Distributed Fault Detection in Sensor Networks using a Recurrent Neural Network

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Abstract

In long-term deployments of sensor networks, monitoring the quality of gathered data is a critical issue. Over the time of deployment, sensors are exposed to harsh conditions, causing some of them to fail or to deliver less accurate data. If such a degradation remains undetected, the usefulness of a sensor network can be greatly reduced. We present an approach that learns spatio-temporal correlations between different sensors, and makes use of the learned model to detect misbehaving sensors by using distributed computation and only local communication between nodes. We introduce SODESN, a distributed recurrent neural network architecture, and a learning method to train SODESN for fault detection in a distributed scenario. Our approach is evaluated using data from different types of sensors and is able to work well even with less-than-perfect link qualities and more than 50% of failed nodes.

Key words: Echo state networks, recurrent neural networks, anomaly detection, distributed computation, wireless sensor networks

1. Introduction

Wireless sensor networks (WSN) are increasingly being deployed over extended periods of time [3], in particular for environmental monitoring applications. To facilitate long term deployments in remote areas, nodes are typically powered by solar energy and rechargeable batteries. Consequently, much of the research has focussed on energy-aware design of hardware and software as well as on building models of energy supply and demand. The continuing progress in this area has lead to longer autonomy of WSN, but also revealed that deploying a sensor network over a long period of time requires automatic monitoring of the quality of gathered data and of the condition of solar panels, sensors and batteries. With information about the performance of these components, maintenance trips to remote monitoring sites can be better planned or possibly avoided, leading to a reduction of management costs. Some of the faults might be easier to detect than others: when some of the expected data is missing, fault seem obvious to recognize. Even in this simple case, an automatic notification relieves the administrator from continuously monitoring a database. When the network delivers data as expected, there might also be more subtle problems, like mis-calibration or build-up of dust on sensors and solar panels, leading to incorrect sensor readings or shorter duty-cycles and thus less data. To prevent this, sensor networks have to become more user-friendly: existing systems often require to manually detect and diagnose potential problems. First steps towards higher reliability and user-friendliness are automatically building a model of the normal system behavior and to use this model to detect anomalies. With the result of this process, it is possible to notify administrators who then can decide on appropriate actions. Consequently, the system can run unobserved with less danger of losing important data.

For this work, we are interested in detecting problems that manifest in changes of sensor readings for some of the nodes of an entire network as a result of a sensor fault. Typically, some of the sensors at different nodes are correlated over space or time. We present an approach that is able to learn spatio-temporal correlations and make use of them for detecting anomalies in a decentralized way, without using global communication during normal operation. Instead, sensor nodes participate in a large, distributed recurrent neural network, where each of the sensor nodes hosts only a few neural units and communicates only with its local neighbor sensor nodes. Our neural network approach is inspired by echo state networks (ESN) [5], a recurrent neural network approach which has shown to be successful in learning even complex time series. ESN have already been applied in anomaly detection in sensor networks [8], but only in a way that requires one instance of an ESN on each node. This results in an unnecessary consumption of memory resources and processing power. A straightforward distribution of an ESN over the entire sensor network is also not a solution, because it requires all of the nodes to communicate with each other. More often than not, this sort of communication is neither available nor desired in sensor networks.

To address the problem of detecting sensor faults in WSN in a distributed way, we introduce spatially organized distributed echo state networks (SODESN), an architecture that allows for distributing a single recurrent neural network over an entire sensor network even when the WSN imposes a local communication structure on its connectivity matrix (Sect.3). In Sect.4 we present a training method for SODESN and an approach to train SODESN for fault detection in WSN. SODESN learn a model of normal behavior of sensor nodes based on information from other sensors. The fault detection in turn monitors differences...
between the model and actual sensor readings in a distributed way. We demonstrate the capabilities of our approach with data from different temperature and radiation sensors (Sect. 5) and discuss our results in Sect. 6. In the following section, we start with a brief overview of related work, and give a short review of the ESN approach, the starting point for our work.

2. Background

Detecting and diagnosing faults is a challenge that has been addressed in many different areas for different purposes. Logic-based approaches, for instance, can be applied if a complete description of the desired behavior of the system is available (see e.g. [10]). In distributed systems, approaches like in [11] detect faults by using connections between processors to implement a voting based diagnosis system. WSN are distributed systems where different components, from batteries over sensors to processors, contribute to potentially many different types of faults. There may be problems with the energy supply, with the routing or other communication problems, resulting in missing data from single nodes, or causing the whole system to deliver no data at all. In long-term deployments, problems like degradation of hardware can result in inaccurate measurements, caused by dust and continued exposure of sensors to the environment.

