Weather-aware Wake-up of Sleeping Cyber-Physical IoT Nodes

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***Abstract*—Cyber-physical IoT nodes located in environments which are resource-constrained and physically hard to access, like the Arctic tundra, must achieve long operational lifetimes from a single battery and report data over data networks. The nodes sleep most of the time, and only wake up to perform mission tasks, including reporting data. However, networks can become unavailable, or have low bandwidth and require many re-transmissions for multiple reasons, including a sparse network infrastructure and adverse weather. The state of the network can be quantified by the Received Signal Strength (RSS). If nodes wake up to report data when the signal strength is low they waste energy, because the reporting of data will require more energy or take more accumulated time. RSS decreases with increasing temperature and precipitation. Therefore, nodes should wake up when the temperature and precipitation are low. We explore four algorithms for picking a single time to wake up per 24-hr day over one year. For each wake-up-time, we compute the change in RSS as a function of the change in temperature and precipitation. We use historic weather forecasts and measurements from MET Norway. The data covers 37 locations in Northern Norway over one year. The weather-forecast-based algorithm is able to frequently select a timeslot near the highest expected RSS. It also avoids the large decrease in RSS caused by precipitation more often than the other algorithms presented.**

***Index Terms*—Cyber-physical system, CPS, edge computing, energy efficiency, tundra, monitoring;**

I. Introduction

Nodes suitable to be deployed to the arctic tundra comprise one or more battery-powered microcontrollers, and computers. Each node has on-node storage, data networks, and sensors. We call such a node an Observation Node (ON). Nodes are structured into a set of nodes called neighbourhoods [1].

Data collected by ONs may include multimedia data like images or small videos [2], or sensor data of ambient conditions like temperature and humidity[3]. However, the arctic tundra is a challenging environment for a distributed multi-node cyber-physical system. The weather is unique, with frequent precipitation and long, cold winters. Furthermore, the arctic tundra is resource-constrained. In particular, both networks and energy are limited resources. In a neighbourhood, at least some nodes have technologies to reach back-haul networks, while all nodes may have one or several radios for local area ad hoc networking. However, the networks cannot be expected to be available at all times, if at all. When a network does become available, the connection may be marginal and the bandwidth can be expected to be low.

The arctic tundra has no infrastructure for delivering energy to nodes. Therefore, each node is powered by batteries. Furthermore, due to the harsh weather conditions, and the lack of infrastructure, the common case is that nodes, in practice, only rarely can be visited by humans. Even for the low-arctic Varanger peninsula on main-land Norway, visits to a neighbourhood of nodes happen only about once per year [3].

ONs reduce the energy cost of transmitting data in a number of ways. One option is to reduce the number of bytes required to represent the data before sending it. This option has previously been explored [2]. Another option is to defer transfer of bulk data until the signal strength is high. This can reduce the energy usage considerably [4], because the time and energy required to transmit data increase exponentially with decreasing signal strength [5]. In an LTE network the power usage is higher when the received signal strength is lower [6]. Weather-related impact on signal strength may lead to packet loss [7]. Signal strength also has an effect on communication range. It has been shown, how it is necessary to correct for the effect of temperature when using RSSI-based ranging [8]. It has been proposed that an outdoor sensor network should take the effects of temperature and rain on wireless communication into account [9] [10].

In this paper, we first summarize findings from other studies in terms of the impact of weather conditions on wireless network performance metrics like RSS. Change in Received Signal Strength Indicator (RSSI) is often reported in the literature. RSSI is a radio specific measurement which is then translated to a signal strength in units of dBm. We separate the findings in the literature by network type, but find that the contributions are similar and caused by the same phenomena. Based on prior art for how temperature and precipitation influence signal strength, we build a simple model allowing us to compute the expected change in RSS. We report on four algorithms for selecting a single time per 24-hr day for when the RSS is high. One algorithm ignores the changes in temperature and precipitation, while the other three do not. One year of temperature and precipitation forecasts, and measurements for 37 locations in Northern Norway have been downloaded from MET Norway. We use the data as input to the algorithms, and as input to the temperature-precipitation-RSS model to estimate the change in RSS caused by local weather.

We make the following contributions:

- An analysis of possible improvement of signal strength by selection of transfer time.

