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# Estimation of the Probability of Successful Transmission of Uplink Messages in LoRaWAN

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**T**his report is a short overview of applying forecasting methods on data from real LoRaWAN deployment in Swebølle, Denmark. The main idea is to examine whether there is a possibility of predicting successful transmission of LoRa messages for the given future time interval. Proposed model for prediction is Long Short-Term Memory (LSTM), an artificial recurrent neural network (RNN) architecture used in the field of deep learning.

## 1 Introduction

TBA

## 2 Network Topology

LoRaWAN - Long Range Wide Area Network - low power, wide area media access protocol designed to wirelessly connect 'things' to the internet. LoRaWAN is useful in IoT deployment, specially in smart environments where there are thousands of end-devices (i.e. sensors) that require minimal bandwidth and minimal energy.

The network architecture is deployed in a star-of-stars topology in which gateways relay messages between end-devices and a central network server [3]. Topology overview is shown in Fig. 1.

End-device is transmitting data to base station using LoRa technology, which means that data is modulated using CSS technique and transmitted using 868MHz RF, also it is worth mentioning that data is encrypted using AES128 in Counter mode (CTR). If the packet's FPort is set to 0 then the NwkSKey is used, otherwise the AppSKey is used. An important feature of all messages in LoRa is that the counters for sent (FCntUp) and received (FCntDown) messages are maintained by the Node and Network Server, and that these counters never repeat [6]. Base stations relay messages from end-nodes to network server using a back-haul wireless network with higher frequency (often 2.4GHz) or using wired connection (Ethernet, optics). Network server decodes the packets received from base station and performs security checks and adaptive data rate so it can generate the packets that should be sent back to end-devices [3].

Observed LoRaWAN network model deployed in Swebølle is consisted of a single base station which communicates with few hundreds of different end-devices; network topology is quite simple and shown on Fig. 2.

Data was collected during the period of 4 months and 14 days, during which approximately 689 thousands measurements were generated and captured. There is only one base station and, judging by the exploration of the data set, 251 end-devices in the network. Measurements were carried out on the base station side and there are more than few relevant labels:

- Time - basic datetime format to microsecond precision
- DevAddr - device address written as HEX string
- Freq - carrier signal radio frequency