Some of the existing work tackles the problem of automatically detecting node failures with centralized approaches (e.g. [11]), where relevant information is forwarded to a dedicated manager performing the fault detection. Methods to detect faults in a distributed way have been investigated, because global communication becomes prohibitive with increasing network sizes. The approach in [2] is an example of such a decentralized approach, where sensor faults are detected based on differences in the readings between neighbors. It uses only local communication between nodes, but assumes that all sensors measure the same variable. Likewise, [9] is able to detect faults with a distributed approach, but here, the assumptions are not as strong. Neighbor sensors are not required to measure the same variable, but are assumed to be correlated as long as they are working normally, and uncorrelated as soon as they are faulty. This fault detection method uses a graph-based approach to isolate faulty nodes in the network, where correlation between the time series over a time window is used to identify faults.

In our work, we are also interested in detecting sensor faults in a distributed way. Instead of explicitly basing our fault detection on spatial correlations between sensors, we want our system to detect the relevant spatio-temporal correlations on its own. If we are able to distribute a large recurrent neural network over the entire sensor network, each sensor node can estimate its own true values based on information from its neighbors in a training period. Because recurrent neural networks model dynamical systems (i.e. with a memory of past events), correlations can be both temporal as well as spatial. Using the estimated true values, and a threshold on deviation between estimated value and recent readings, each node can decide if it can be assumed to work correctly.

2.1. ESN technical background

Recurrent neural networks have only recently become more widely used in practice, because many approaches have been difficult to set up and to train for. An ESN is a specific type of recurrent neural network which is able to successfully predict complex time series [5]. At the same time, the complexity of training an ESN is much lower than with traditional recurrent neural networks. Like any other neural network, ESN consist of neural units and synaptic connections between these units. A neural network is recurrent if there is at least one cycle in these connections. Units are typically organized in different layers and possess a state (called “activation”). This activation is computed (using a typically non-linear “activation function”) based on inputs from incoming connections. Connections between units perform a linear transformation and can be either excitatory (positive connection weights) or inhibitory (in case of negative connection weights). Traditional approaches to training recurrent neural networks, like backpropagation through time [12], change all of the weights between different units. The lower training complexity of ESN is a result of using a fixed, randomly connected “reservoir” of neural units in the recurrent layer, and only changing connections to output units during training (see Fig. 1). Once the training is finished, connections are changed no longer. Both output and the next state of the network are determined by the current state of the network and the current input.

To make the approach work, however, connections cannot be entirely random, but need to fulfill the so-called echo state condition [4]. For an illustration of this condition [7], consider a time-discrete recursive function \( f_{x,\tau} = F(f_x, u_t) \) that is defined at least on a compact sub-area of the vector-space \( f_x \in \mathbb{R}^n \), with \( n \) the number of internal units. The \( f_x \) are to be interpreted as internal states and \( u_t \) is some external input sequence. Now, assume an infinite input sequence: \( u^{\infty} = u_0, u_1, \ldots \) and two random initial internal states of the system \( f_{x0} \) and \( f_{y0} \). To both initial states \( f_{x0} \) and \( f_{y0} \), the sequences \( f_x^{\infty} = f_{x0}, f_{x1}, \ldots \) and \( f_y^{\infty} = f_{y0}, f_{y1}, \ldots \) can be assigned.

\[
\begin{align*}
\bar{f}_{x,\tau} &= F(f_x, u_t) \quad \text{(1)} \\
\bar{f}_{y,\tau} &= F(f_y, u_t) \quad \text{(2)}
\end{align*}
\]
The system $F(\cdot)$ fulfills the echo state condition if it is independent from the set $t_{u_i}$ and if for any $(f_{x_0}, f_{y_0})$ and all real values $\epsilon > 0$, there exists a $\delta(\epsilon)$ for which $d(f_{x_0}, f_{t_t}) \leq \epsilon$ for all $t \geq \delta(\epsilon)$, where $d$ is a square Euclidean metric. Two rules are a helpful for creating a connectivity matrix $W$ with this condition:

C1 it is a necessary condition that the spectral radius of the biggest eigenvalue of $W$ is below one.