- A simple model based on prior art for the impact of weather on signal strength
- A description and implementation of naive as well as analytics-based algorithms for selection of time for data transfer based on local weather conditions.
- An insight: It is possible to select a time to communicate at or near the time with the highest weather-related increase in RSS. We show how three different algorithms select better timeslots than randomly selecting a timeslot.
- An insight: A large decrease in RSS can be avoided by predicting precipitation events. This can be done by a weather forecast.

The rest of this paper is structured as follows: In section II we describe the motivating use-case for this paper: The Arctic tundra and the challenges it poses for a multi-node cyber-physical system. In section III we summarize the effects of weather on wireless signals in three different wireless network types. Section IV-A describes the data used in the analyses in this work. Section IV-B summarizes the estimated benefit of predicting future conditions on the Arctic tundra. We then present strategies for improving the likelihood of communicating when network conditions are favourable in section IV-C. We describe results of our analysis in section V. Finally, we discuss the findings and conclude on our observations in section VI.

II. Motivating use-case: The Arctic tundra

Monitoring ecosystems and the environmental conditions on the Arctic tundra is important, as the tundra is highly sensitive to climate change [11]. Performing these observations typically requires several phases and considerations.

Small devices with sensors are deployed by humans. The devices are located both above and below snow and ice. The sensors can typically sense and measure a range of conditions including images, temperature, and humidity. The devices are dependent on batteries, because there is no infrastructure for power delivery. Solar panels and windmills cannot be used because of weather conditions and legal restrictions.

A deployment of nodes for an experiment collecting data in situ at the arctic tundra is, typically, organized into one or several neighbourhoods. We assume that nodes in the same neighbourhood are located close enough, physically, such that they experience the same weather conditions. Inside a neighbourhood, the nodes can do ad hoc networking with each other when network conditions are favourable. The neighbourhoods communicate with each other over back-haul networks. The neighbourhoods can have different weather conditions. Here, we ignore the multi neighbourhood case.

The ONs are left alone for an extended period of time, e.g., one year, to do observations. In some cases, the observations can be reported over a back-haul network. However, the common case is that no back-haul network is reachable for large parts of the arctic tundra. Unless there is a back-haul network in reach, humans must visit the devices to collect observational data, and to replace batteries. In practice, many observations sites cannot be frequently visited, due to the limited infrastructure, and harsh weather conditions[3]. Several challenges arise if the devices cannot be frequently visited, and the nodes have no direct access to a back-haul network. First, the delay before data becomes available can be many months. For some missions this is acceptable, for others it is not. Second, to make data available when it is needed or even on-demand, several data networks may have to be supported by the nodes. It is typically necessary to do multi-hopping over one or more different ad hoc local area networks to carry data between nodes to reach a node with a back-haul network. This complicates the software and hardware. It also increases the energy usage at multiple nodes. Consequently, the nodes must aggressively save energy. Third, the observational missions of the nodes become fixed at deployment time, and later adaptations are in practice not possible. Fourth, without a network, or human visits, the software for the devices cannot be updated after deployment. Software bugs which cannot be repaired can make a whole season of observational data unusable. Fifth, the state of the devices are unknown until next visit. This is a problem because it is unknown which spare parts and software updates are needed for the next visit, and even if the devices are operating at all. Sixth, the arctic tundra often has precipitation and temperatures known to influence radio signal strength and therefore the reachability of data networks. When the data networks are, already, only sporadically available and with low signal strength, this can result in lost connectivity. We describe several network technologies with regard to how they are affected by weather conditions. Long range networks like 4G LTE and LoRa may be used as backhaul networks or for transferring data between local neighbourhoods of observation nodes. Shorter range networks like ZigBee may be used for communication between nodes in a neighbourhood. In addition to the above challenges, the arctic tundra also poses physical challenges to nodes. It is not uncommon for nodes to be destroyed or damaged even when housed in weather resistant housing [3]. Nodes can also be damaged by avalanches, animals, and humans.

In summary, for many of the functionalities of observation nodes, it is *critical* that they have access to data networks. Consequently, nodes should make significant efforts to establish network connectivity. Nodes can increase the chance of success of achieving this by always being awake, monitor the network signal strength, and trying to associate with networks. However, it is also critical that the nodes are very energy frugal because they must operate for long periods of time from a single battery charge. This prevents nodes from always being awake and have one or more radios turned on. One of the techniques used by nodes to decrease energy usage is to spend most of the time sleeping, and be restrictive on when to wake up to do functionalities.

