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# IMPROVING THE EFFICIENCY OF GREENHOUSE CONTROL BY USING A MARKOV DECISION-MAKING PROCESS MODEL

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***The object of this paper is the process of greenhouse control. The study solves the task of rational greenhouse control based on the Markov decision-making process taking into account two-level optimization. A random Markov decision-making process has been defined for the problem of greenhouse operation improvement.***

***A greenhouse control model was built, which makes it possible to determine rational microclimate parameters to grow agricultural crops. To validate the greenhouse control model, real data from an experiment on growing strawberries in a greenhouse complex were used.***

***Observations lasted from May 17 to June 8, 2025. Monitoring of microclimate parameters was carried out around the clock with an interval of 1 minute, which ensured high accuracy of the analysis. The experimental scenario included three irrigation circuits, a heating system, LED lighting, ventilation, and $CO_2$ monitoring.***

***The proposed approach to greenhouse management based on the Markov decision-making process model demonstrates high practical value, especially in the context of growing sensitive crops such as strawberries. The simulation shows that the implementation of two-level optimization in autonomous greenhouse control systems could provide an increase in yield by 10.15%. At the same time, due to the significant volume of the greenhouse and the high thermal inertia of the structures, the actual values of the microclimate parameters deviate from the rational ones by 10–15%, as a result of which the calculated yield increase for the model built is about 7%***

***Keywords: greenhouse microclimate, two-level optimization, stochastic Markov decision-making process, precision agriculture, control problem***

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## 1. Introduction

Managing a greenhouse for growing crops while ensuring resource conservation and taking into account the concept of climate-friendly agriculture is a complex and multidimensional task. Optimizing greenhouse operation obviously makes it possible to achieve higher yields and reduce costs but this task has a number of unresolved issues, which, taking into account agrotechnical features, significantly complicate the task of optimal greenhouse management. On the other hand, enabling optimal greenhouse management is part of ensuring the goals of climate-friendly practices in agriculture. These practices involve the implementation of measures to prevent the negative impact of agriculture on the environment, contribute to water conservation, energy security, and ensure resilience to climate change in general.

Over the past few decades, significant climate changes have occurred, which creates challenges for agro-industrial enterprises. This affects crop yields, food security, and increases the environmental load. The negative consequences of agriculture are accumulating, which disrupts the ecosystems of regions, leads to significant water resource consumption, soil depletion, etc.

The use of climate-oriented agricultural practices is currently one of the effective strategies for achieving high productivity and maintaining ecological balance in agricultural production. The strategic goal of any agricultural enterprise is to maintain yield stability in the long term, and the agricultural system should be organized in such a way as to minimize the harmful impact on the environment [1, 2]. Such systems take into account the climatic conditions of a particular region where crops are grown. Sustainable agriculture also involves the introduction of renewable energy sources, effective resource management, in particular, rational use of water [3, 4]. In [5] it is shown that the use of climate-oriented agricultural practices makes it possible to increase agricultural productivity, especially under conditions of climate change.

The application of climate-oriented practices in greenhouse agriculture involves the optimization of the microclimate in greenhouses, design if a drip irrigation system with humidity sensors, $CO_2$ control, etc. All this can be combined into a common platform for monitoring and forecasting yields, detecting plant diseases, optimizing irrigation and fertilizer application. In this case, the greenhouse should be equipped with an IoT network of sensors that acquire information about the conditions of growing crops and transmit it to the server for processing. It should be noted that to ensure effective greenhouse management, a combination of long-term and short-term goals should be taken into account. That is, there should be minute-by-minute regulation of temperature, humidity, lighting, and other indicators. In addition, long-term goals should be taken into account at the same time, i.e., selection of the best varieties of crops for cultivation, formation of a management reserve, as well as a reserve fund, etc. The task of combining operational goals with long-term planning is one of the problems of ensuring effective greenhouse management. At the same time, sufficient transparency of decision-making should be ensured, taking into account seasonal fluctuations, sudden anomalies, sensor failure, physical processes in the soil, and the biology of the crops being grown. Another issue is the consideration of multi-criteria conflicts, in particular the choice between increasing yield and saving resources (water, electricity, fertilizers, human resources, etc.). Another unsolved problem is the application of the approach of dynamic adaptation of parameters to different phases of plant growth, which can complicate the model and not give tangible results and, accordingly, should be studied separately. The lack of data is another issue that can significantly affect the choice of optimal parameters for growing agricultural plants and the adjustment of lighting, heating, irrigation, etc. Some of these problems can be solved by building models for a random Markov decision-making process to optimize the operation of greenhouse agriculture. The tasks to simultaneously take into account operational and strategic management goals could be solved using two-level optimization.

Therefore, it is a relevant task to construct and improve models of rational control in agriculture, as well as management models that contribute to achieving the goal of improving the efficiency of agricultural activities.

## 2. Literature review and problem statement

In [6], technological solutions that could help effectively conduct agriculture under the conditions of climate change were analyzed and proposed. It was established that such solutions are the use of precision agriculture, Internet of Things technologies, and artificial intelligence. However, in [6], methods for calculating the efficiency of agricultural management under such conditions were not considered, the features of optimization and adjustment of agricultural system parameters were not examined. These technical details are important for controlling the achievement of the goal of saving resources while maintaining crop yields. That is, technological, agronomic, mathematical solutions should be considered here in a complex in the form of a developed agricultural system. In particular, in [7], the implementation of such an agricultural system is described, which is arranged in such a way that it makes it possible to improve and protect the ecosystem from negative impacts on it. For the implementation of such agricultural systems, it is necessary to implement the concept of precision agriculture. In particular, in [8], the use of sensors, drones, IoT, GPS and GNSS technologies for agricultural management is described. The use of Internet of Things technologies in this case makes it possible to optimize the use of critical resources for environmental safety, in particular water, electricity, etc. However, work [8] does not describe how to plan the use of resources for precision agriculture, taking into account the indicators obtained from sensors. Works [9, 10] describe the use of the Internet of Things with cloud computing for the development of smart agricultural solutions; in particular, work [11] designed a smart irrigation system for remote control. Of course, these solutions are important technologically but there are no proven solutions for the automatic formation of greenhouse management strategies, which involves optimizing the use of resources by solving the corresponding mathematical problem, taking into account the necessary goals and constraints.

In general, the agricultural sector needs changes. This is due to both climate change and new technological capabilities that allow for increased yields and efficient use of resources. An important area in agriculture is the use of climate-oriented practices in greenhouse farming. This is explained by the technological capabilities of controlling the internal environment of greenhouses, which creates favorable conditions for plant growth. In particular, high-tech autonomous greenhouses are integrated with the Internet of Things through sensors and actuators, as well as cloud computing technologies. This makes it possible to remotely monitor plant growth in real time and provides precise control, which translates into stable yields at relatively low resource costs. Study [12] indicated that often the management of autonomous greenhouses is largely entrusted to experienced workers, which complicates the scaling of production. In addition, monitoring and operational decision-making regarding greenhouse management should occur continuously during the process of growing plants, and due to the significant amount of accumulated data, it seems difficult to do that automatically. In addition, the difficulty is taking into account operational and strategic goals when managing a greenhouse. In [13], it is indicated that the use of the Markov decision-making process and two-level optimization makes it possible to solve the problem of optimal greenhouse management. However, such a solution in [13] is not sufficiently verified taking into account the various features of growing agricultural crops in greenhouses, different varieties of crops, etc. It is known that greenhouse parameters should vary according to the stages of plant development and their needs for heat, lighting, temperature, etc. Therefore, it is advisable to consider the greenhouse management problem separately to adjust the parameters in accordance with the specified conditions.

