Using Artificial Neural Networks to Predict Climate in a Greenhouse

L. Miranda, B. Lara and U. Schmidt

Humboldt-Universität zu Berlin. Biosystems Engineering Division. Berlin, Germany.

AgrosNet-Doktorandentag - Berlin, March 11th. 2015

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- One-Step Predictions of Temperature and Relative Humidity
- Recursive OSP $\rightarrow$ Long-Term Predictions
- Discussion and problems found

Fig. 1. Tomato plants grown in the ZINEG[1] semi-closed greenhouse.

[1] www.zineg.net

One model was built using data from two greenhouses

Fig. 2. ZINEG Greenhouses. Left: Collector greenhouse. Right: Reference greenhouse.

ANN can learn to predict greenhouse climate

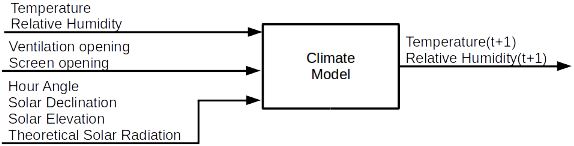

Fig. 3. Climate forcasting model: Inputs.

- Dataset: Two Greenhouses, 2010 through 2013, collected every 5 minutes and filtered (Savitzky-Golay)
- Data registers: 272 578 for training, 48 102 for test, 59 902 for validation (71.62%, 12.64%, 15.74%)
- ANN: 3-layered feedforward net (rprop). Nodes: $[8, 8, 2]$

ANN can learn to predict greenhouse climate

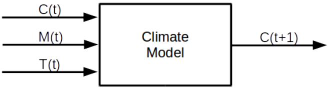

Fig. 4. Climate forcasting model: Inputs.

- Dataset: Two Greenhouses, 2010 through 2013, collected every 5 minutes and filtered (Savitzky-Golay)
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ANN can learn to predict greenhouse climate

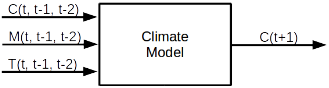

Fig. 5. Climate forcasting model: Inputs.

- Dataset: Two Greenhouses, 2010 through 2013, collected every 5 minutes and filtered (Savitzky-Golay)
- Data registers: 272 578 for training, 48 102 for test, 59 902 for validation (71.62%, 12.64%, 15.74%)
- ANN: 3-layered feedforward net (rprop). Nodes: $[8, 8, 2]$

Simulation for a case study: April 17th 2013

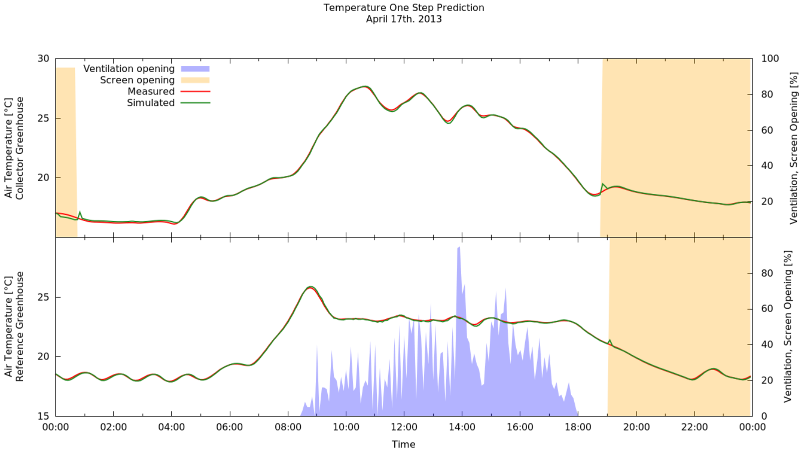

Fig. 6. One-Step Prediction of Temperature.

