Predictive modelling for air temperature and humidity in a mushroom production process

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Abstract. Mushrooms (Agaricus bisporus) are produced in a growing room with a heating, ventilation and air conditioning (HVAC) system. Cultivation is cyclical and consists of several successive phases. Every production phase has different environmental requirements. Microclimate is a system with multiple input signals (e.g. control signals of the solenoid valves of HVAC system) and multiple output signals (compost temperature, air temperature, air relative humidity and carbon dioxide concentration inside the growing room). This paper presents model for prediction for air temperature and air relative humidity inside the mushroom growing room. To determine the dynamic behaviour of the microclimate, the parametric identification method was used. Several models with ARX structures were created. A fit index was chosen to evaluate the quality of models. Finally, optimal prediction horizon for each model was determined.

1. Introduction
Poland is the European leader in the white bottom mushroom production. Polish producers export the most mushrooms in the world. It is estimated that every third imported mushroom in the world comes from Poland [1, 2]. Concurrently, growth of the mushroom industry is noticeable. Over the years 2003-2013, mushroom harvest in Poland increased by nearly 62% (from 165 thousand tonnes in 2003 to 267 thousand tonnes in 2013) with a simultaneous increase in a cultivated area only by 25% (from 190 ha in 2003 to 239 ha in 2013) [3]. It suggests an increase in professional experience of technologists, as well as an improvement in technology itself. Not without significance is the involvement of technology increasing the level of automation. Expectations of producers in the field of production process automation are getting higher, the aim of which is to improve product quality and reduce energy consumption of the process. Optimisation of energy consumption requires development of prediction models for controlled processes [4]. In production of mushrooms, a control object is the microclimate of the growing room. The microclimate of the mushroom-growing plant is described by several physical quantities, including compost temperature, air temperature, relative air humidity and carbon dioxide concentration in the air [5-7].

Many research projects have been described in literature with regard to greenhouse microclimate modelling [8-11]. However, it is not possible to transfer these models directly to the field of mushroom
cultivation. The main reason is different plant physiology. The signals measured in the greenhouse and the mushroom growing chamber are different. Examples include a role of artificial light and protection against intense sunlight [12]. Due to the fact that mushrooms do not perform photosynthesis, these signals in the model can be omitted. Substantial differences can also be identified with regard to the common microclimatic factors [13]. An example is carbon dioxide concentration. Greenhouse plants require an additional CO$_2$ supply, while in mushroom cultivation, the concentration of CO$_2$ is excessive, and it has to be removed from production chamber. The mushroom microclimate model available in literature is usually based on laws of physics [7]. Models of this kind are very accurate, what is very important in simulation studies; however, their complexity makes them impractical for control systems. This is the reason why we decided to build the parametrical models.

Model development for prediction of temperature and relative humidity inside a growing room is the main goal of the paper. An additional goal is to determine the optimal prediction horizon. The model may be used as an element of a predictive control system of the microclimate in the growing room. Additionally, thanks to the prediction of air parameters it will be possible to more precisely schedule technological operations, e.g. mushroom harvest.

2. Materials and methods

The measurement data was obtained from HVAC system of the mushroom growing room. Figure 1 shows diagram of the HVAC system of the mushroom growing room with all measurement points marked. The signals were sampled every 10 minutes. The mushroom farm was located in the city of Nowosielec in Mazowieckie Voivodship, Poland. The parameters describing the mushroom farm are shown in Table 1.

Due to specificity of mushroom production, the cultivation process has been divided into three stages (Figure 2). Each of the stages have different microclimate requirements. Stages were determined in such a way, that they directly preceded the period of mushroom harvesting. The process of harvesting mushrooms is repeated three times during the production cycle, and harvesting periods are called flushes [14]. For each of the designated stages, a local model of the microclimate has been built. Describing the process using several local models is more accurate than using one global model. Determining a global model very often requires many simplifications [15].