In [14], the concept of optimal plant production in all seasons by adjusting greenhouse microclimate parameters, such as temperature, humidity, light intensity, and $CO_2$ concentration, is described. However, in [14], soil moisture monitoring is not taken into account, which is important when using climate-oriented agricultural practices. In particular, in a sharply continental climate, in the event of a sharp decrease in temperature, it is possible to achieve an optimal temperature inside the greenhouse using the system heating technology described in [15]. It should be noted that this microclimate management task is complex due to numerous interdependent variables [16, 17]. The greenhouse environment is a complex and nonlinear system, especially if the greenhouse parameters are to comply with the concept of implementing climate-oriented agricultural practices. In [18], technological tools for future decisions of farmers regarding the transformation of their farms are described by developing artificial intelligence algorithms for predicting crop yields. However, these solutions are not integrated into a system that can provide higher yields and contribute to environmental safety. In [19], a decision support system for the transfer of agricultural technologies is described, which helps evaluate and apply crop models for various purposes. A limitation of this system is that, due to climate change, the indicators that were used for growing crops in the past are no longer relevant.

Another hybrid solution to the problem is the combination of Internet of Things protocols and reinforced learning methodologies. In [20], it is shown that the integration of these technologies not only increases operational efficiency but also ensures the maintenance of set temperature regimes and optimizes energy consumption more effectively than traditional control methods. In [20], it is shown that such technological integration minimizes labor costs, but it is not highlighted how this technology could optimize the costs of other resources (water, electricity, fertilizer application, etc.).

Despite numerous studies, all the solutions considered do not make it possible to enable high accuracy of temperature, humidity control, and efficient resource consumption in real time. The selection of control parameters can be carried out on the basis of the Markov process model. However, there is no effective solution that makes it possible to adapt the actions of the controlling mechanisms depending on the state in which the system is. In addition, the possibilities for optimizing parameters taking into account the operational and strategic goals of greenhouse management have not been studied in detail. That is why unresolved issues do not make it possible to provide for a stable level of yield while saving resources, which meets the goals of climate-oriented agriculture. It is this gap that should be addressed by building an appropriate Markov process model for greenhouse management.

Our review of the literature [1–3, 5–8, 10–15, 18–20] reveals that, despite a significant number of studies aimed at automating the management of greenhouse agrisystems, the scientific discourse still lacks a comprehensive solution that would simultaneously take into account both operational and strategic goals of greenhouse microclimate management, enable optimization of resource consumption in real time, and undergo verification on different crops and in different climatic zones. Most existing approaches [6–8, 10–12, 18–20] focus mainly on individual technological aspects, in particular, automation of irrigation, ventilation, or $CO_2$ supply, and do not take into account the complex interaction among physical, biological, and economic factors. Other proposed solutions [5, 13–15] consider building management models but do not integrate multi-criteria constraints associated with the need to simultaneously enable high yields and rational use of resources. The identified gaps are due to both the technical limitations of sensor networks and IoT systems [8, 11], and the complexity of mathematical modeling of complex agricultural systems [14, 15], the limited amount of available empirical data for training models [5, 12], and the high cost of implementing integrated solutions on an industrial scale [10, 18].

Thus, the scientific and practical problem that needs to be solved is to build a verified model of the Markov decision-making process with two-level optimization, which would enable stable yields and minimize resource costs when growing crops sensitive to microclimate, including conditions of limited resource supply [6, 10, 18].

## 3. The aim and objectives of the study

The aim of our work is to define a model for a rational greenhouse control based on the Markov decision-making process, which takes into account the concept of climate-oriented agriculture. This will make it possible to increase the yield and profitability of agricultural enterprises.

To achieve the goal, the following tasks were set:

– to define a random Markov decision-making process for the task of improving greenhouse operation;

– to propose a model for the dynamics of temperature, humidity, and $CO_2$ concentration changes under the influence of external factors and control actions;

– to validate a model of the rational greenhouse control for the case of strawberry cultivation.

## 4. The study materials and methods

The object of our study is the processes for controlling a greenhouse. The hypothesis of the study assumes that the use of Markov process models for decision-making taking into account two-level optimization makes it possible to improve the efficiency of greenhouse management, in particular to ensure sustainability and resource savings.

Solving the greenhouse control problem, which simultaneously takes into account operational and strategic goals, is possible using Markov process decision-making models. Unlike conventional heuristic management methods, the proposed model will make it possible to improve greenhouse agriculture in terms of optimizing resource consumption under the condition of stable yield. This will potentially make it possible to increase the profitability of greenhouse agricultural enterprises. Therefore, to solve the problem, a Markov process model was used for decision-making regarding greenhouse management with two-level optimization of parameters to take into account operational and strategic management goals.

The simplification assumed that one greenhouse is considered, in which one homogeneous agricultural crop is grown. Another simplification is that a stable microclimate with a certain temperature, humidity, and other parameters is maintained in the greenhouse. It was assumed that the greenhouse system is isothermal during short-term control cycles. Heat exchange with the external environment in the greenhouse was modeled as a linear function of the temperature difference. The influence of transpiration, solar radiation, and other factors was assumed to be uniform throughout the greenhouse and can be approximated by sensor data. Differential equations were used to build the model for greenhouse control. To find rational values for the parameters of control actions, continuous differential equations were replaced with their difference representations. It was also assumed that the modeling was performed for conditions of stable functioning of the sensor network without taking into account equipment failures.

To validate the proposed model, data from a real experiment on growing strawberries in a greenhouse complex located in Chernivtsi oblast (Ukraine) were used. Observations continued in the second quarter of 2025. Monitoring of microclimate parameters was carried out around the clock with an interval of one minute, which ensured high accuracy of the analysis. A total of 30227 full-format observations were acquired. The dataset is available at [21]. The random Markov decision-making process was implemented programmatically using the Python programming language and built-in functions from the pymdptoolbox library [22]. To find a rational control strategy, the simulation modeling method was used, which provides an approximate solution to the problem in the absence of an analytical representation. The stabilization of the value of the objective function was used as a convergence criterion.

The Markov process model was implemented programmatically in the Python environment using the pandas, numpy libraries, and the specialized pymdptoolbox library. The pandas library was used to process tabular data. The numpy library was used for numerical operations. The pymdptoolbox library provides tools for solving problems based on Markov decision processes. The rational control strategy π was found by applying the value-based iteration and policy-based iteration algorithms, which make it possible to find an approximate solution in cases where the analytical approach is difficult or unavailable. The consistency of the $\pi$ strategy and the maximum change in the cost function between iterations, which did not exceed a predetermined threshold $\varepsilon$, were used as the convergence criterion. The input matrices of transition probabilities and reward functions were formed based on the simulation data, which were processed using pandas. Statistical calculations for sensitivity analysis and validation of the results were performed using numpy.

## 5. Improving the methods for controlling greenhouse agricultural enterprises

### 5. 1. Random Markov decision-making process for the task of improving greenhouse operation

Improving greenhouse operation involves automatic control over operating modes (ventilation, irrigation, lighting, $CO_2$ dosing). The goal is to maximize the total benefit or minimize the total costs throughout the growing season of agricultural plants. This task can be solved using a model of a random Markov decision-making process. However, the model must be adapted and clearly correspond to the characteristics of growing specific plants and the technological features of the greenhouse.