Peaks appear when the actuators change their state

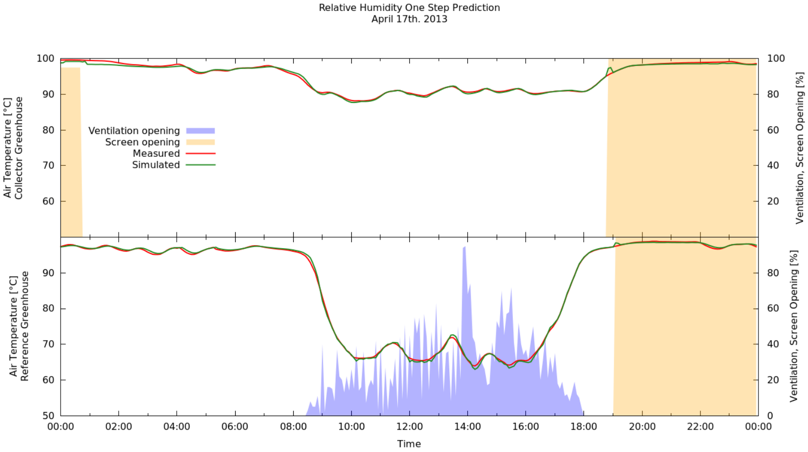

Fig. 7. One-Step Prediction of Relative Humidity.

Peaks appear when the actuators change their state

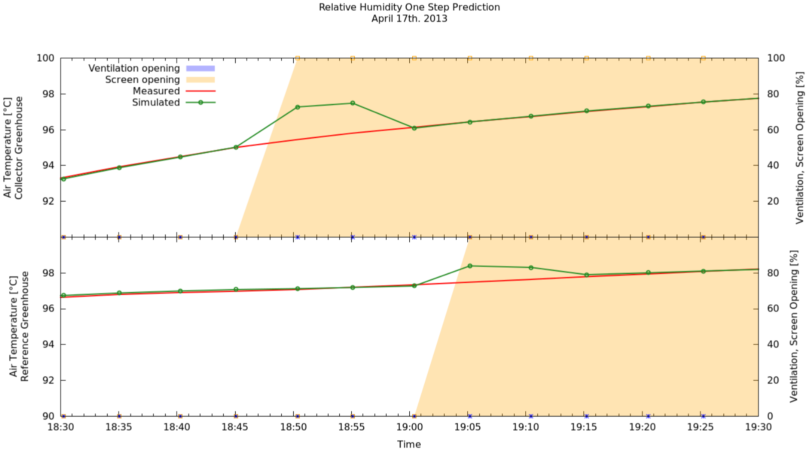

Fig. 8. One-Step Prediction of Relative Humidity (detail).

OSP can be used recursively to get Long-Term Predictions

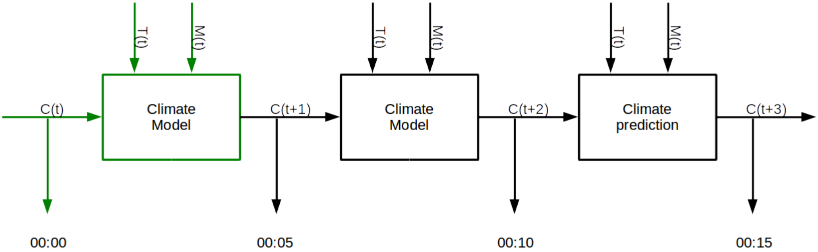

Fig. 9. Recursive architecture. Only the first simulation uses actual measurements.

LTP deviate from the measurements as error accumulates

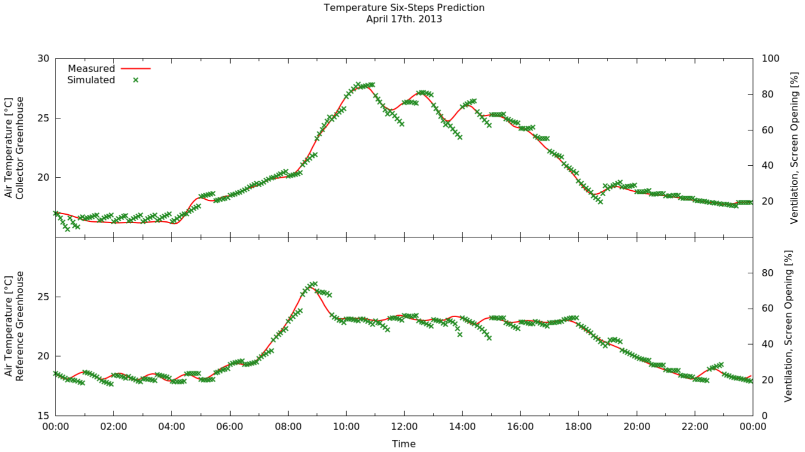

Fig. 10. Time series of a recursive simulation of Temperature.
Start value was reset every 30 minutes.