III. Changes in signal strength due to weather

Several studies have examined the effects of weather phenomena on various networking technologies. In this section, we summarize their results on the effects of three measurable weather conditions on three networking technologies. The weather conditions are temperature, humidity (relative and absolute), and precipitation. The radio technologies are ZigBee, LoRa, and 4G LTE. We focus primarily on signal strength, and secondarily on other performance metrics, like Packet Reception Ratio (PRR). This section has four subsections: One for each of the mentioned weather conditions and a summary. Each subsection is separated into three parts: One for each radio type.

A. Temperature

Increase in temperature is known to reduce signal strength.

1) ZigBee: There have been several studies measuring the relation between temperature and signal strength in ZigBee networks. The signal strength decreases by $0.1\,\mathrm{dB}$ to $0.2\,\mathrm{dB}$ when the temperature increases by $1\,°\mathrm{C}$. Different numbers are found in different studies: $-0.1996\,\mathrm{dB}\,°\mathrm{C}^{-1}$ [12], $-0.127\,\mathrm{dB}\,°\mathrm{C}^{-1}$ [13], $-0.205\,\mathrm{dB}\,°\mathrm{C}^{-1}$ [14], $-0.1\,\mathrm{dB}\,°\mathrm{C}^{-1}$ [9]. Temperature also influences other parameters: PRR is negatively correlated with temperature - especially near the limit of the communication range [14], [15]. The minimum transmission power required for successful communication increases with higher temperatures [16]. The gradient in temperature and humidity has been used to control the power in the antenna to account for changes in RSSI [17]. It is possible to improve efficiency of a wake-up radio by considering the relation between signal strength and temperature [18]. The deployment of an outdoor sensor networks should take the current temperature into account [9].

2) LoRa: Like for ZigBee, a negative correlation between temperature and received signal strength has been found in LoRa networks [7], [19]–[23]. A relationship is shown with incline around $-0.1\,\mathrm{dB}\,°\mathrm{C}^{-1}$[19], [21]. The change in RSS is likely due to sensitivity in the radio hardware [20]. It has also been found, that the Signal to Noise Ratio (SNR) is lower at higher temperatures [7], [10]. For a node at the edge of its communication range, the PRR decreases when heating the node. Eventually, the node becomes unable to communicate at all [20].

3) 4G LTE: Increasing temperature is found to cause a ”sharp decrease” in signal strength in an LTE network [24].

B. Humidity

Water in the atmosphere at higher humidity could cause attenuation of a wireless signal.

1) ZigBee: An increase in relative humidity of 10% causes a change in signal strength of roughly $0.3\,\mathrm{dB}$. However, the change in signal strength may also be caused by temperature variation, and the contribution from absolute humidity is small [13]. For IEEE 802.15.4 links, a negative correlation is found between absolute humidity and RSSI and PRR, respectively. After further analysis, it is questioned whether there is a causal relation between absolute humidity and received signal strength [15].

2) LoRa: Like was the case for ZigBee networks, it cannot be concluded that humidity influences signal strength in a LoRa network [23]. In a LoRaWAN network, a linear relation between humidity and RSSI is found when the absolute humidity is in the range $4\,\mathrm{g\,m^{-3}}$ to $10\,\mathrm{g\,m^{-3}}$ [19]. Increasing relative humidity leads to a reduction in both RSSI and SNR in a LoRaWAN deployment [7].

3) 4G LTE: Some work suggests a decrease in received signal strength with an increase in relative humidity [24]. However, correction for the relationship between temperature and humidity was not done.

C. Precipitation

It has been shown that rainfall has an effect on link quality [4]. However, some studies find a significant negative effect on RSS from rain, whereas others find a small positive effect.

An energy-efficient transmission scheme for varying weather conditions has been proposed [25]. Equations are provided for the attenuation of any wireless signal in rain, dry, and wet snow. The equations all follow a power-law like $A = \alpha R^{\beta}$, where A is the attenuation, R is the distance travelled by the signal, and α and β are parameters specific to the wireless signal and the medium it travels through. The attenuation of signal strength due to precipitation is small compared to the influence by temperature [25]. Conversely, several studies do observe noticeable decrease in signal strength due to precipitation.