Formally, the Markov decision-making process is given by a tuple $(S, A, P, R, \alpha)$, where $S$ is the set of system states, $A$ is the set of available actions. $P(s_j|s_i, a)$ is the probability of transition to state $s_j$ if action $a \in A$ was performed in state $s_i$. $R(s_j, a, s_i)$ is the expected reward received when performing action $a \in A$ in state $s_i$ and transition to state $s_j$, $\alpha \in (0,1]$ is the discount factor that determines the importance of rewards that are remote in time. On the set of available actions $A$, we can determine the probability that action $a \in A$ will be performed in state $s_i$, which we shall denote by $\pi(a|s_i)$, which determines the rule of system functioning. Thus, a trajectory can be constructed for $t=\overline{1,N}$ that determines the transitions of the system from one state to another under the influence of the execution of actions $T=(s_1, a_1, r_1, s_2, a_2, r_2, \ldots, s_N, a_N, r_N)$, and for $\forall a \in A$, $\forall s \in S$, $a_t \sim \pi(a|s_t)$, $s_{t+1} \sim P(s|s_t, a_t)$, a $r_t = R(s_t, a_t, s_{t+1})$.

The problem is to find a strategy $\pi(a|s_i)$ that maximizes the sum of rewards discounted over time. That is, given that $\forall a \in A$, $\forall s \in S$, $a_t \sim \pi(a|s_t)$, $s_{t+1} \sim P(s|s_t, a_t)$, and $r_t = R(s_t, a_t, s_{t+1})$, it is necessary to determine the optimal rule $\pi^*(a|s)$ that

$$\pi^*(a|s) = \arg\max_{\pi} E_{\pi}\left[\sum_{t=1}^{N} \alpha^t R(s_t, a_t, s_{t+1})\right], \quad (1)$$

where $E_\pi$ is the mathematical expectation of random variables under the condition that the rule $\pi$ holds.

In this case, the vector of observation of parameters at time $t$, $s_t \in S$ is determined by the air temperature in the greenhouse, relative humidity, light intensity, $CO_2$ concentration. Actions $a \in A$ are determined by a set of control influences such as turning on or off artificial lighting, heater, ventilation level, irrigation volume, and $CO_2$ dose. The $P(s_{t+1}|s_t, a_t)$ transition probability reflects how physical processes affect actions and external disturbances, i.e., determines a model built on historical data. The yield function is formed in accordance with the characteristics of growing agricultural crops and technological characteristics of the greenhouse and must take into account yield growth, electricity, water, $CO_2$ costs, etc. The discount factor $\alpha \in (0, 1]$ is determined around $\alpha \approx 0.95$. The goal is to balance long-term and short-term benefits.

The goal is to find a rule that makes it possible to reduce the costs of growing agricultural plants in a greenhouse. This is fully consistent with the strategy for developing climate-oriented agricultural practices since saving resources while maintaining crop yields makes it possible to reduce costs and increase the profit of an agricultural enterprise. In addition, installing regulators for irrigation, lighting, etc. makes it possible to approach the process of growing plants in an ecological way, which has a global impact on the use of resources in a specific region of the country and the state as a whole.

It should be noted that, taking into account the specific features of growing agricultural plants in a greenhouse, numerous factors must be taken into account. However, the work of sensors is limited and for the experiment, only a part of the indicators that affect the process of growing plants, obtaining a harvest, and determining the amount of resource consumption can be collected and processed. It should also be noted that at different stages of growing plants, the optimal parameters of greenhouse indicators may differ.

That is why a two-level optimization was chosen to solve the problem. The first level concerns strategic and long-term parameters, system configuration, as well as overall budget.

The second level determines the operational control over the microclimate in the greenhouse through the formed strategies $\pi$, which are determined from a random Markov decision-making process within specific strategic boundaries. Then

$$y^*(x)=\arg\max_y E_{\pi_y}\left[\sum_{t=1}^{N}\alpha^t R_x\left(s_t,a_t,s_{t+1}\right)\right], \qquad (2)$$

where $y^*(x)$ are the optimal parameters of strategy $\pi$, then the objective function is as follows

$$F\left(x,y^*(x)\right)=E_{\pi_{y^*(x)}}\left[\sum_{t=1}^{N}\alpha^t R_{y^*(x)}\left(s_t,a_t,s_{t+1}\right)\right]-R_S\left(a_t\right), \qquad (3)$$

where the first term means long-term benefit, and the second one, $R_S$, – strategic costs. The components of strategic costs are determined taking into account the needs of operational management, for example, budget constraints, i.e.

$$\sum_{t=1}^{N}R_S\left(a_t\right)\le R_S^{\max}. \qquad (4)$$

The task is to maximize this objective function to obtain the maximum benefit under the existing constraints

$$\max_{x\in X}F\left(x,y^*(x)\right). \qquad (5)$$

Optimization of Markov decision-making processes involves determining the best action strategy for an agent in a stochastic environment. In each state, the agent chooses an action, receives a reward, and moves to the next state according to probabilistic rules. The goal is to maximize the total expected reward for a certain period. To find the optimal strategy, algorithms are used that are based on iteratively improving the estimates of the significance of states or actions. Such approaches are effective, in particular, when transition matrices and reward functions are known, but there is no analytical solution. There are standard implementations of the main algorithms for Markov decision-making processes in open libraries, in particular pymdptoolbox, which significantly simplifies practical application.

According to model (1) to (5), the following states were considered for the process of growing agricultural crops in a greenhouse, reflecting the dynamics of microclimate changes and plant response:

1. Rational microclimate. This condition means that all the main parameters (temperature, humidity, $CO_2$, light) are within acceptable limits; plant growth is stable.

2. Overheating. This means that the temperature inside the greenhouse exceeds the target values, which is accompanied by a decrease in humidity and the risk of overheating the plants.

3. Cold. This condition means that the temperature is below the rational range, which leads to a slowdown in growth and possible condensation.

4. Moisture deficiency. This condition means that the relative humidity of the air and/or soil is lower than normal, signs of water stress are observed.

5. Excess moisture. This condition means that the humidity exceeds the permissible limits, there is a risk of plant diseases and reduced gas exchange.

6. Excess $CO_2$ means that the concentration of carbon dioxide exceeds the safe level, which can inhibit photosynthesis.

7. Plant stress is a complex condition that occurs when the microclimate parameters go beyond rational values, and growth rates decrease.

8. Reduced yield is a consequence of prolonged exposure to adverse conditions, which leads to a decrease in overall productivity.

9. Emergency mode is a critical state of the system (for example, failure of ventilation or heating), which requires immediate resolution. Detailed characteristics of these states and their mutual transitions are given in Table 1.

To build a Markov greenhouse control model, several variants of transition matrices were formed. Among the dozen variants proposed by researchers, the one was selected in which the greenhouse functioning model most closely matched the data obtained from sensors in the greenhouse complex (the data are given in the acquired dataset [21]). Transition matrix $P(s'|s)$ gives the probabilities of transitions between certain states (Table 2) as a result of the influence of external factors and control actions of the system.