LTP deviate from the measurements as error accumulates

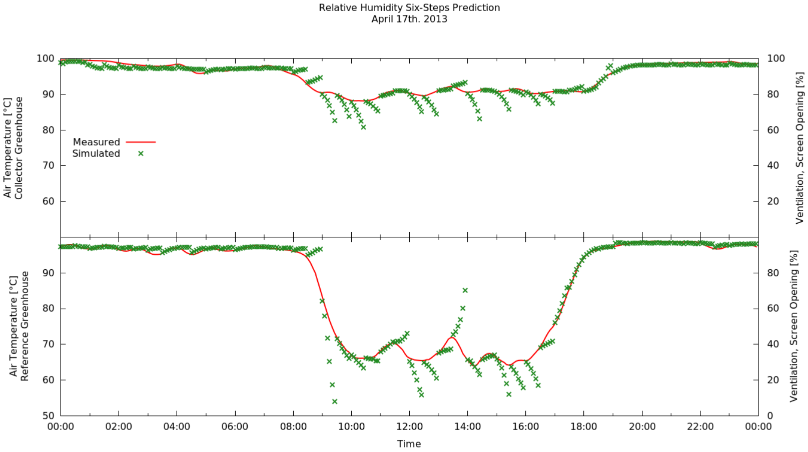

Fig. 11. Time series of a recursive simulation of Relative Humidity.
Start value was reset every 30 minutes.

The error increases but remains symmetrical

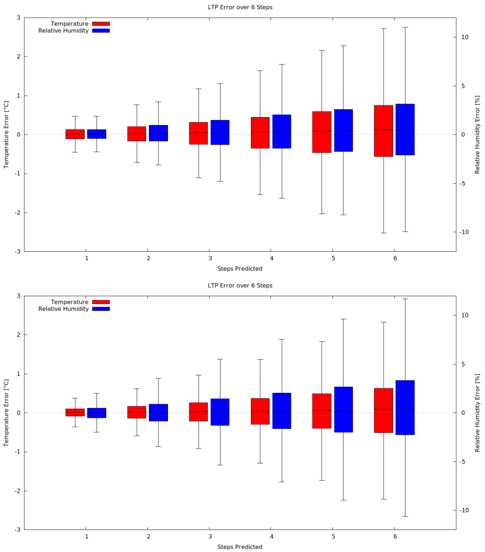

Fig. 12. LTP-Error over all the validation dataset. Top: Collector greenhouse. Bottom: Reference greenhouse

Discussion

- The main problems of this model are:
  - The sensibility to abrupt changes in the inputs (i.e. actuators)
  - The ANN architecture is very inflexible
- Strenghts of this approach:
  - It copes with complex relations using little information
  - Allows to mix data from different sources: towards generalisation
- LTP can give "a hint" on how the climate is expected to change. They will not substitute sensors, but can help to plan actions in advance.