1) ZigBee: A $5\,\mathrm{dB}$ to $10\,\mathrm{dB}$ decrease in signal strength has been observed even in light rain or snow [26]. In another study, a drone was used to connect to IoT modules on the ground. The results show a $20\,\mathrm{dB}$ difference between “Rainy” and “Sunny (15C)” conditions [27]. A decrease in signal strength in a ZigBee network may be caused by presence of water on the device enclosure, rather than attenuation of the signal due to precipitation [4]. Over a period of six months, variations in RSSI and PRR for IEEE 802.15.4 links were stronger correlated with temperature than precipitation [15].

2) LoRa: In a comparison of using ZigBee and LoRa in a landslide detection system, no correlation was found between rain rate and RSSI, however a larger rate of packet loss was detected during rain [28]. Similarly, measurements of RSSI on a signal day with rainfall, did not show a significant difference in RSSI at higher rain rates [23]. Significant changes in SNR and RSS has been found during snowfall compared to dry conditions [7]. Using multiple radios operating at both 868MHz and 2.4GHz (not specifically with LoRa) rain and fog is found to have small effect on the RSSI. However, a significant increase in the packet loss rate, and interruption of ongoing communication is found [9].

3) 4G LTE: The decrease in received signal strength in an LTE network has been used to estimate the amount of rainfall. The difference in received signal level between “no rain” and “heavy rain” is around $12\,\mathrm{dB}$[29]. Likewise, changes in LTE network conditions have been used to classify rainfall into “no rain” and four distinct classes of precipitation intensity[30]. Precipitation can explain some short-term variations in RSRP in a 4G LTE network [31].

	Temperature	Relative humidity	Absolute humidity	Precipitation
ZigBee	$(-0.1 \text{ to } -0.2)\,\mathrm{dB\,^\circ C^{-1}}$	$(0 \text{ to } 0.03)\,\mathrm{dB}$ / RH%	$\{0, (-0.2 \text{ to } -0.7)\,\mathrm{dB/(g/m^3)}\}$	$\{0, -(5 \text{ to } 10)\,\mathrm{dB}, -20\,\mathrm{dB}\}$
LoRa	$(-0.1 \text{ to } -0.2)\,\mathrm{dB\,^\circ C^{-1}}$	0	$\{0, -3.5\,\mathrm{dB/(g/m^3)}\}$	Magnitude unclear from literature
4G/LTE	"sharp decrease" [24]	Decreasing with RH% [24]	Unknown	$(-8 \text{ to } -12)\,\mathrm{dB}$

TABLE I
EFFECT OF AMBIENT ENVIRONMENT CONDITIONS ON SIGNAL STRENGTH.

D. Summary of changes in signal strength due to weather

Table I summarizes the influence of weather conditions on signal strength. We have found prior art documenting that air humidity influences the RSS. However, for an increase in humidity, some report an increase in RSS, while others report a decrease. Since the reported effect is inconclusive, we ignore air humidity as a contributing factor on the RSS in the further analysis.

There is a relationship between RSS and temperature for each of the considered network technologies. For the relation we use eq. (1), which has the same impact from temperature as [12].

$$\Delta RSS_T = -0.1996\,\mathrm{dB\,^\circ C^{-1}}\Delta T \tag{1}$$

ΔT is the change in ambient air temperature, and ΔRSS_T is the temperature-related change in the RSS. It is possible that part of the decrease in RSS with increasing temperature is because of a higher noise floor of the radio as it becomes warmed up, rather than attenuation of the signal through the air. For a cyber-physical node being awake only for a short period of time, around 60–120 seconds, after sleeping for several hours or days, changes in ambient air temperature will affect RSS.

Prior art documents that precipitation impacts signal strength. However, some have found larger decreases in signal strength than others. This can perhaps not be explained just by attenuation of the signal through air. If accumulation of water or ice happen on or around the antennae, this may result in larger decreases of the RSS. It should be expected that water and ice accumulates on the antennae when nodes are deployed to cold and wet environments like the arctic tundra.

To account for both the possible effect from water and ice on the antennae, and the results listed in table I, we propose eq. (2) for how precipitation causes a decrease of the RSS.

$$\Delta RSS_p = \begin{cases} (-8 - 4 \cdot (1 - e^{-p}))\,\mathrm{dB} & , p > 0 \\ 0 & , p = 0 \end{cases} \tag{2}$$

p is the precipitation rate in units $\mathrm{mm\,h^{-1}}$. ΔRSS_p is the decrease in signal strength due to precipitation.

