Using Artificial Neural Networks to Predict Climate in a Greenhouse

L. Miranda, B. Lara and U. Schmidt


AgrosNet-Doktorandentag - Berlin, March 11th. 2015
One-Step Predictions of Temperature and Relative Humidity

Recursive OSP → 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.
ANN can learn to predict greenhouse climate

Fig. 3. Climate forecasting 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

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%)

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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.
The main problems of this model are:
- The sensibility to abrupt changes in the inputs (i.e. actuators)
- The ANN architecture is very inflexible

Strengths 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

Temperature
Relative Humidity

Ventilation opening
Screen opening
Heating
Cooling

Leaf Area Index
Out Temperature
Out Relative Humidity
Out Wind Velocity
Out Solar Radiation

Hour Angle
Solar Declination
Solar Elevation
Theoretical Solar Radiation

Climate Model

Temperature(t+1)
Relative Humidity(t+1)
Input selection

Input comparison: Minimum + One input & All - One input
Climate prediction using two previous information steps: ANN2

Graph showing the Mean Squared Error (MSE) after 500 Epochs for different inputs. The inputs range from individual variables like Heating, Cooling, LAI, Out Temp, Out Rel Hum, Out Rad, Out Wind Vel, to the combination of all inputs (ALL). The data points indicate the variation in MSE for each input configuration.
Error during training

ANN for Climate Prediction in Greenhouse
Solar coordinates for Berlin on March 21st.
Solar coordinates for Berlin over 2013

Selected solar calculations

- sin(omega)
- declination
- elevation
- theoretical radiation

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ANN for Climate Prediction in Greenhouse