Table 1

The set of states $S$, their characteristics, control actions, and possible transitions

| Condition | Attribute (observation parameter) | Possible action ($A$) | Probable transition ($P$) |
|---|---|---|---|
| Rational microclimate | Temperature ($T_{air}$), humidity (RH), $CO_2$, and lighting within the norms; growth is stable | Support mode: minimal changes | → Overheating; → Cold; → Moisture deficiency; → Excess moisture |
| Overheating | Temperature ($T_{air}$) higher than rational; drop in relative humidity (RH); risk of stress | Increase ventilation, reduce lighting, additional watering | → Rational microclimate; → Plant stress |
| Cold | Temperature ($T_{air}$) lower than rational; possible condensation; growth retardation | Turn on/increase heating, reduce ventilation | → Rational microclimate; → Plant stress |
| Moisture deficiency | Relative humidity (RH) and/or soil moisture are normal; risk of wilting | Increase irrigation, adjust ventilation | → Rational microclimate; → Dry stress |
| Excess moisture | Relative humidity and/or soil moisture is higher than normal; condensation, risk of disease | Reduce irrigation, increase ventilation, heat for drying | → Rational microclimate; → Plant stress; → Reduced yield |
| Excess $CO_2$ | Concentration of $CO_2$ exceeds upper limit; risk of slowing down photosynthesis | Ventilation, reduction of supply $CO_2$ | → Rational microclimate; → Emergency mode |
| Plant stress | A set of deviations: temperature, relative humidity, $CO_2$ concentration, illumination outside the norm; stunted growth | Complex actions: combined regulation of irrigation, light, heat, $CO_2$ | → Rational microclimate; → Reduced yield |
| Decrease in productivity | Cumulative impact of stress; yields are lower than forecast | Strategic changes: correction of lighting plan, irrigation, varieties | → Resumption of growth; → Emergency mode |
| Emergency mode | The system fails: ventilation failure, critical deviation of parameters | Automatic/manual emergency intervention | → Rational microclimate (rare); or completing a loop |

Table 2

State transition matrix

| State/transition | 1. Rational microclimate | 2. Overheating | 3. Cold | 4. Moisture deficiency | 5. Moisture excess | 6. Excess $CO_2$ | 7. Plant stress | 8. Reduced yield | 9. Emergency mode |
|---|---|---|---|---|---|---|---|---|---|
| 1. Rational microclimate | 0.70 | 0.08 | 0.07 | 0.06 | 0.05 | 0.02 | 0.02 | 0.00 | 0.00 |
| 2. Overheating | 0.55 | 0.20 | 0.00 | 0.05 | 0.00 | 0.00 | 0.15 | 0.00 | 0.05 |
| 3. Cold | 0.55 | 0.00 | 0.20 | 0.00 | 0.10 | 0.00 | 0.10 | 0.00 | 0.05 |
| 4. Moisture deficiency | 0.60 | 0.00 | 0.00 | 0.20 | 0.00 | 0.00 | 0.15 | 0.05 | 0.00 |
| 5. Excess moisture | 0.55 | 0.00 | 0.00 | 0.00 | 0.20 | 0.00 | 0.15 | 0.07 | 0.03 |
| 6. Excess $CO_2$ | 0.70 | 0.00 | 0.00 | 0.00 | 0.00 | 0.15 | 0.05 | 0.00 | 0.10 |
| 7. Plant stress | 0.40 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.25 | 0.20 | 0.10 |
| 8. Yield reduction | 0.20 | 0.00 | 0.00 | 0.00 | 0.10 | 0.00 | 0.20 | 0.40 | 0.10 |
| 9. Emergency mode | 0.10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.20 | 0.00 | 0.70 |

The given set of states and the transition matrix can be directly applied to form a greenhouse control strategy within the Markov decision-making process model. The choice of control action in each state is based on the forecast of expected transitions to other states and the calculation of the total reward, which takes into account yield and resource costs. Thus, our approach allows for the implementation of both short-term system responses to microclimate deviations and long-term optimization of crop growing modes.

At the same time, it should be noted that the greenhouse is an inertial system where changes in microclimate conditions do not occur instantly. Heating or cooling of the air, stabilization of humidity, and the dynamics of plant growth require a certain time to reach a new equilibrium. This means that even with a correctly chosen action, the effect of its implementation manifests itself with a delay.

**5. 2. Model of dynamic changes in temperature, humidity, and $CO_2$ concentration under the influence of external factors and control actions**

For the effective cultivation of new agricultural crops under greenhouse conditions, it is necessary to enable dynamic control over basic microclimatic parameters: air temperature, humidity, lighting, $CO_2$ concentration, soil moisture, etc. These parameters change over time due to both external factors (change in weather, time of day) and internal processes (plant transpiration, heat exchange, system inertia). In this regard, the greenhouse control problem acquires a dynamic nature and is naturally formalized as an optimization problem in terms of the Markov decision-making process (1).

Within this paradigm, the state of the system includes a combination of parameters of the external environment, internal microclimate, crop growth state, and predicted yield. The action space describes the possibilities of active influence on the system: temperature control, irrigation, lighting, $CO_2$ supply, etc. The transition between states occurs according to a probabilistic law, which can be approximated using simulation modeling, the parameters of which are selected based on sensor data.

If rational values of climatic parameters for the selected crop are calculated in advance, then the task is reduced to determining the optimal time points for activating or deactivating the executive systems of irrigation, heating, ventilation, lighting. Thus, the control process turns into a dynamic task of planning actions over time in order to maximize the total reward (yield at minimal costs). Accordingly, the greenhouse environment simulation model should combine modules for microclimate change, crop growth, and harvest accumulation within a three-level neural network structure. On its basis, two-level optimization is carried out: the lower level ensures adaptation of the simulator to current data coming from sensors, and the upper level – refinement of the control strategy to achieve target results. Due to this, flexibility and adaptability of the system is achieved even under changing environmental conditions or lack of historical data.

The formulas describing the change in temperature, humidity, and $CO_2$ concentration in a greenhouse are based on classical approaches to mathematical modeling of the microclimate in protected soil. In [23], a physically based model of a greenhouse in the form of a system of differential equations was proposed, which combines the laws of conservation of energy and mass to describe the dynamics of parameters of the internal environment. This model takes into account the inertia of the greenhouse, time lags in the change of the microclimate, and the stochastic nature of the influence of external factors. Similar approaches are used to test hypotheses for optimal control and build simulators that reproduce the real dynamics of the internal environment of greenhouses with high accuracy.

Based on the above methodological principles, a simplified physical and mathematical model was stated in our study, reflecting the most important processes of heat exchange, moisture exchange, and mass exchange under greenhouse conditions. On this basis, the following assumptions were adopted.

The model combines external factors and control factors that affect the establishment of the microclimate inside the greenhouse. In particular, to enable cultivation in the greenhouse, a stable air temperature and $CO_2$ concentration are required, which can be managed by the control model.

The air temperature in the greenhouse is determined from the following formula

$$\frac{dT_{air}}{dt}=C_{air}^{-1}\left(Q_s+Q_h-Q_v-Q_t-Q_l\right), \tag{6}$$

where $C_{air}$ is the heat capacity of air in the greenhouse, $Q_s$ is the heat from solar radiation, $Q_h$ is the heat from the heating system, $Q_v$ is the heat removed by ventilation, $Q_t$ is the heat removed by plant transpiration, $Q_l$ is the heat loss through the greenhouse walls.

In equation (6), only the heat capacity of the greenhouse air $C_{ai}$ is a constant value. All other terms vary in time. In this case, two parameters – the heat from the heating system and the heat removed by ventilation – can be controlled. That is, these parameters correspond to control actions $a \in A$; the remaining variables are determined by external conditions and can be estimated based on sensor data.

The $CO_2$ concentration is determined over time as ratio $\frac{dÑO_2}{dt}$

$$\frac{dCO_2}{dt} = \frac{1}{V_{air}} \cdot \left( R_{soil} + Q_e - P_{rate} \cdot M_P - Q_w \right), \tag{7}$$

where $V_{air}$ – volume of air in the greenhouse, $R_{soi\ l}$ – $CO_2$ release by the soil, $Q_e$ – $CO_2$ supply by the enrichment system, $P_{rate}$, $M_p$ – $CO_2$ consumption by plants, $Q_w$ – $CO_2$ losses through the ventilation system.