IV. EVALUATION

As described in section II, observation nodes can be expected to be at the limit of their communication range. This is a problem because prior art documents that the weather conditions at and between sending and receiving nodes can decrease the RSS. This can make borderline networks becoming temporarily unreachable, or result in lower bandwidth and more re-transmissions, thereby wasting energy.

However, if an observation node can select a time to transfer data when the RSS is higher it can possibly restore reachability, increase network bandwidth, and reduce network disruptions. This will reduce the energy usage for the communicating nodes. We note again that the primary influence of weather can be considered to be local to the observation nodes.

We have devised and explored four algorithms for determining when to wake a node. One algorithm ignores weather conditions, and three have weather conditions as input. The algorithms are ranked by the relative change in the RSS caused by weather conditions at the time picked. The highest positive change in the RSS is considered best. For this paper, we assume that the cyber-physical observation nodes are located around the weather stations producing the historic weather data we use (described in section IV-A). This allows us to assume that the historic weather data is indeed valid for the weather conditions that the nodes will experience.

A. Historic Data Set

When the four algorithms pick a wake-up time for a node, weather measurements are needed to compute the change in RSS as a result of weather conditions at the picked time. Having historic data on weather conditions allows for computing the weather-related change in RSS both for the picked time, and for all other times we have data for. This allows for comparing how well the four algorithms pick a time with a high RSS. We use data from MET Norway [1] available under an open licence[2]. It comprises weather forecasts as well as temperature and precipitation measurements for 37 weather stations located in the low or sub-arctic in northern Norway. We selected all stations in the area with measurements of both temperature and precipitation from January 1st, 2021 to December 31st, 2021.

Temperature data is typically available at 10 minute intervals. Precipitation is typically available at one-hour intervals. Forecast data is available with one hour between data points. We only use data from each location taken at the beginning of every hour. Some locations are missing precipitation data for one or more periods. When data is missing, it is ignored in the analyses. For two of the days, the first forecast for the day is missing. Instead, we use forecasts which were made

[1]https://frost.met.no and https://thredds.met.no

[2]Creative Commons Attribution 4.0 International License http://creativecommons.org/licenses/by/4.0/

a few hours earlier: On 2021-05-31 and 2021-11-03 we use forecasts which are 12 and 18 hours old, respectively.

B. Computing change in RSS

The change in RSS due to change in temperature and precipitation is approximated by eq. (1) and eq. (2), respectively. We apply the equations to the data from MET Norway. We compute the hourly change in RSS over a year for all 37 locations as follows. 1) For each location, we use the first temperature measurement for that location as a reference temperature. 2) To compute the change in RSS, we use the observations for a time slot and use the difference to the reference temperature as input to equation eq. (1) and the precipitation as input to equation eq. (2).

To study how much weather influences RSS for each day (24 hours), we compute the range of RSS changes for each day as the dB-difference between the largest and smallest change in RSS for that day. Figure 1 shows how many days over a year a range occurs. For about half the number of days, the range is between approximately zero to four dB. For most of the remaining days, the range is from approximately 8.5 to 14 dB.

Figure 2 shows the hourly change in RSS over one year due to changes in temperature and precipitation. The changes in RSS are found by first computing the hourly changes in temperature relative to the temperature on midnight on 1. January 2021. Then eq. (1) is applied to the temperature change, and eq. (2) to the precipitation, to find the corresponding changes in RSS. While this is done for all 37 locations, fig. 2 shows the results for a single location. An increase or decrease of the temperature and the precipitation, result in a decrease or increase of the RSS, respectively. However, the precipitation results in significantly larger changes of the RSS than the temperature does. The implication of the observations in fig. 1 and fig. 2 is that there is often precipitation during a day. If a node wakes up at a time with precipitation, it will experience a lower RSS than during other times that day. Because there is precipitation in about half of the days, it is worth considering precipitation when selecting a time to wake up in order to avoid a large decrease in RSS. There is also a clear difference between the seasons in that the RSS decreases by about 5 dB during the summer compared to winter.

C. Selection algorithms

In this section, we describe four different strategies for selecting a single one-hour time-slot during a day for waking up nodes. For the time picked by the algorithms, the change in the RSS relative to 1. January 2021 is computed as previously described. The purpose is to see how well the algorithms are picking a time when the RSS is at or near its highest during the day.