C2 it is a sufficient condition that the biggest singular value of $W$ is smaller than one

Using one ESN for each sensor node, or one ESN in a central location, would require a combination of high memory resources on each node, an explicit selection of correlated sensors or global communication. Instead, we describe a new approach where we distribute a recurrent neural network over an entire sensor network, fulfill the above mentioned echo state condition, and use only communication between neighbor nodes.

With sensor networks and recurrent neural networks, two different kinds of networks play a role in the following. In order to avoid confusion between the two in our description, we use node when we talk of sensor network nodes, whereas we use unit for the components of a neural network. In our notation we use bold capital letters for matrices, bold small letters for vectors or vector-sized functions, and italics for scalars.

3. Spatially organized distributed echo state networks

To distribute a recurrent neural network over a WSN, connections between units have to be restricted to the spatial neighborhood of sensor nodes in order to avoid unrestricted global communication. We also would like to retain the efficient learning of ESN. Therefore, we create neural units on each sensor node, and follow the original idea of ESN in that all connections between internal units are randomly initialized and fixed. Connecting units only to spatial neighbors on different devices leads to our idea of spatially organized distributed echo state networks (SODESN), where the underlying communication structure of the sensor network prohibits to use arbitrary synaptic connections between distributed units. More specifically, we allow hidden units to be connected to each other only if they are hosted on the same or on a neighbor network node. Moreover, neural inputs are only connected to units on the same sensor node in order to further reduce communication. Instead of globally connected output units, we use local output units on each sensor node. Output units get their input from the local part of the reservoir and from reservoirs on neighbor nodes.

ESN typically use a sparsely connected reservoir, so that different internal units develop different dynamics. Outputs are then calculated as a linear combination of the (non-linear) internal units. Using only local connections in SODESN almost automatically leads to a sparse connection matrix, albeit with a different distribution of connections. From a global perspective, regarding a SODESN as a single neural network, we also want to make sure the system fulfills the echo state condition mentioned in the previous section.

In a setup with $M$ sensor nodes, each node $m$ hosts $K_m$ input units, $N_m$ hidden units, and $L_m$ output units. The total number of neural units thus is

$$K = \sum_{m=1}^{M} K_m \text{ inputs}, \quad N = \sum_{m=1}^{M} N_m \text{ hidden units}, \quad L = \sum_{m=1}^{M} L_m \text{ output units}.$$  

Then, from a global perspective, the SODESN model consists of $K$ input units with an activation vector

$$u(n) = (u_{11}(n), ..., u_{K_1}(n), ..., u_{1M}(n), ..., u_{K_M}(n))^T,$$  

of $N$ hidden units with an activation vector

$$x(n) = (x_{11}(n), ..., x_{N_1}(n), ..., x_{1M}(n), ..., x_{N_M}(n))^T,$$  

and of $L$ output units with an activation vector

$$y(n) = (y_{11}(n), ..., y_{L_1}(n), ..., y_{1M}(n), ..., y_{L_M}(n))^T.$$

For the rest of this paper, we assume all neural units to be evenly distributed over all sensor nodes, i.e. each node contains the same number of units.

For theoretical considerations, it is convenient to represent synaptic connections weights between units in several global matrices, which have to be distributed in a practical implementation. Connections between hidden units are represented in a $N \times N$ matrix $W = (w_{ij})$, connections from input units to hidden units in a $N \times K$ matrix $w^{in} = (w^{in}_{ij})$, and connections from input and hidden units to output units in a $L \times (K + N)$ matrix $w^{out} = (w^{out}_{ij})$.

The activation of internal units is computed as

$$x(n + 1) = f(W^{in}u(n + 1) + Wx(n)),$$  

where $u(n + 1)$ represents the readings from all sensors, and $f$ the vector of activation functions $f$ of all internal units. We use $f = tanh$ as activation function in each internal unit, and linear input- and output units ($f = 1$). In some cases, ESN use connections projecting back from outputs into the reservoir. This is also possible in SODESN and requires an additional matrix $W^{back}$. Consequently, the activation of internal units $x(n + 1)$ is then computed as $f(W^{in}u(n + 1) + Wx(n) + W^{back}y(n))$. For our application, we do not make use of these connections.