Air humidity in the greenhouse is defined as the balance of moisture intake and loss as a result of transpiration, irrigation, ventilation, and condensation

$$\frac{dRH}{dt} = \frac{1}{V_{air}} \cdot \left( E_{tranp} + E_{irrig} - E_{vent} - E_{cond} \right), \tag{8}$$

where $RH$ is the relative humidity of air in the greenhouse; $E_{transp}$ is the transpiration evaporation of moisture from plants, $E_{irrig}$ is the evaporation of moisture as a result of irrigation, $E_{vent}$ is the loss of moisture through ventilation, $E_{cond}$ is the condensation of moisture on internal surfaces, $V_{air}$ is the volume of air in the greenhouse.

In model (1) to (5), which formalizes the statement of a greenhouse control problem in the form of a Markov decision-making process, the set of states $S$, the set of possible actions $A$, transition probabilities $P(s'|s, a)$, and reward function $R(s, a)$ form the problem of finding the optimal strategy $\pi^*(a|s)$. The optimization functional sets the goal of maximizing the total discounted reward, which reflects the balance between yield and resource consumption.

The mathematical model for greenhouse control (6) to (8) describes the dynamics of changes in temperature, humidity, and $CO_2$ concentration under the influence of external factors and control actions. This model allows us to detail the states of the system $s \in S$, determine the target values of the parameters for a specific crop, and reflect how the controlling actions (heating, irrigation, ventilation, $CO_2$ supply, lighting) affect the internal microclimate. For example, in the case of equation (6), which describes the change in air temperature in a greenhouse, a rational value of temperature $T_s$ can be obtained from the optimization problem (1) to (5). The current value $T_{air}$ is obtained from the sensor. If $T_{air} < T_s$, it is necessary to increase the temperature using the action "heating". Equation (6) makes it possible for us to calculate the required value of heat flow $Q_h$, which must be supplied from the heating system to achieve the target level. Since heat generation requires energy consumption, the corresponding costs are taken into account in cost function $R_s$ (1) to (5). Thus, using the Markov process for decision-making, what to do is determined, and the control model allows us to establish how exactly to implement the action and what costs will be associated with it.

It is important to note that the rational values of $T_s$, $RH_s$, $CO_2$ parameters depend on the stage of plant development (e.g., germination, flowering, fruiting). Therefore, in the process of growing, these target indicators are adjusted, which requires adaptation of the control strategy. Continuous updating of optimal parameters in real time is difficult for practical application since it requires significant computing resources and could lead to instability in the control system. Therefore, it is advisable to switch to a discrete interpretation when the optimal parameter values are updated at certain time intervals (e.g., every 6 hours). This approach provides a compromise between the accuracy of adaptation to growth phases and the practical feasibility of the algorithm at industrial greenhouse operation.

Standard numerical schemes are used to integrate the physical equations of dynamics. For example, equation (6) is discretized with step Δt (e.g., 60 s) in the form of the Euler equation

$$T_{air}^{k+1} = T_{air}^{k} + \Delta t \cdot C_{air}^{-1} \left( Q_s^k + Q_h^k - Q_v^k - Q_t^k - Q_l^k \right), \tag{9}$$

where $T_{air}^{k+1}$ – air temperature in the greenhouse at the next time point, $T_{air}^{k}$ – air temperature in the greenhouse at the previous time point, $Q_s^k$ – heat from solar radiation at the previous time point, $Q_h^k$ – heat from the heating system at the previous time point, $Q_v^k$ – heat removed by ventilation at the previous time point, $Q_t^k$ – heat removed by plant transpiration at the previous time, $Q_l^k$ – heat losses through the greenhouse walls at the previous time point.

The calculation of control action for the temperature at step $k$ is found from discrete equation (9). Similarly to formula (9), control actions for the relative humidity of air (8) and the $CO_2$ concentration (7) are found.

After building a model of the environment for growing agricultural crops, the system parameters are determined not by direct experimentation but as a result of solving the control problem taking into account the Markov decision-making process.

The result of solving the optimization problem within the Markov decision process is an optimal strategy, i.e., a rule that determines the best action for each possible state of the greenhouse, taking into account the expected transitions and rewards. In our work, the states are microclimate events such as a rational microclimate, overheating, cold, moisture deficiency or excess, excess $CO_2$, plant stress, yield reduction, or emergency mode. The transition between these states occurs probabilistically, depending on which action is performed, for example, turning on ventilation, increasing irrigation, or activating heating. The strategy describes which action should be chosen in each state in order to maximize the expected total reward, i.e., to maintain yield and minimize resource consumption. To determine such a strategy, a Markov process model is formed for greenhouse management decision-making with two-level optimization of parameters with a set of states, actions, a transition matrix, and a reward function, after which a two-level optimization is performed that combines operational and strategic management goals.

In the greenhouse control model, control actions defined in the problem statement (1) to (5) are implemented through the parameters included in physical equations (6) to (8). These include the following parameters:

– heat from the heating system $Q_h$ and heat removal by ventilation $Q_v$ are controlled parameters, the remaining thermal components are determined based on sensor data and may change depending on time;

– irrigation intensity $Irr$ is a controlled parameter, while evaporation and condensation are estimated from sensor data;

– artificial light intensity $Light$ is a controlled parameter that affects heat and mass transfer indirectly through photosynthesis and transpiration.

As a result, the set of actions A is specified as a control vector, which is used in equations (6) to (8). The rational microclimate parameters are determined by solving problem (1) to (5) and are updated under a discrete mode with a certain time interval (for example, every 6 hours). This approach takes into account the changing needs of crops at different stages of development and at the same time reduces the computational load and the risk of fluctuations in the control system. In the intervals between discrete updates, the circuit operates under a continuous mode, gradually approaching the current values to rational ones.

The rational strategy $\pi(a|s)$, obtained from relations (1) to (5), determines the necessary actions for each state (s), while equations (6) to (8) specify the mechanisms and volumes of these actions. This approach makes it possible to combine discrete optimization of strategies with continuous dynamics of the greenhouse microclimate. In practical implementation, control strategy consists of two components:

1. Discrete target parameter planner, which updates the optimal parameter values every 6 hours according to the results from (1) to (5).

2. Continuous controller, which corrects actions in real time using equations (6) to (8).

The controller operation is implemented as a set of rules with dead zones. For example, if $T_{air} < T_s - T$, the required $Q_h$ is calculated, which is supplied from the heating system; if $T_{air} > T_s + T$, $Q_v$ is increased due to ventilation. Energy costs for $Q_h$ and fan operation are taken into account in the cost function $R_s$. Humidity, lighting, and $CO_2$ concentration are controlled similarly. Thus, the $\pi(a|s)$ strategy forms a sequence of specific signals to the actuators. All associated costs are reflected in the cost function $R_s$ and in the general reward functional (1) to (5). This ensures consistency between the optimization statement and the physical dynamics of the greenhouse, allowing the transition from an abstract model to practically implemented control.

This approach is particularly appropriate in cases where full-scale experiments are not possible, for example, when growing new crops or under new climatic conditions. Instead, the model is adapted based on available data from other greenhouses or regions, and control strategies and expected results (e.g., predicted yield) are calculated automatically as a solution to a Markov decision-making process problem. This allows the parameters to be adjusted to take into account the long-term impact of actions and the stochastic nature of processes in the greenhouse. Adjusting parameters to take into account the long-term impact of actions and the stochastic nature of processes in the greenhouse is done by stating the problem as a Markov decision-making process.