1) Random time of day: The random time of day strategy picks a random time per day over one year for when to wake up nodes. It will serve as a reference for comparison with other strategies where the timeslot is selected based on observations and weather forecasts.

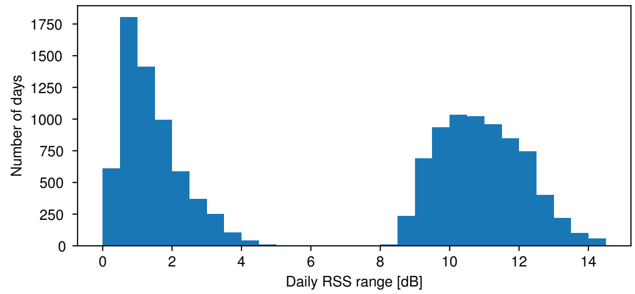

Fig. 1. Histogram of daily range of weather-related RSS changes. The figure only includes observations where both temperature and precipitation are available.

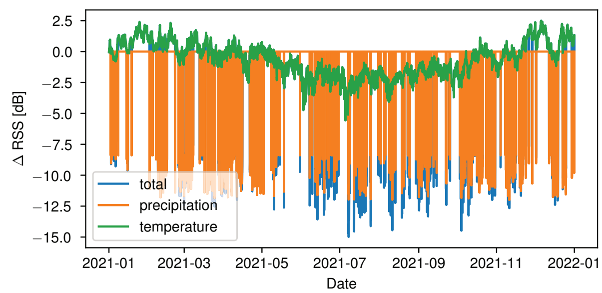

Fig. 2. Expected difference in RSS relative to first measurement on Jan 1 2021 for one location.

2) Fixed time of day: The fixed time strategy inspects historical weather data to pick the timeslot which most often results in the highest RSS. A single fixed wake-up time is selected for *all* days. To determine the fixed time, first the historic weather related changes in RSS is computed for all 37 locations over one year for total of 13505 (37x365) 24-hr days. For each day, the one hour timeslot with the highest expected RSS is selected. This is when the change in the RSS causes the RSS to reach its highest value for the day. Finally, from the 13505 days, the time which most frequently has the highest expected RSS is the one selected as the wake-up time. The selected time is not necessarily the one resulting in the highest RSS for every day, but most often is.

3) Weather forecast: The weather forecast aware strategy picks a wake-up time per day for when the RSS is at its highest according to the forecasted conditions. We use the first 24 hours of the weather forecast starting at the beginning of each day. For each weather station location, we select the closest forecast grid cell. In practice, for deployed nodes to be able to benefit from the weather aware algorithm, they must either have received the wake-up times from a back end or edge service, or the nodes must have received the relevant forecast and have done their own computations to pick the wake-up times. However, in this paper we ignore how to do this, and just explore if having a weather forecast will aid in picking a wake-up time when the RSS is high.

4) Time series forecast: The time series forecast strategy picks a wake-up time per day for when the RSS is at its highest according to a time series forecast of the temperature from an autoregressive-moving-average (ARMA) model. ARMA was used instead of SARIMA because the time series we have is stationary and non-seasonal. This was determined by using *pmdarima version 1.8.5* [32] with 60 days of temperature measurements from a single location. The *auto_arima* function from *pmdarima* also determined the parameter values (p, q) for ARMA to be (3,4). Each forecast by the ARMA model is made by fitting the measurements from the previous 168 hours, and then predicting the conditions up to 24 hours into the future. We then select the time to wake up a node to be when the temperature is at its coldest according to the forecast.

V. Results

In this section, we present the results from applying the prediction strategies presented in section IV-C. The expected change in RSS at each selected timeslot for each location is compared to the highest expected RSS in the corresponding 24-hour window. Since the ARMA model requires prior observations to make predictions, it only makes a selection on 13246 days. Therefore, we compare all the selection strategies on those days. The results are summarized in fig. 3 and fig. 4. Figure 3 contains a histogram, for each of the four selection strategies, of the difference in RSS at the selected timeslot compared to the timeslot with the highest RSS for the corresponding day. This difference uses the notation ΔRSS_{24}. Figure 4 shows how often the selections made by each strategy has a ΔRSS_{24} that is more negative than six different thresholds. In the following subsections, we provide further information about each selection strategy.