3.1. Proxy units

In a practical implementation, activation vectors are distributed over multiple sensor nodes. Moreover, there are connections between units on different sensor nodes, which require to have a specified physical location. We store incoming connections from units hosted on neighbor sensor nodes on the local node. Units with outgoing connections to units on other devices just forward their activations with no changes to the neighbor device. Additional proxy units on the neighbor act as a place holder for remote units and take activations from connected units. From proxy units, there are only local connections.
to the reservoir or to output units. Proxy units also eliminate the need for all sensor nodes being synchronized as long as they all use the same interval to process data (e.g. once every minute or every 15 minutes). After new activations have been computed, their values are forwarded to connected proxy units where they can be used by the neighbor device. Once their values have been used, proxy units are reset to 0. This is to avoid using old values in case of a link failure between two network nodes. In our experiments described in Sect. 5, we used link qualities of from 10% to 100%.

3.2. Initializing an untrained SODESN

To set up the untrained SODESN, we construct the desired number of units on each sensor node. We create local internal connection matrices \( W_j \) with a specified density, and scale each of them so that the spectral radius is smaller than one. In addition, we create sparse random connections between internal units on neighbor devices, represented by connection from proxy units for incoming connections, and references to sensor nodes and respective proxy units for outgoing connections. Local input connection matrices \( W^\text{in}_j \) with random weights fully connect input units to all local internal units on the node (with one input unit for each local sensor). For output units, we create local random matrices \( W^\text{out}_j \) to provide them with input from input units, proxy units and internal units.

The local internal connection matrices are scaled by their largest eigenvalue so that each spectral radius is at most one. For the entire connection matrix composed of all local matrices, this procedure does not in general lead to a spectral radius of smaller than one yet, but it leads to similar conditions for the internal units on each sensor node. After all local matrices are created in this way, the resulting global connection matrix is scaled to meet the echo state condition.

Algorithm 1: Initialization: on each node \( j \) ...

1. Generate \( K_j \) input units, \( N_j \) internal units, and \( L_j \) output units
2. Generate \( M_j = \sum_i N_i \) proxy units for all neighbor sensor nodes \( i \) as placeholders for the internal units on neighbor nodes
3. For each neighbor sensor node \( i \), create \( N_j \) pointers to proxy units on node \( i \)
4. Generate a sparse, random matrix \( W_j \) for connections between local internal units
5. Find \( \lambda_j \) as the largest eigenvalue of \( W_j \)
6. Scale \( W_j \) by \( 1 / \max(\lambda_j, 1) \)
7. Choose \( x \in \{0, ..., 1\} \), a connection density between neighbor units
8. Generate random connections from \( x \times M_j \) of the local proxy units to local internal units
9. Generate and initialize an all zero \( L_j \times (M_j + N_j + K_j) \) matrix for connections to local output units from all other local units.

4. A training algorithm for SODESN

After initial setup, SODESN needs to be trained. We describe an approach to offline training a SODESN in a supervised fashion, i.e. we need time series of both input and output units as training data. Once the training is finished, no further adaptation is made. For our application to diagnose problems in sensor readings, we train output units to predict readings of a sensor in a neighbor node. In this case, the training data can be derived from any input time series of “normal” sensor readings.
4.1. Offline training SODESN

For a first description of the training algorithm, we regard SODESN as one recurrent neural network with specific connectivity – from there, a distribution of the algorithm over all sensor nodes is straightforward. Unfortunately, the standard training approach for ESN (see [4] for a detailed description) cannot be applied, because it assumes that output units can be connected to any of the input or the hidden units. In SODESN, we want to connect output units only to local input, internal or proxy units.

Training is executed in two steps, in a similar way to training ESN: as a first step, we sample a matrix \( \mathbf{M} \) of internal network states, and a matrix \( \mathbf{T} \) of output activations. Samples are taken while feeding a training data time series into input units (when using connections projecting back from output units into the reservoir, a teacher time series has also to be fed to output units). For each time step of the training data, we collect a vector of internal activations and a vector of output activations from our SODESN. The sampled vectors are stored in new rows of \( \mathbf{M} \) and \( \mathbf{T} \). With \( N \) the total number of hidden units, \( L \) the number of output units, and \( S \) the number of training steps, the final sizes of \( \mathbf{M} \) and \( \mathbf{T} \) are \( S \times N \) and \( S \times L \), respectively. The first samples of a training are typically discarded in order to wash out the initial network state.