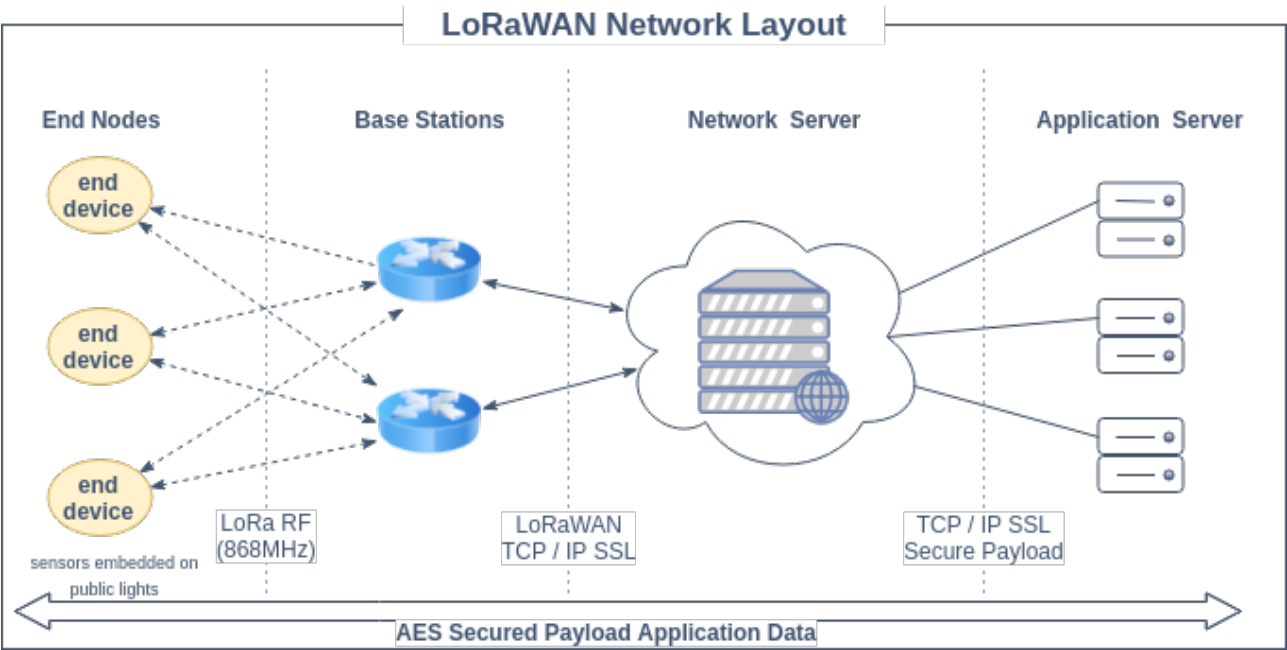


Figure 1: LoRaWAN Network Layout

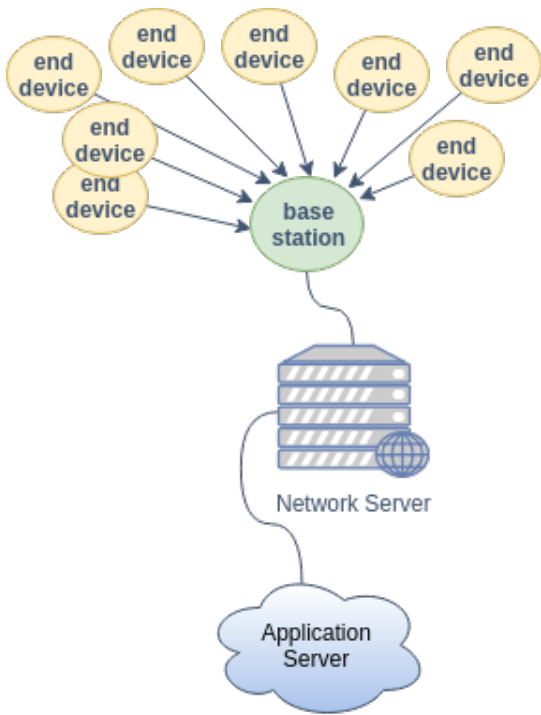


Figure 2: Overview of Svebølle LoRaWAN network

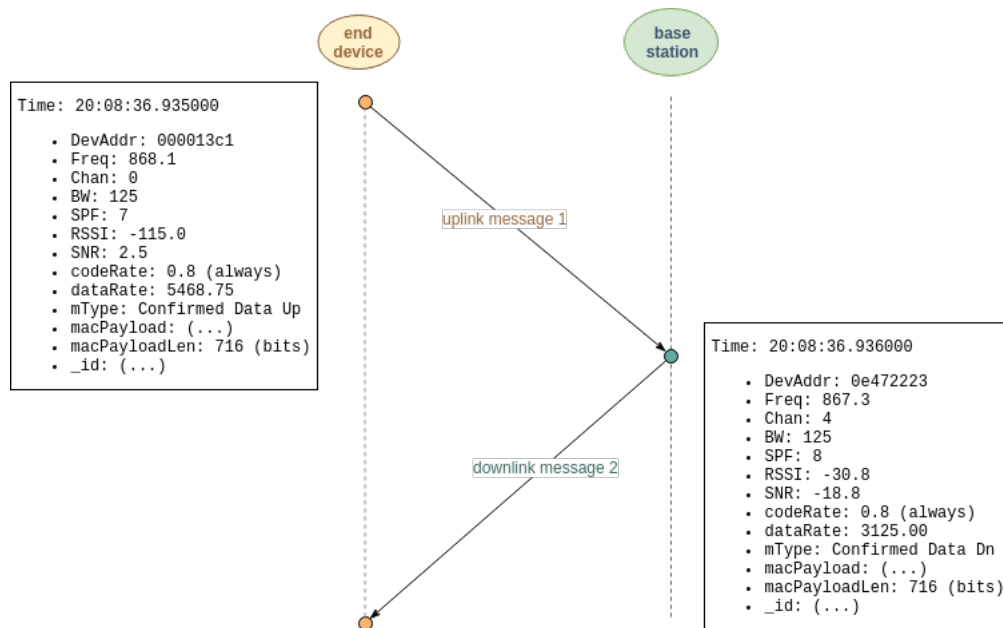


Figure 3: Communication between end-device and base station in LoRaWAN network in Svebølle

- Chan - channel number
- BW - bandwidth
- SPF - spreading factor
- RSSI - received signal strength indication
- SNR - Signal-to-Noise ratio
- CR - code rate
- DR - data rate
- crcStatus - cyclic redundancy check
- mType - type of MAC message
- macPayload - part of transmitted data that is the actual intended message
- id - packet identification

All of these indicators are described in details in [2].

Considering the data, simple communication model of this LoRaWAN network could be deduced and is shown in Fig. 3

### 3 Introducing the Idea of ANN

Measurements in data set were not structured as time-series data, only times when transmission of LoRa message actually happen in uplink direction are captured and stored. Time series data is a series of data points indexed in time order and taken at successive equally spaced points in time. A time series is generally described through parameters such as trend, seasonality, irregularity and cyclicallicity [1].