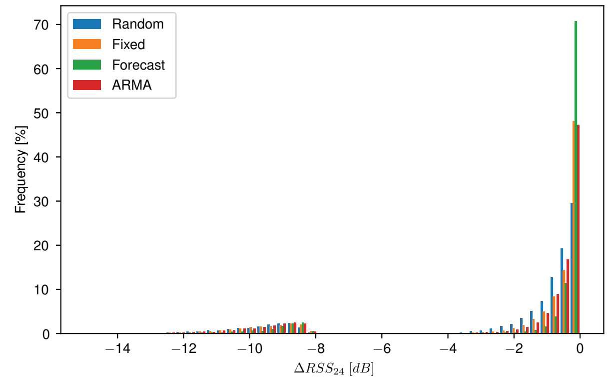

Fig. 3. Histogram of weather-related expected difference in RSS compared to the highest RSS in each 24-hour window for the selections made by each of the prediction strategies. The weather forecast is particularly good at selecting near the highest expected RSS, as well as not selecting near the lowest.

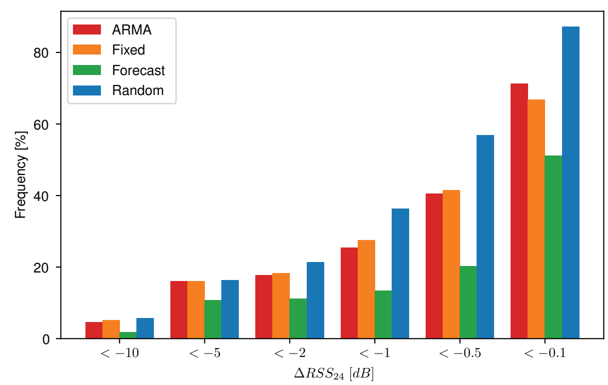

Fig. 4. The frequency of when the expected RSS difference to the highest RSS on each day is more negative than the threshold on the first axis. Lower frequency is better

A. Random time of day

Random selection of a timeslot serves as our baseline for comparison with other strategies. In about 5% of the days, the randomly chosen timeslot is the one with the highest expected RSS. We see in fig. 3 that among the four selection strategies, the random selection makes the fewest selections near the timeslot with the highest RSS. We also observe from fig. 4, that it selects timeslots with large decrease in RSS more frequently than the other strategies.

B. Fixed time of day

For timeslot selection based on a fixed hour, we first determine, at which hour it is most likely to observe the highest expected RSS within the used data set. The highest RSS is most often observed at hour 23. 23 is slightly surprising, as the temperature should continue to decrease until sunrise. We can then compare the differences in expected RSS between always attempting to communicate at 23:00 and the best time to communicate. In fig. 3 we see, that the strategy using a fixed timeslot to communicate selects a timeslot with an expected difference in RSS near zero more frequently than the random selection strategy. This is expected, since the fixed timeslot was selected to be the single timeslot, which most frequently had the highest expected RSS. However, the strategy only avoids large decrease in RSS slightly more frequently than the random selection strategy. This can be seen in fig. 4.

C. Weather forecast

Assuming that weather forecasts are accurate, selecting times for communication based on them can be expected to result in higher RSS. The weather forecast strategy selects timeslots with expected RSS near the highest expected RSS more frequently than the other selection strategies. Figure 3 shows that the difference in expected RSS between the selected and best time is more often near $0\,\mathrm{dB}$ than the other selection strategies. We see in fig. 4 that the weather forecast is able to avoid large decreases in RSS (caused by precipitation) more often than the other three strategies. When it does select a timeslot with precipitation, it is better able to avoid timeslots with large decrease in expected RSS than the other strategies.

The weather forecast does perform better than any of our other selection strategies. In particular, it is worth noting, that