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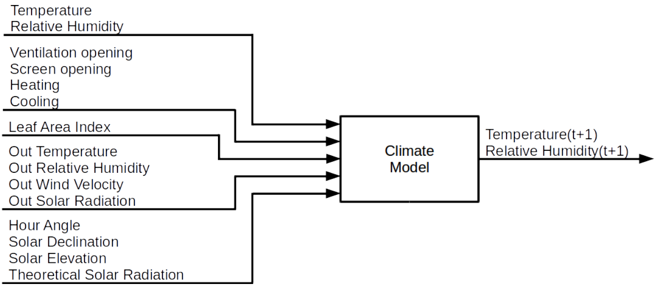
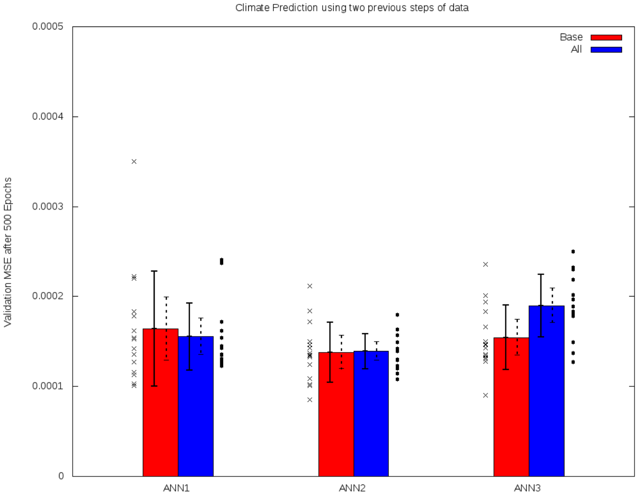
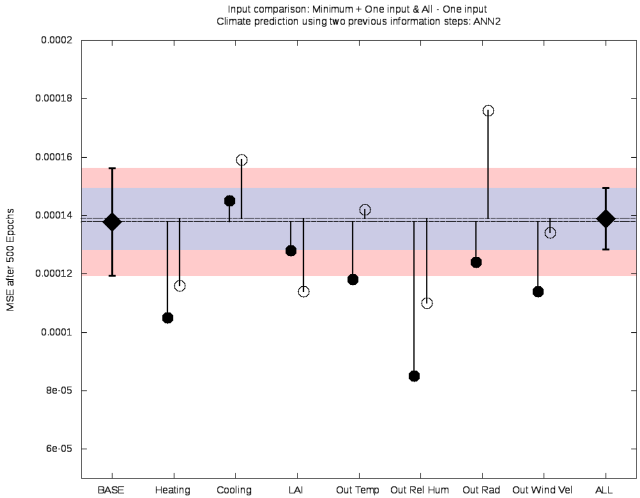
Complete set of inputs tested



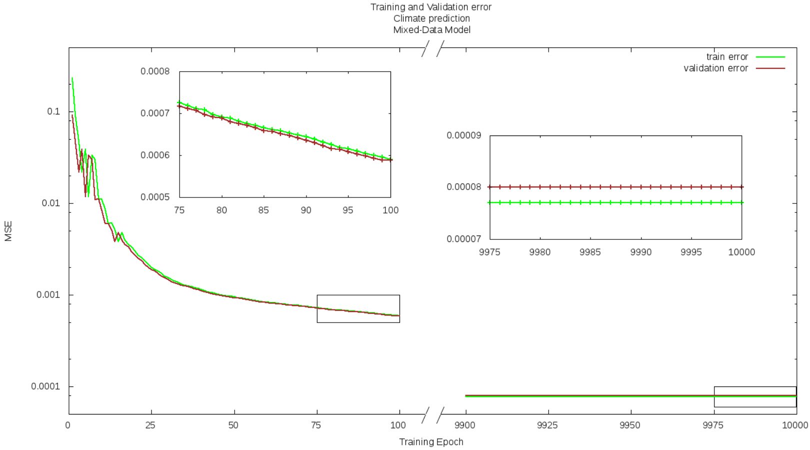
Input selection



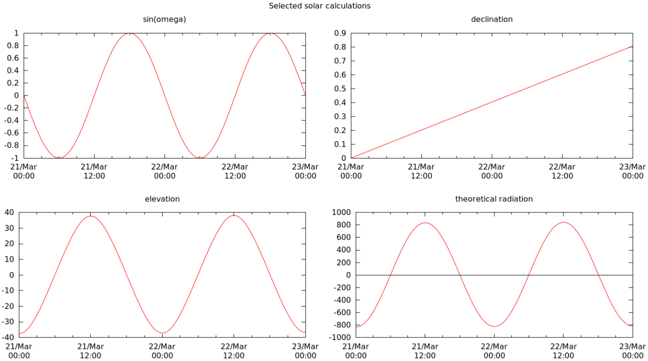
Input selection



Error during training



Solar coordinates for Berlin on March 21st.



Solar coordinates for Berlin over 2013