As a second step, we compute the output weights \( \mathbf{W}_{\text{out}} \) to let the training time series \( \mathbf{d}(n) \) for each output unit \( j \) approximate a linear combination of the internal activations \( \mathbf{x}(n) \). “Approximate” means to minimize the mean squared error on the training signal, which, in the case of ESN, can be achieved by multiplying the pseudoinverse of \( \mathbf{M} \) with \( \mathbf{T} \): \( \mathbf{W}_{\text{out}} = \mathbf{M}^{-1} \mathbf{T} \). In SODESN, however, this operation is not possible, because it will create connections from all internal units to all the output units. A solution to the problem is to adapt the output weights \( \mathbf{x} \) the training time series \( \mathbf{d}(n) \) as a new row to \( \mathbf{M} \)

An additional advantage of this operation, at least in theory, is that it can be performed on each sensor node in parallel. In many practical cases, however, the amount of desired training data and the complexity of the operation will exceed the available memory and limited processing power of small sensor nodes. This is not a severe restriction, though, because the training needs to be done only once and can be executed on a remote machine. The result of the training, a set of output weights, has then to be sent back to all nodes and installed in the local connection matrices.

4.2. Training SODESN to detect sensor faults

With the supervised training approach described above, we need to provide input as well as output signals for each sensor node. In our application to detect sensor faults, we expect the input signal and output signal for a sensor to be the same when the sensor works normally. To gather training data, the sensor network has to be deployed and collect sensor readings for a period of time. During this period, we assume there are no sensor faults, so that the training output for each sensor is exactly the same as the input time series.

Using only normal data for training results in the learning to pick up this correlation. The output weights will be adjusted.