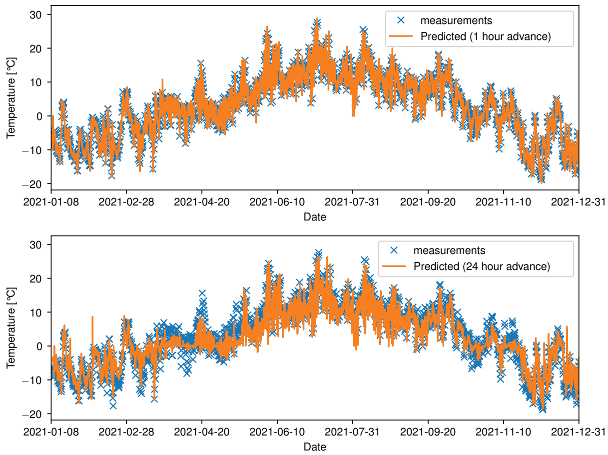

Fig. 5. Predicted temperature values from the ARMA model. Predictions are made 1 and 24 hours prior to the shown data points. For readability, only every 5th point is plotted. The predicted temperatures are later converted to expected changes in RSS.

it often makes selections at or very close to the best possible timeslot. Figure 4 does not show the interval where the RSS is within $0.1\,\mathrm{dB}$ of the best RSS of the day. The weather forecast selects a timeslot in this interval on 48.8% of the days. For comparison, the random selection strategy selects within $0.1\,\mathrm{dB}$ only on 12.8% of the days. Furthermore, as shown in fig. 4, the weather forecast is better at avoiding large decreases in RSS than any of the other strategies. It selects a timeslot with difference in expected RSS of more than $10\,\mathrm{dB}$ compared to best timeslot on 1.8% of the days compared to 5.7% for the random selection strategy. On those days there is typically precipitation in most timeslots. A comparison between all the selection strategies is shown in fig. 4.

D. Time series forecast

To examine how well the ARMA model predicts future conditions, we plot in fig. 5 the predictions made 1 and 24 hours after the last observation for an arbitrary location. The predictions deteriorate the further into the future they are made for. In fig. 3 it is possible to see that the ARMA method selects a timeslot near the best possible option more frequently than random timeslot selection and at about the same rate as the fixed-time selection. On 13 days the fit fails to converge for one of the locations. No predictions are made on those days. In fig. 3, and fig. 4 we see, that the ARMA-based selection strategy performs comparably to the fixed time selection. It has avoided a few more timeslots with large expected decrease in RSS than the fixed time selection, but it has fewer selections close to the best timeslots.

VI. Discussion and Conclusions

Prior art argues taking the influence of weather into account for nodes to be deployed in-situ into resource-limited environments. We have used historic observations and weather forecasts for 37 observation sites located in Northern Norway. We then apply four different strategies for selecting communication timeslots and use a model to compute expected change in RSS. The model is based on estimates from related studies of the influence of temperature and precipitation on the RSS.

Based on our model and prediction strategies, we make the following observations: It is indeed possible to select times to communicate close to times with the highest expected RSS. Large drops in RSS due to precipitation may be better avoided by selecting a timeslot to communicate based on a weather forecast. We hypothesize such an improvement can be beneficial for observation nodes, especially when they are at the edge of their communication range. Even for nodes connected to a network, a small increase in RSS can result in higher bandwidth, and fewer re-transmissions. Our findings may also prove useful in other locations with larger temperature variations. Furthermore, since the communication range is dependent on signal strength, the effective communication range can be increased by selecting times to communicate with the highest expected RSS. This can increase the number of nodes which can be reached. The large influence of precipitation is based on an assumption that water accumulates near or on the antennae. We make this assumption from our intended use-case, the arctic tundra, which has unique weather with high humidity and frequent precipitation.

When the ARMA model makes predictions about future conditions, it does so at a fixed time. Since the accuracy of predictions decrease the further into the future they are made, the selection of when predictions are made may influence the results. More frequent computation of predictions could increase the accuracy, at the cost of waking up the node more. It also adds complexity in ensuring one selection is made per 24 hours if data is updated, pointing to new time slots.

This work can be expanded in a number of ways: More advanced prediction models like LSTM or Random Forrest may increase the likelihood of choosing the timeslot with the highest expected RSS. The real-world energy consumption of the different prediction strategies should be measured to show if there is any practical benefit to applying these concepts. Energy considerations may also need to include the discharge rate of batteries at varying temperatures. It may be interesting to study dynamics between using a weather forecast and relying on local predictions as a fall-back option. Basing predictions on a weather forecast assumes the availability of a forecast. This implies either downloading a forecast from somewhere, or doing a forecast on the nodes. In this paper we do not expand on the implications of either approach.

Acknowledgment

The DAO project is supported by the Research Council of Norway (RCN) IKTPluss program, project number 270672. Thank you very much to the COAT ecologists, UiT.

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