For practical implementation of the control model, it is necessary to design an integrated greenhouse information management system. Such a system should include IoT infrastructure for continuous monitoring of microclimate parameters, automated actuators for regulating irrigation, ventilation, lighting, and $CO_2$ supply, as well as a computing platform for data processing and calculating control strategies. This enables a connection between the mathematical model of the Markov decision-making process and real processes in the greenhouse, which makes it possible to quickly respond to changing conditions and maintain parameters within target values.

The IoT system for growing strawberries in a greenhouse consists of key components:

– IoT devices – physical devices that acquire data about the environment and perform certain actions;

– a communication network provides data transmission between IoT devices and the central system;

– a cloud platform (or local server) stores, processes, and analyzes the collected data;

– a user interface allows operators to monitor the system and manage it.

Wireless technologies were used to connect IoT devices to the cloud platform.

The key system characteristics are described in Table 3, and the device system is described in Table 4.

The general greenhouse control scheme is shown in Fig. 1.

The constructed model for greenhouse management provides the choice of a regulation strategy to maintain target parameters, which is directly related to the practical need to reduce resource costs and increase yield. The implementation of this approach involves the use of a greenhouse management information system with IoT infrastructure for monitoring parameters and controlling mechanisms for automated implementation of the calculated strategies.

Table 3

Descriptions of key characteristics of an IoT system

| IoT device | Purpose | Location |
|---|---|---|
| Air temperature sensors | Monitoring and maintaining optimal temperature conditions.<br>For growing strawberries:<br>– daytime temperature should be 35–40°C to ensure optimal photosynthesis and initiation of flowering;<br>– night temperature – 10–12°C to accumulate sugars in the fruits;<br>– average daily temperature of about 25°C for uniform growth and development | Placed at different levels of the greenhouse to ensure uniform control |
| Air humidity sensors | Monitoring and maintaining optimal humidity (for strawberries, usually 60–70% humidity) | Placed at different levels of the greenhouse to ensure uniform control |
| Soil moisture sensors | Measures soil moisture levels to determine when watering is needed. Prevents over- or under-watering | Placed at different depths, taking into account the strawberry root system |
| Soil pH sensors | Soil acidity/alkalinity monitoring. Strawberries prefer slightly acidic to neutral soil (pH 5.5–6.5) | Placed at different depths, taking into account the strawberry root system |
| Soil EC (electrical conductivity) sensors | Measurement of nutrient concentration in the soil. Allows one to optimize fertilizer application | Placed at a depth of 10–30 cm from the soil surface |
| Light sensors (luxmeters) | Measuring light intensity. Strawberries need a lot of light (14–16 hours a day) | Placed in such a way as to take into account the shade from the plants |
| $CO_2$ concentration sensors | Monitoring $CO_2$ levels in the air. Increased $CO_2$ concentration can accelerate photosynthesis and, consequently, plant growth | Placed inside the greenhouse |

Table 4

System of devices

| IoT device | Purpose |
|---|---|
| Irrigation system (solenoid valves, pumps) | Automatic watering of plants based on soil moisture sensor data. Can be integrated with fertigation system (fertilizer supply with water) |
| Temperature control system (heaters, fans, shading systems) | Maintaining optimal temperature by automatically turning on/off heaters, fans or using shading curtains |
| Ventilation system (fans, electric windows) | Providing air circulation and humidity/temperature regulation. Removing excess heat and moisture |
| Lighting system (LED plant lights) | Additional lighting during periods of insufficient natural light, especially in winter or in regions with low light |
| $CO_2$ supply system | Automatic $CO_2$ supply to increase its concentration to the optimal level for photosynthesis |

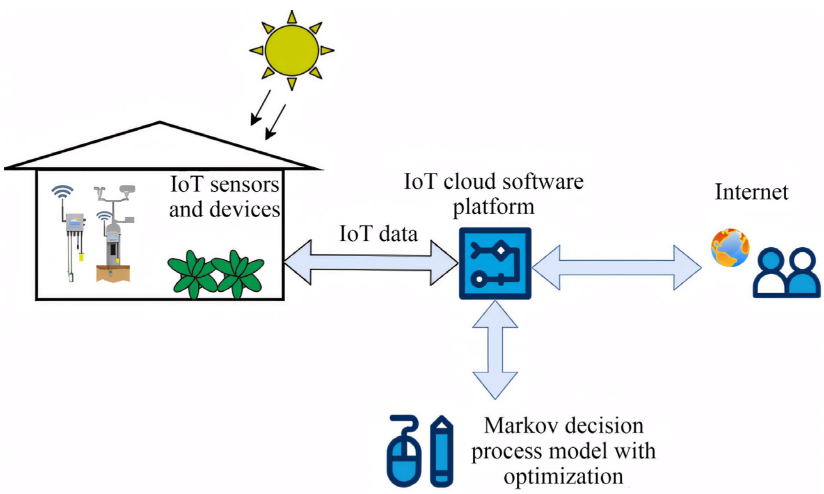


Fig. 1. Greenhouse control scheme

**5. 3. Validation of the model for rational greenhouse control for the case of strawberry cultivation**

To validate the proposed model for greenhouse management, a dataset with strawberry cultivation parameters was acquired, based on a real experiment conducted at a greenhouse complex located in Chernivtsi oblast. Observations lasted from May 17 to June 8, 2025. Monitoring of microclimate parameters was carried out around the clock with an interval of 1 minute, which ensured high accuracy of the analysis. A total of 30227 full-format observations were collected. The dataset is available at [21]. Strawberry was chosen as a model crop because of its high sensitivity to microclimate: deviations in temperature or humidity significantly affect the yield. This makes strawberry a demonstration case for testing the effectiveness of the control system. In addition, strawberry is an economically important berry, popular for greenhouse cultivation, so the results have practical value. In addition, the strawberry ripening period is from 21 to 28 days, so a small amount of data is sufficient for analysis.

The values of air temperature, relative humidity, illumination, $CO_2$ concentration, temperature, and acidity of the nutrient solution, conductivity, as well as equipment operating parameters were recorded. Special attention was paid to the analysis of the operation of actuators that directly affect the microclimatic conditions in the greenhouse.

The control system implemented three independent circuits of influence on humidity and plant nutrition:

– circuit 1 – drip irrigation into the root zone through Pump 1 and Valve 1;

– circuit 2 – backup irrigation circuit through Pump 2 and Valve 2, used when humidity dropped below critical values;

– circuit 3 – fogging system, which was turned on under conditions of air overheating (>30°C) or excessive dryness (<50%), providing finely dispersed humidification of the upper layer of the greenhouse atmosphere.

Each of the pumps had a binary state (on/off), similarly – the valves. The actions of actuators were recorded in real time. That made it possible to track the reaction of the microclimate to control actions and further validate the model. Fig. 2 shows a diagram of the first and second irrigation circuits. They are built using IT Lynx technologies (Fig. 3).

In addition to the irrigation systems, the following actuators operated in the greenhouse:

– lighting: activated automatically when natural light decreased below 6000 lux, taking into account the photoperiod of the plants (Fig. 4);

– heater: turned on to maintain temperature at night or on cloudy days;

– ventilation ensured temperature and humidity control by opening the shutters or activating the exhaust fans;

– air circulation was carried out using low-power fans installed in the lower part of the greenhouse near the soil surface. This mechanism is critically important for growing strawberries as it contributes to the uniform distribution of temperature in the root zone, preventing the formation of overheating zones or moisture stagnation.