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Algorithm 2: Offline training SODESN

```plaintext
Input: \( u(n), d(n), n = 0...T, T_0 < T \)
1 Initialize the network state \( x(0) = 0 \)
   // Sample network state for training series
2 Initialize \( M = 0, T = 0 \)
3 for \( n = 0...T \) do
4   \( x(n+1) = f(W_{\text{in}}u(n+1) + Wx(n)) \)
   // Discard initial states
5 if \( n >= T_0 \) then
6   Add \( x \) as a new row to \( M \)
7   Add \( \tanh^{-1} d(n) \) as a new row to \( T \)
8 end
9 // Compute sample matrices for each node
10 foreach sensor node \( j \) do
11   Initialize \( M_j = 0, T_j = 0 \)
12   // Compute all output weights for node \( j \)
13   if \( x' \) are the activations of an internal unit on the same or on a neighbor node then
14     Add \( x' \) as a new column to \( M_j \)
15   end
16   if \( y' \) are the activations of an output unit on the same or on a neighbor node then
17     Add \( y' \) as a new column to \( T_j \)
18   end
19 \( W_j = M_j^{-1} T_j \)
20 end
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Figure 3: Reservoir connectivity of a standard ESN (left) with 400 internal units and a SODESN (right), with 400 internal units distributed over a 5 × 8 grid of sensor nodes.
so that input and output always match closely. When a sensor is faulty and delivers unexpected values to its input unit, the respective output will be similar to the input rather than an estimate of the true value. In such a case, we cannot distinguish between normal or faulty sensors, so that our prediction is useless.

To fix the approach so that the prediction of the true value of one sensor is independent on its actual value, a possible solution is to not connect this sensor to the neural network during both training and exploitation. The prediction is then solely based on inputs from other sensors. This is, however, only possible if we are interested in monitoring just very few sensors in the network. To monitor all of the sensors, this would require to disconnect all of the sensors from the neural network. With no remaining inputs, we cannot make any predictions, so that this approach is not an option.

A more promising attempt is therefore to make only the training of one output unit independent of the respective input unit. This can be achieved by training one output unit at a time, and disconnecting the input unit we are trying to predict during the training. However, this approach leads to a further problem: the prediction will be based on the assumption that there is no input from the sensor in question. During normal operation the input signal of the sensor will be added to some of the internal units from the sensor in question. During normal operation the input signal of the sensor will be added to some of the internal units from the sensor in question. During normal operation the input signal of the sensor will be added to some of the internal units from the sensor in question. During normal operation the input signal of the sensor will be added to some of the internal units from the sensor in question.

Instead of just disconnecting individual input units during training of their respective output units, we make sure there is an actual signal from all of the inputs. For the input of the sensor we are currently training, the signal should be uncorrelated to the true sensor value. This can be achieved by for example replacing the input by a white noise signal. The correct signal is used as teacher output, and the goal of the training is to learn the correlation between the true local sensor value and the value of neighbor sensors.

As mentioned above, the training aims to minimize the mean square error on the training signal. In all our experiments, we tested the capability of the SODESN to generalize for new data by computing the normalized root mean square error (NRMSE) of the predictions on an independent test set. The NRMSE of $n$ predictions $p$ of the SODESN against the test data $t$ is defined by

$$\text{NRMSE} = \sqrt{\frac{\sum_{i=1}^{n} (t(i) - p(i))^2}{n \cdot \text{var}(t)}}.$$  

where $\text{var}(t)$ is the variance of the test data.

### 4.3. Distributed fault detection

Using SODESN for fault detection involves making predictions on each sensor node. It requires also to set a threshold for sensor readings to be considered abnormal. Possible methods for defining thresholds can be based on measuring deviations from the predicted value of a sensor (for example a deviation exceeding the maximum deviation of predictions on the test set), or on the NRMSE between prediction of the sensor value and its actual reading for a specified time window.

In the previous section, we set up the training so that predictions of a sensor are independent of its current value. By using random noise as local input during training, we base the fault detection of each sensor on input from the rest of the network. If sensors fail only rarely, only a few of them will feed faulty values into the SODESN at the same time. If there is a faulty sensor, it will continue to feed incorrect readings into the network until the problem is fixed. This will affect fault detection in the remaining sensors, even more so if more than one sensor is faulty at the same time.

In systems with a high likelihood of simultaneous sensor failures, it might therefore be a good idea to prevent faulty sensors from feeding their readings into the SODESN. For the same reasons we used random noise as input during training in the previous section (as opposed to no input), we expect that simply disconnecting faulty sensors does not improve the predictions:
after all, output units in other nodes used a fraction of their input for training. In order to decrease their effect on the system, we do flag and disconnect faulty sensors from the SODESN. Instead of using no input from faulty sensors at all, we replace their input with the predictions of their readings as computed by the SODESN. We expect this helping to maintain a high prediction quality for the remaining sensors with a larger number of faults in the system.

5. Experiments and results