![Diagram of HVAC system](image)

**Figure 1.** Diagram of HVAC system: 1 – heater; 2 – mixing chamber; 3 – cooler (used as dehumidifier also); 4 – fan; 5 – humidifier; $U_{dry}$ – dehumidifier control signal; $U_{hum}$ – humidifier control signal; $T_{sa}$ – supply air temperature; $T_{air}$ – air temperature inside growing room; $T_{com}$ – compost temperature; $RH$ – air relative humidity inside growing room.
Table 1. Cultivation characteristic parameters.

| Parameter                          | Value |
|------------------------------------|-------|
| Number of growing rooms            | 6     |
| Growing room length [m]            | 29    |
| Growing room width [m]             | 7     |
| Growing room height [m]            | 4     |
| Growing room volume [m$^3$]        | 812   |
| Number of shelves                  | 4     |
| Number of rows                     | 2     |
| Shelves width [m]                  | 1.34  |
| Shelves length [m]                 | 25.2  |
| Crop area [m$^2$]                  | 270   |
| Growing room volume to crop area ratio | 3.007 |

Figure 2. Changes of microclimate parameters during mushroom production process.
3. Model development

The model describing air temperature and air relative humidity inside mushroom growing room has a MIMO structure (many inputs and outputs). There are following input signals: supply air temperature $T_{sa}$, compost temperature $T_{com}$, dehumidifier control signal $U_{dry}$ and humidifier control $U_{hum}$. Air temperature $T_{air}$ and air relative humidity $RH$ signals are coupled, therefore they are also present among the input signals. Every MIMO model can be divided into two MISO models (multiple inputs, one output). We marked MISO models as $M_{Tair}$ and $M_{RH}$ (Figure 3).

![Figure 3. Model block diagram.](image)

ARX model structure was used for each of the models. ARX models are widely used to predict thermal behaviour of microclimate in different buildings, such as greenhouses and offices [9, 11, 16, 17]. The following equations describe models’ structure:

$$M_{Tair}: A(z) \cdot T_{air}(t) = B_1(z) \cdot T_{air}(t - n_{k1}) + B_2(z) \cdot T_{com}(t - n_{k2}) + B_3(z) \cdot RH(t - n_{k3}) + e(t)$$

$$M_{RH}: A(z) \cdot RH(t) = B_1(z) \cdot T_{air}(t - n_{k1}) + B_2(z) \cdot U_{dry}(t - n_{k2}) + B_3(z) \cdot U_{hum}(t - n_{k3}) + e(t)$$ (1)

where: $T_{sa}(t-n_{k1}), T_{com}(t-n_{k2}), RH(t-n_{k3})$ – input signals of $M_{Tair}$ model at time $t-n_{k1}, t-n_{k2}, t-n_{k3}$; $T_{air}(t)$ – output signal of $M_{Tair}$ model at time $t$; $T_{com}(t-n_{k1}), U_{dry}(t-n_{k2}), U_{hum}(t-n_{k3})$ – input signals of $M_{RH}$ model at time $t-n_{k1}, t-n_{k2}, t-n_{k3}$; $RH(t)$ – output signal of $M_{RH}$ model at time $t$; $e(t)$ – noise signal at time $t$; $z$ – discrete operator; $a_i$ – coefficients of polynomial $A$; $b_{1i}, b_{2i}, b_{3i}$ – coefficients of polynomials $B_1, B_2, B_3$; $n_i$ – degree of polynomial $A$; $n_{b1}, n_{b2}, n_{b3}$ – degrees of polynomials $B_1, B_2, B_3$; $n_{k1}, n_{k2}, n_{k3}$ – delays of input signals.

Values of delays $n_k$ were selected by means of the Model–Based Estimation method. In this method, the delay for which the value of the loss function $V$ is the lowest should be searched out [18, 19]. The loss function is equal to

$$V(\theta) = \frac{1}{N} \sum_{i=1}^{N} e^2(t)$$ (2)

where: $\theta$ – model parameters vector, $N$ – number of measurement data, $e$ – residuals.

Figure 4 presents selection of delays $n_k$ for the three stages of the $M_{Tair}$ model. Selection was limited to a range of 1-10 samples. Values of delays equal to $n_{k1} = [1 \ 3 \ 1]$ for stage I, $n_{k2} = [1 \ 2 \ 1]$ for stage II, and $n_{k3} = [1 \ 1 \ 1]$ for stage III have been selected.
Selection of delays for the $M_{Tair}$ model has been made accordingly to the same procedure. The delays were equal to $n_{k1} = [2 \; 1 \; 2]$ for stage I, $n_{k2} = [1 \; 1 \; 1]$ for stage II, and $n_{k3} = [3 \; 1 \; 1]$ for stage III.