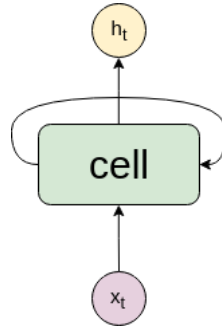
In order to create time series data, the only important label is whether the end-device has successfully transmitted the message to the gateway or not. For each time point (second-precision) there is activity flag assigned. If the device was active for observed time point, activity flag is 1 otherwise activity flag is 0. Since the measurements were carried out through almost 5 month period, newly created data set was huge and as such perfect candidate for applying deep learning methods to perform forecasting of future time points.

Artificial Neural Networks, or ANN for short, are modeling the intelligence of human brain: recognizing regularities and patterns of the given data, learning from past experience and providing inference on the output [1]. Why are ANNs such good predictors for time series type of data? There are couple of reasons:

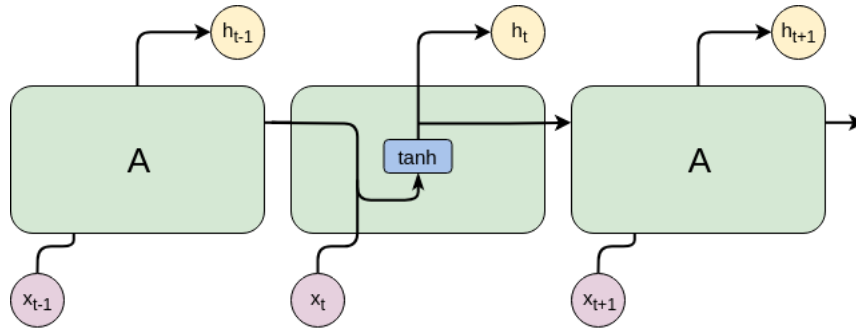
**Data-driven and self-adaptive** There is no need to make *a priori* assumption about statistical distribution of the data before feeding ANN with the data [1].