In order to perform a preliminary analysis of the stability of the input parameters of the system and to justify the feasibility of using adaptive scaling methods, basic statistical characteristics, the mean value, and variance were calculated for the key physical and technological indicators recorded during the experiment. As shown in Table 3, some parameters (for example, air temperature, solution temperature, pressure, and acidity of the medium) demonstrate relative stability and low variability, which indicates their inertia. At the same time, other characteristics, in particular humidity, illumination, $CO_2$ content, and solution conductivity, have significant fluctuations, which forms the basis for adaptive management of computing resources. Such statistical analysis makes it possible to categorize parameters by the degree of influence on the load and is an important stage in validating the scaling model. Analysis of the dynamics of key physical and technological indicators (Fig. 5) demonstrates a pronounced daily cyclicality of changes in values.

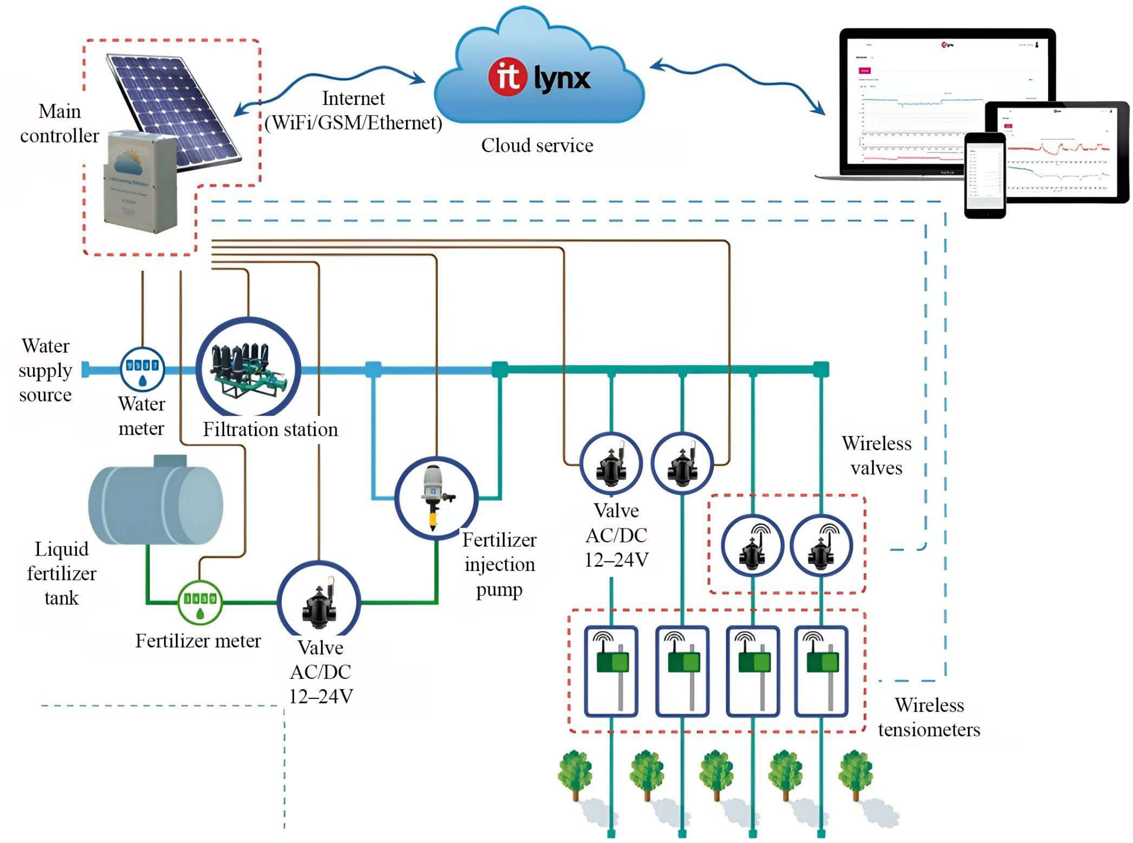


Fig. 2. Greenhouse irrigation scheme

Fig. 3. Hardware implementation of the irrigation circuit

Fig. 4. Greenhouse lighting system

The most vibrant rhythm is observed for air temperature, humidity, illumination, and $CO_2$ concentration; these parameters have regular fluctuations with a period of about 24 hours, which indicates a dependence on daily bioclimatic factors. This behavior corresponds to typical conditions of functioning of a greenhouse or laboratory environment with simulated daylight. Cyclicality is also observed in the behavior of conductivity and temperature of the nutrient solution, although their fluctuations have a smaller amplitude.

Table 5

Statistical parameters of key physical and technological indicators

| Indicator | Mathematical expectation | Variance |
|---|---|---|
| Temperature, °C | 25.701 | 8.509 |
| Humidity, % | 73.145 | 4.886 |
| Lighting, lux | 5290.663 | 4547.538 |
| $CO_2$, ppm | 1460.632 | 23426.674 |
| Solution temperature, °C | 15.493 | 5.9870 |
| Solution acidity, pH | 6.223 | 0.350 |
| Solution conductivity, $\mu$S/cm | 391.303 | 304.499 |

An important feature of the experimental environment is that irrigation was not carried out with ordinary water but with a specially prepared nutrient solution that simulates the conditions of automated drip irrigation in closed soil systems. Control over the state of this solution was carried out by three main parameters: temperature, acidity (pH), and electrical conductivity, which makes it possible to assess the level of mineralization. As shown in Table 3, these indicators are characterized by relative stability over time, which confirms the constancy of the composition of the nutrient medium and the adequacy of the conditions in which the proposed model was validated. This approach provides greater applied reliability of the modeling results since it takes into account the actual technological features of microclimate control in greenhouse or hydroponic systems.