We evaluated our approach in simulations where we used data from a local weather station with several sensors measuring temperatures, radiation, infrared, etc. (the automatic weather station of the Department of Physical Geography of Macquarie University[6]). The simulated setup consisted of 8 sensor nodes arranged in a 2 by 4 grid where each node has one of the sensors and can communicate with its nearest neighbors (see Fig. 4(b)). The sensors we used measured the air temperature, soil temperatures at 1cm, 5cm, 10cm, 20cm, and 50cm respectively, radiation, and infrared. The data we used was taken in 15 minute intervals. Figure 4(a) shows data of our sensors for one week. In the graph it is visible that the different time series are at least weakly correlated to each other. In a setup with all sensors measuring the same variable at slightly different locations, correlations would be expected to be even stronger.

5.1. Experimental setup

Experiment 1 — amount of training data. A number of parameters play a role in training and using SODESN, such as the amount of training data, the number of units on each node, connectivity between units, link qualities between nodes, etc. In a first experiment, we used 15 internal units on each node with totally approximately 10% connectivity between nodes. We used a spectral radius of 0.66 for the connectivity matrix, a link quality of 90% during both training and testing, and an increasing amount of training data to obtain learning curves using an incremental 10-fold cross validation. The training data varied from 300 data points, corresponding to slightly more than 3 days worth of data, up to 30.000 data points, i.e. data from a period of 10 month. The test data set had a size of 16.665 data points in all cases. For each individual experiment, a new SODESN was generated.

Experiment 2 — reservoir size. To evaluate if and how much an increasing number of internal units contributes to higher prediction quality, we varied the number of internal units per sensor node from 3 to 39 units, resulting in SODESN with 24 up to 312 internal units. We used a training data size of 30.000 points for training and 16.665 data points for testing in a 10-fold cross validation. The basic procedure and all other parameters remained unchanged from the first experiment.

Experiment 3 — ESN vs. SODESN. To compare SODESN against a baseline, we simulated a fault detection with global communication using one (centralized) ESN for each sensor in the network. The ESN we used had 120 internal units each, equivalent to a SODESN with 15 units on each of our 8 nodes, and simulated link qualities from 10% to 100% during both training and testing. In the centralized setting, these link qualities represent the quality of the link from sensor to central node (independent of the number of hops).

In contrast to using SODESN, in a setup with one ESN for each sensor it is possible to use input data from only 7 sensors, predicting an 8th sensor of our sensor network.

Experiment 4 — robustness. Sensors in our first experiments deliver time series from different (yet correlated) phenomena, such as temperatures at different depths and radiation. To test SODESN with closer correlated inputs, we computed different time series based on the air temperature data by randomly shifting the original series up to ±30 minutes in time and adding uniform random noise of up to ±10%. (a) A series of tests to determine the prediction quality was run using 8 sensors in a 2×4 grid. (b) Then, we extended the size of the sensor network to 100 nodes, arranged in a 10×10 grid. Using these 100 nodes,
we simulated multiple sensor faults to test the effect on the prediction quality for other sensors. To this end, we randomly selected an increasing number of sensors to fail. Instead of the true value, faulty sensors constantly returned zero and fed this value into the SODESN. (c) Finally, we tested the effect of multiple sensor faults, where faulty sensors were stopped feeding their values into the neural network. As discussed above, the predictions of their true values as computed by the SODESN were used instead.

5.2. Results

Experiment 1. Figure 5(a) gives an impression of the NRMSE we obtained dependent on the amount of training data used. Results are shown for two of the sensors, and an overall average NRMSE for all 8 sensors. With an increasing amount of training data, prediction of our SODESN becomes more reliable, after an initial oscillating phase of 3000 data points. Table 1 shows NRMSE and some absolute maximum errors of predictions on test data. In particular for smaller training sets, absolute errors of the more dynamic time series, such as the air temperature, can become quite large for a short period even though prediction and true value are close over longer intervals. In this case, the NRMSE between predicted readings and actual values over a window of time might be a more reliable fault indicator. For less dynamic time series, such as the different soil temperatures, both NRMSE and absolute errors are small and may be used to indicate faults.

Figure 6 shows the result of a continuous prediction of the soil temperature at 5cm depth, while the sensor for this variable fed just random noise into the SODESN during the whole period (slightly more than 10 days). Similarly, the graph in Fig. 7
Table 1: NRMSE and some maximum absolute errors for varying training set sizes.

| training set size | air temp. NRMSE | soil temp. NRMSE (in °C) | 5cm | 20cm | radiat. |
|-------------------|----------------|--------------------------|-----|------|--------|
| 1500              | 6.76 (155.4)   | 0.14 (1.9)               | 2.64 | 3.40 |
| 15000             | 1.11 (26.6)    | 0.04 (1.0)               | 0.46 | 0.97 |
| 30000             | 0.56 (14.2)    | 0.04 (0.8)               | 0.19 | 0.79 |

is a plot of the prediction of the air temperature during the same period, again while replacing the true temperature measurement by random noise in the input to the SODESN.