**Non-linearity** ANNs are perfect for modeling data with non-obvious patterns [8].

**Universal functional approximators** Any continuous function can be approximated to any accuracy [5].



**Figure 4:** RNN simple overview - feedback provides that the output (or a hidden layer) of the network, together with the new input at the current timestamp, is taken as input



**Figure 5:** RNN are formed in a chain-like nature what makes them applicable for predicting future events of sequence data

Even though vanilla ANNs are very powerful tool to create predictions based on historical events, they lack persistence. Recurrent Neural Networks (RNNs) are trying to solve this problem implementing loops and allowing information to persist, overview of RNN is shown in Fig. 4. RNN looks at the input  $x_t$  and outputs a value  $h_t$ , a loop allows information to be passed from one step of the network to the next. Unpacked RNNs have the form of a chain of repeating nodes defined by very simple structure, Fig. 5 [7].

RNNs are using gradient descent (first-order iterative optimization algorithm, usually used for finding the minimum of a function) as a way to minimize the error caused by changing each weight in proportion the derivative of the error with respect to that weight. Problem with this approach is error gradient vanishing which is causing the RNN to become unable to learn to connect the information if the relevant data is divided by large gap. The problem of long-term dependencies is solved by applying Long Short-Term Memory network, LSTM for short, which are introduced by the Sepp Hochreiter and his team in 1997. in the [4]. They proposed a model that is capable of remembering relevant information for long period of time and avoiding the long-term dependency issues.

## 4 Proposed LSTM model

Just like the RNN, LSTM architecture is also formed as a chain structure. Difference is that every cell has four in-layers each performing specific operations on input data and interacting with others in a special way, general overview of LSTM network is shown on Fig. 6.

An LSTM cell is consisted of 5 components which allow it to model both long-term and short-term data:

- cell state
- hidden state
- input gate
- forget gate
- output gate

Cell state, presented with the upper horizontal line in Fig. 6, runs through the whole cell and is affected by some minor linear changes.

Gates are the mechanism that allows information to be passed in selective fashion from the LSTM to the cell state. They consist of a sigmoid layer, which outputs value between 0 and 1 describing value of each component, and a multiplication operation. There are three types of gates in LSTM network:

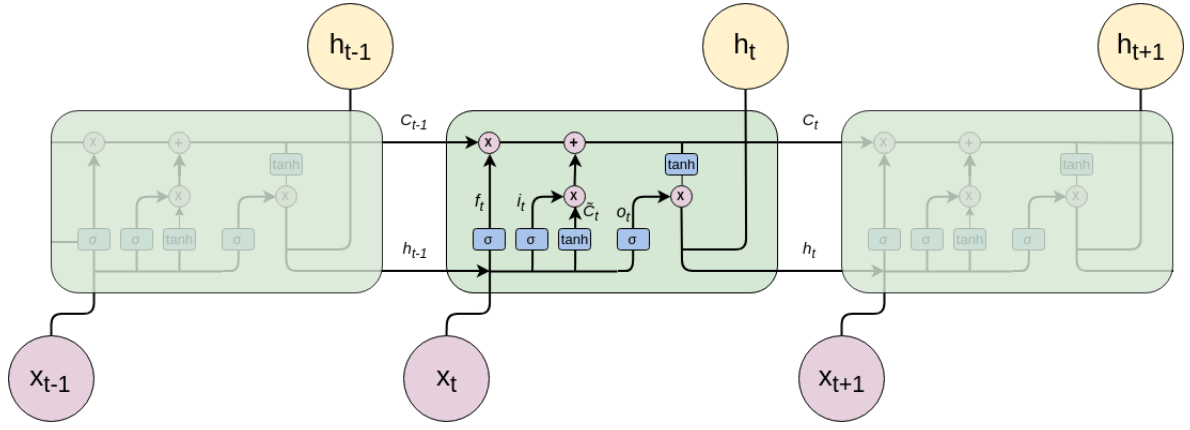


Figure 6: LSTM network preview

- Forget gate - determines which information to remove from the cell state

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

- The second gate - decides which new information should be written to the cell state. First, the sigmoid function decides which values to update and then the  $\tanh$  layer creates a vector of candidates to be added to the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$C_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

- The output gate - decides what is going to be output of the concrete cell. The output is based on the filtered version of the cell state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$

## References

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