The next stage of model development was to determine its order. The order of the ARX model is determined by the degree of polynomial $A$, i.e. $n_a$. Additionally, for each $n_a$ different combinations of models are possible due to the degrees of polynomials $B$, i.e. $n_{b1}$, $n_{b2}$, $n_{b3}$. A model within a range of $n_a, n_{b1}, n_{b2}, n_{b3} \in [1,...,10]$ was the most desired. An additional limitation $n_a \geq \max(n_{b1}, n_{b2}, n_{b3})$ was assumed to make the developed ARX model a proper transfer function. Thanks to this, the number of combinations of possible models was limited from 10 000 to 3 025. Goodness of fit was evaluated by means of fit index, which can be calculated as follows

$$
fit = \left(1 - \frac{\|y(t) - \hat{y}(t)\|_2}{\|y(t) - \bar{y}\|_2}\right) \cdot 100\% \quad (3)
$$

where: $y(t)$ – output signal (measured), $\hat{y}(t)$ – predicted output signal, $\bar{y}$ – mean of output (measured) signal.

For each stage, a learning and testing dataset was determined. The fit index was calculated for the one-step-ahead prediction mode for both learning and testing dataset. The model order has been selected by analysing the fitness of many models with different orders (Figure 3). The conducted analysis was...
based on the principle of parsimony, i.e. fewer complex models were preferred (the lowest possible $n_a$ value), with the best possible fit (the highest possible fit index value) [20]. High fit index value for a testing dataset was a priority. To improve readability of the figure, only the models with the best fit for each order $n_a$ were presented (Figure 5).

![Figure 5. Influence of the model order $n_a$ on the fit value for learning and testing dataset.](image)

Table 2 presents detailed information about the structure of selected models. It also includes values of the fit index calculated for the learning dataset (one-step-ahead prediction), as well as for the testing dataset ($k$-step-ahead prediction).

| Model structure | $fit$ index [%] |
|----------------|-----------------|
|                | learning dataset | testing dataset ($k$-step-ahead prediction) |
| $n_a n_b1 n_b2 n_k1 n_k2 n_k3$ | $k=1$ | $k=2$ | $k=3$ | $k=4$ | $k=5$ | $k=6$ |
| model $M_{Tair}$ | | | | | | |
| stage 1: [3 3 1 1 3 3] | 88,2 | 89,5 | 84,6 | 83,2 | 81,5 | 79,8 | 78,3 |
| stage 2: [2 3 2 2 3 2] | 83,1 | 83,8 | 78,9 | 76,1 | 73,5 | 70,0 | 67,2 |
| stage 3: [2 2 2 1 3 1] | 63,3 | 60,2 | 49,1 | 44,7 | 42,6 | 40,5 | 38,9 |
| model $M_{RH}$ | | | | | | |
| stage 1: [3 1 3 2 1 2] | 78,9 | 78,0 | 76,8 | 76,4 | 75,1 | 74,6 | 73,9 |
| stage 2: [2 1 2 1 1 1] | 76,2 | 76,0 | 69,4 | 64,8 | 60,4 | 56,5 | 53,3 |
| stage 3: [2 2 2 3 1 1] | 67,3 | 63,0 | 51,7 | 45,0 | 38,8 | 33,3 | 28,9 |
4. Conclusions

The aim of this paper, i.e. development of a model for prediction of air temperature and relative humidity has been achieved. The values of fit index for stages I and II are at a similar level and are much higher than for stage III. This suggests difficulties with the development of a model describing the microclimate in the final stage of production. The reason for these difficulties may be the changing over time force of crops impact on the microclimate in the growing room, e.g. decreasing biological potential or decreasing compost activity.

In most cases, fit index values for the $M_{RH}$ model were lower. This may be influenced by the selection of input signals of the model in the form of control signals of humidifier $U_{hum}$ and dehumidifier $U_{dry}$. These signals can be replaced by an additional measurement of humidity of the air supplied to the growing room. It could also improve the $M_{RH}$ model fit index. Unfortunately, this measurement is not currently carried out in production practice.

The model for stage I retained acceptable predictive properties for the whole tested predictive horizon (up to 6 samples, which for 10 minutes sampling time corresponds to an hour predictive signal value). For stage II, the prediction horizon should be shortened to 4 and 2 samples for $M_{Tair}$ and $M_{RH}$ respectively.

The results indicate that the developed model can be used in the design of automatic control systems in practice. Models can be a part of predictive control systems. The next stage of research will be the development of an optimiser. The task of the optimiser will be to calculate the value of control signal of the actuators in such a way as to ensure the optimum value of objective function. The objective function should be multi-criteria, so as to combine in itself to maximise the control quality and minimise the energy consumption of the process.

5. References

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