**Experiment 2.** On average, an increasing number of internal units in the reservoir of our SODESN did not significantly improve the prediction quality. Figure 5(b) is a plot of the NRMSE for several reservoir sizes from 3 to 39 units per node. It can be seen from both the plot and from Table 2 that the prediction of air temperature seems to benefit from an increased number of units. In other cases, using more internal units does not lead to smaller errors, and in some, the error increased even slightly. The average NRMSE over all sensors for SODESN with 312 internal units is only slightly lower than the average NRMSE for SODESN with only 24 internal units.

**Experiment 3.** With a decreasing link quality, the accuracy of the centralized approach using one ESN for each predicted sensor decreases rapidly (see Table 3). In contrast to that, SODESN can maintain the same level of accuracy even with poor link qualities between local nodes. The graph in Fig. 5(c) shows that the ESN can achieve results close to SODESN only under almost perfect conditions. This seems surprising at first, but the difference in performance is a result of the different methods to pass on sensory information: In a centralized approach, loss of data has much bigger impact on the result because the missing information is not replicated elsewhere. In our distributed approach, data is broadcasted to several neighbors (2 or 3 neighbors in our 8 node experiment, up to 4 neighbors in our experiments with 100 nodes). Because in our experiments links between nodes fail independently, the information lost as a result of one link failing may still be present in the network and can be used for prediction.

**Experiment 4.** (a) Using 8 more closely correlated air temperature time series, we achieved an almost constant NRMSE of 0.2 for SODESN independent of the number of units (from 3 units/node up to 39 units/node), and a maximum absolute prediction difference of 6°C. The lowest NRMSE in experiment 2, where we used soil temperatures and radiation data to predict air temperature, was 0.47 (Table 2). The better performance in this scenario was expected. (b) Scaling the experiment up to 100 sensor nodes, the prediction has about the same quality as with only 8 sensors. Then, we begin to subsequently fail random sensors. A first qualitative (visual) inspection of the predicted time series vs. the true values shows acceptable performance up to more than 60% of failed sensors (see Fig. 8(b) for a sample prediction with 60 failed sensors). More quantitatively, from the graph in Fig. 8(a) we see that failing up to 16 of the sensors does not change the performance of the system at all. In our experiments, the average maximum absolute error for up to 16 failed nodes was below 11°C, and for up to 32 failed nodes, it remained below 16°C. For 60 failed nodes, the NRMSE has grown from 0.26 to about 1.0, with an maximum absolute error of around 19°C. (c) Feeding back the predictions of the true value instead of faulty sensor values results in a greatly improved prediction quality, so that the average error lower is almost constant for up to 50% of failed nodes. Even for more than 50% failed nodes, the error increases only slowly until around 90%.

### 6. Discussion

Our first experiment showed that the amount of training data used strongly influences the prediction quality. Further aspects seem to be the “correlatedness” of different sensors and the dynamics of the time series. Some of the “easier” sensors in our experiment could be successfully modeled after training on 1500 data points (≈ 15 days of training data), while for “harder”, less correlated sensors we needed at least 5000 points (≈ 52 days). Our offline learning approach requires to perform a computation on the whole training time series. In particular for larger data sets this will usually be done on a machine outside the network. The learning then computes sets of output weights for each sensor node. A way to deal with less correlated sensors may therefore be to successively improve the SODESN by re-training on increasingly larger data sets and exchanging the learned weights over time.

A second important factor is the amount of local communication introduced. From the description of our architecture in Sect. 5 it follows that neighbors exchange activations of their

Table 2: Some NRMSE and maximum absolute errors for different reservoir sizes from 3 to 39 units per node.

| units/nodes | air temp. | soil temp. NRMSE (in °C) | 5cm | 20cm | radiat. |
|-------------|-----------|--------------------------|-----|------|--------|
| 3           | 0.67 (18.2) | 0.07 (1.2) | 0.12 | 0.74 |
| 15          | 0.51 (15.4) | 0.04 (0.8) | 0.21 | 0.76 |
| 27          | 0.48 (12.0) | 0.06 (1.2) | 0.15 | 0.73 |
| 39          | 0.47 (11.6) | 0.09 (2.1) | 0.15 | 0.73 |

Table 3: NRMSE in a centralized approach using one ESN with 120 internal units compared to NRMSE of SODESN under varying WSN link qualities from 10 to 98%.

| link % | air temperature | 5cm | 20cm | soil temperature |
|-------|----------------|-----|------|-----------------|
| 10    | 1.41 | 0.51 | 1.72 | 0.04 | 1.83 | 0.19 |
| 50    | 0.89 | 0.54 | 1.00 | 0.04 | 1.04 | 0.23 |
| 90    | 0.63 | 0.51 | 0.50 | 0.04 | 0.56 | 0.22 |
| 98    | 0.55 | 0.49 | 0.27 | 0.04 | 0.32 | 0.17 |
local internal units – one value per unit and sample step. Results from our second experiment are therefore interesting, because we have seen that the number of internal units did not play a crucial role – we used only 3 units in some experiments. SODESN communication and sample rate of sensors does not have to run synchronously with each other. Alternatively it is also possible collect some data locally, and to run the SODESN on larger blocks of data, as long as all nodes run their part of the SODESN at the same rate (proxy units would have to be changed to queues in this case).

The amount of local computation required is similarly dependent on the number of units. In contrast to the offline training, exploitation requires only a few operations, for each internal unit a number of additions, multiplications, and computation of tanh(x).

7. Conclusions

In this paper, we presented SODESN, a novel distributed recurrent neural network architecture for creating models of dynamical systems. We introduced an offline learning approach for SODESN that is closely related to training ESN and inherits the low computational complexity of the original approach. We then presented an approach to train SODESN for fault detection in WSN, where predictions of sensor values are made based on information from neighbor nodes.

Our evaluations on real-world data show that our approach can be used to build models of dynamic time series and help to detect sensor faults. We have shown that the approach is robust to WSN link failures through its distributed computation and local communication. SODESN outperform a comparable, centralized approach assuming realistic link qualities. Using only local communication also contributes to SODESN scaling well with an increasing number of WSN nodes.

We have also shown that our approach is robust against multiple node failures. In our evaluation using the predictions of failed sensors as input, 50% of the sensors failed without affecting prediction quality, and the performance degraded gracefully up to slightly more than 80% failed nodes.

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