions during that period, reliably results and conclusions cannot be drawn yet. In addition, the predictive algorithm parameters were changed few times during the period. Originally, the parameters were set too conservatively and the predictive control did not activate easily.

Data from local weather station and weather forecast for that location have been collected during autumn 2018. The rainfall forecast and actual rainfall from local weather station is presented in Fig 3. from 9 October 2018 to 13 November 2018 in hour on an hour basis. Measuring period is rather short but at least during that observation period the correlation

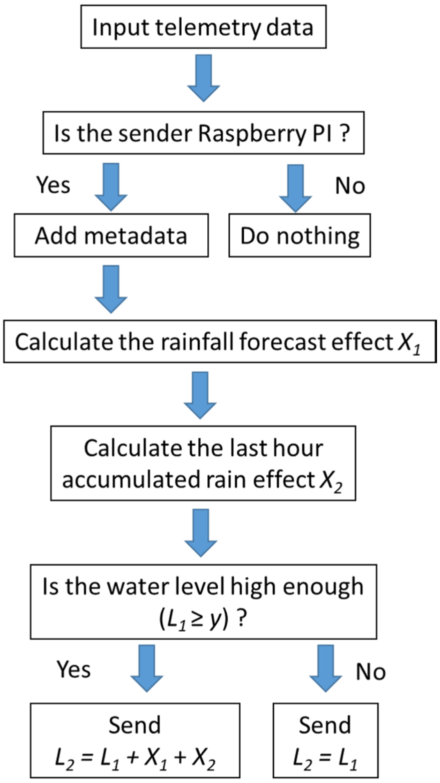


Fig. 2. Control chain in IoT platform.

between forecast and actual level is rather small. If the weather forecast is predicting rain and it actually does not start to rain, the pumping can start without the real need. Anyway, this is not a big problem; however, it gives rise to water flow after the filtering field. As a disadvantage, this system starts pumping with nominal speed. In a predictive mode, it could be better to start pumping with modest speed. This way the water flow would be more even and the unnecessary pumping (due to false rainfall prediction) would not cause as large burst in water flow after the filtering field. This is one of possible tasks in further development.

## VI. Conclusions and Future Work

By using short-term (one hour) rainfall forecast we get quite good accuracy to the pump control. That way the rainfall prediction and pump control are simple. Better result to the control will be achieved by predicting rainfall using local weather information. In addition, one possibility is to use the rainfall forecast for the next few hours, not just the next hour. The forecast for following hours could have a smaller effect on the algorithm due to bigger inaccuracy.

The next step in the research will be to add the weather forecast, local weather station information and the peat bog's current capability of water absorption into the pump control algorithm. Water absorption depends on long-term rainfall and season. With these changes to algorithm, it is possible to get more even water discharge from the peat bog elsewhere to the nature. By adding water flow measurement information from the filtering field with water pumping information we get feedback from the algorithm by regression analysis.

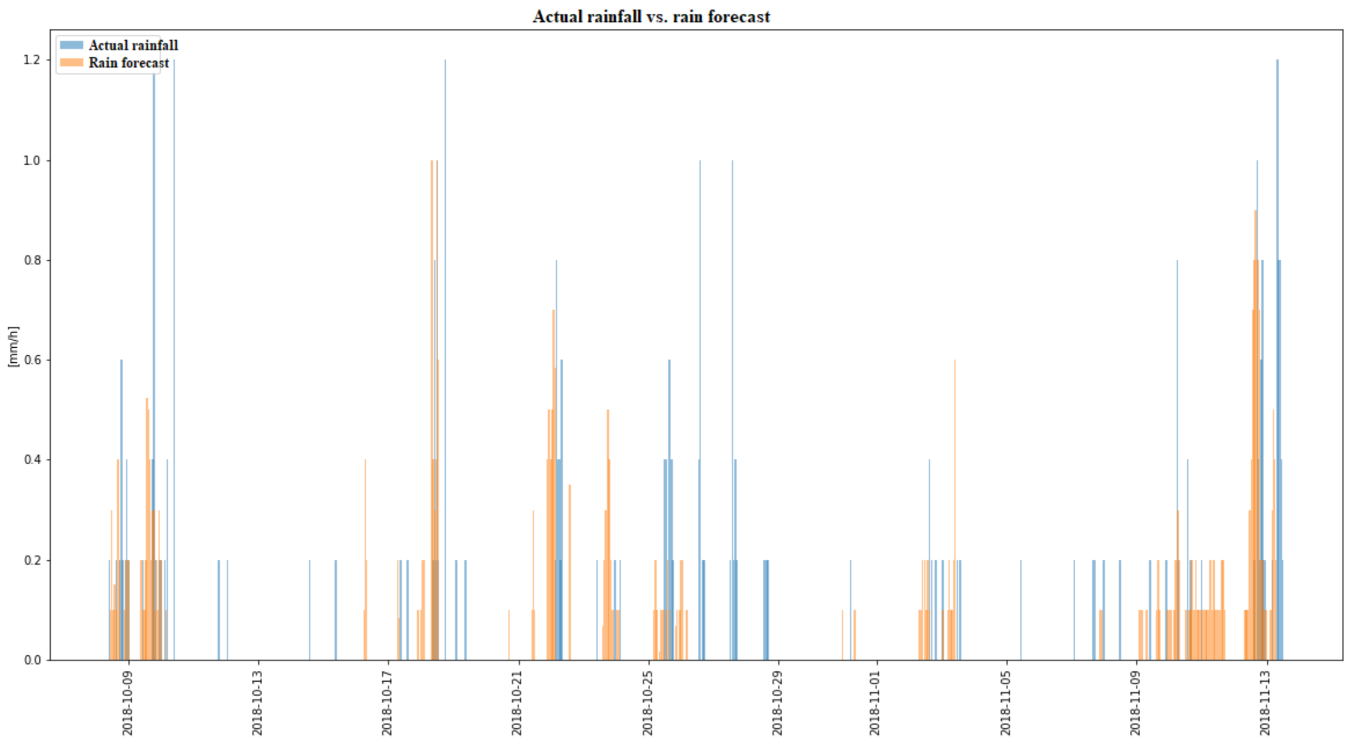


Fig. 3. Actual rainfall versus rain forecast from hour to hour.

In this system, all the intelligence and calculations are done in the cloud server (IoT platform). This kind of system requires a reliable wireless internet connection from the field to the cloud and back. The water level data is constantly sent to the IoT platform and the IoT platform sends the new control data at the same rate back to the Raspberry PI. In rural areas, the internet connection is not always reliable enough. The algorithm used is not very complex; thus, the calculations could be done locally in the Raspberry PI. This kind of approach is called edge computing. The weather forecast from open data used is updated every six hours so in edge computing approach there is no need for a constant internet connection. The amount of data in weather forecast is also rather small. It could be possible to download this amount of data to the edge device with a rather slow internet connection. Edge computing could also help significantly in possible connection shortages. Local weather station data could be connected directly to the control device without available internet connection.

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