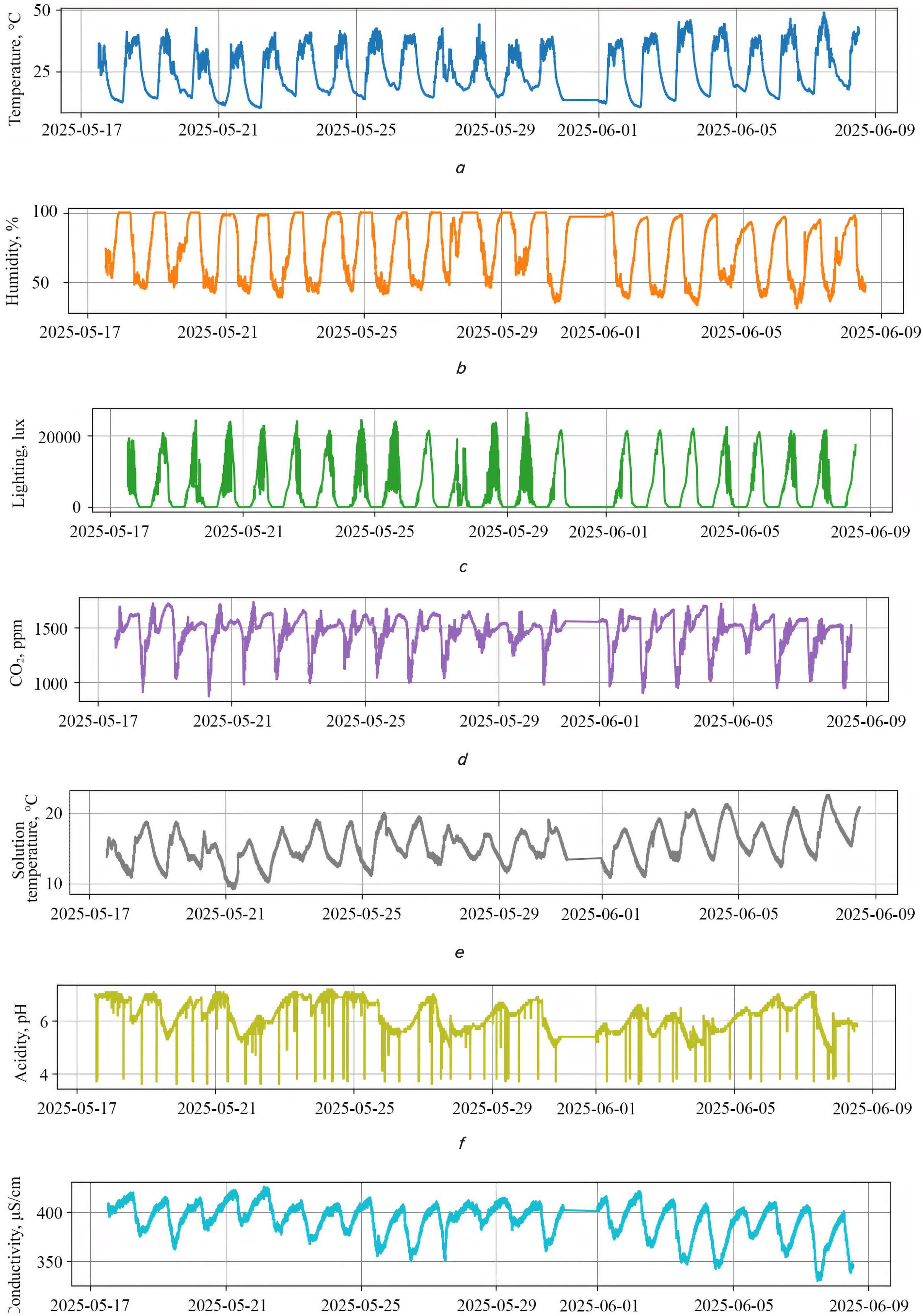


Fig. 5. Dynamics of key physical and technological indicators of greenhouse operation: *a* – temperature in the greenhouse; *b* – relative humidity; *c* – lighting; *d* – $CO_2$ concentration; *e* – temperature of the irrigation solution; *f* – acidity of the irrigation solution; *g* – conductivity of the irrigation solution

To validate the adequacy of the proposed greenhouse control model, experimental validation was carried out at an operating greenhouse complex located in the Chernivtsi oblast. The choice of strawberry as a model crop is due to its high sensitivity to microclimate parameters, which makes it an illustrative case for testing automated control systems. The ripening period of this crop is 21–28 days, which makes it possible to obtain a sufficient amount of data for statistically significant analysis.

Additionally, the deviation of actual values from the specified settings was estimated. As shown in Table 6, the parameters mostly remained within rational ranges 76–84% of the time, confirming the stability of system operation.

Table 6

Greenhouse control parameters

| Parameter | Setpoint (range) | Average actual | RMSE | Percentage of time in range |
|---|---|---|---|---|
| Temperature, °C | 22 ± 1 | 22.4 | 1.9 | 84% |
| Relative humidity, % | 65 ± 5 | 66.2 | 7.5 | 78% |
| $CO_2$, ppm | 800 ± 50 | 785 | 62 | 81% |
| PAR, $\mu mol \cdot m^{-2} \cdot s^{-1}$ | 250 | 245 | 35 | 76% |

Within the framework of the experiment, a strawberry crop with an average yield of 5.0 kg/m$^2$ was chosen as an example. Based on our calculations, it was found that the use of the Markov model, taking into account daily changes in parameters, ensures the stability of the microclimate and reduces resource consumption compared to conventional methods.

To assess economic indicators, the current tariffs for legal entities in the city of Chernivtsi were taken into account. As of 2025, the cost of water supply and wastewater disposal is 47.15 ₴/m$^3$, which is equivalent to approximately 0.98 €/m$^3$ at an exchange rate of 48 ₴/€. Separately: water supply – 32.24 ₴/m$^3$ (≈0.67 €/m$^3$), wastewater disposal – 14.90 ₴/m$^3$ (≈0.31 €/m$^3$). These tariffs were used to calculate costs in validation experiments.

The results confirmed that taking into account the dynamics of greenhouse microclimate parameters and timely activation of actuators make it possible to enable stable growth conditions with minimal resource consumption. The calculated yield increase was about 7%, which, although somewhat lower than the results of the two-level optimization described in [10], nevertheless confirms the economic feasibility of implementing automated greenhouse microclimate control systems.

The validation included an analysis of resources (electricity, water, labor) and costs in the baseline scenario and when using the Markov decision-making process model. As shown in Table 7, the use of the model made it possible to reduce electricity costs by 12%, water – by 8.9%. The total cost savings amounted to about 10%.

Table 7

Calculation of resource costs for greenhouse operation

| Indicator | Unit | Baseline | Markov process model for decision making | Change, % |
|---|---|---|---|---|
| Electricity | kW·h | 12500 | 11000 | –12.0 |
| Water | m$^3$ | 450 | 410 | –8.9 |
| Electricity cost | € | 2250 | 1980 | –12.0 |
| Water cost | € | 405 | 369 | –8.9 |

The implementation of the Markov process model for decision-making has made it possible not only to reduce resource costs but also to increase yield. As shown in Table 8, the average yield increased by 7% (from 5.00 to 5.35 kg/m$^2$), which led to a significant increase in revenue and profit. The overall financial result improved by more than 30%.

Table 8

Calculating the efficiency of growing strawberries in a greenhouse

| Indicator | Unit | Baseline | Markov process model for decision making | Change, % |
|---|---|---|---|---|
| Yield | kg/m$^2$ | 5.00 | 5.35 | +7.0 |
| Total yield | kg (500 m$^2$) | 2500 | 2675 | +7.0 |
| Revenue | € | 7500 | 8025 | +7.0 |
| Profit | € | 3115 | 4076 | +30.9 |

Our validation results confirm the effectiveness of the Markov process model with two-level optimization. It ensures stability of microclimate parameters, reduced resource consumption, increased yield, and a significant increase in profitability. The results indicate the practical value of implementing automated greenhouse control systems built on the basis of Markov decision-making processes.

## 6. Discussion of the decision-making model for greenhouse agricultural enterprise activities

Our model of greenhouse control based on the Markov decision-making process demonstrates high practical value, especially in the context of growing sensitive crops such as strawberries. The results of experimental validation confirm that taking into account the dynamics of microclimatic parameters and timely activation of actuators makes it possible to enable stable growth conditions with minimal resource consumption. As shown in study [10], the implementation of two-level optimization in autonomous greenhouse control systems provided a profit increase of 92.7% and an increase in yield by 10.15% compared to conventional methods based on expert judgment. Our study included both modeling of greenhouse management processes and real measurements in an operating greenhouse. Due to the significant volume of the greenhouse and the high thermal inertia of the structures, the actual values of the microclimate parameters could deviate from the rational ones by 10–15%. According to yield models [24, 25], the calculated yield increase for our model is about 7%. At the same time, even such a result remains economically profitable and confirms the feasibility of implementing automated greenhouse microclimate control systems. The result is attributed to the fact that the Markov process model with two-dimensional optimization (1) to (5) makes it possible to take into account the history of changes in greenhouse parameter values and adjust them in accordance with the stages of growing specific crops. The validation of our model was carried out on real data from an operating greenhouse; they are hosted on the Zendo platform [21].

The considered equations (6) to (8) make it possible to directly compare theoretically determined rational values of parameters with actual sensor data. For example, from (6) it can be determined that in order to achieve a rational temperature, as a solution to problem (1) to (5), it is necessary to provide a certain heat flow. In this case, the equation acts as a connection between the target state and practical actions that must be performed by the control system. Equations (7) and (8) for $CO_2$ and humidity are interpreted similarly. Thus, the model confirms the consistency between abstract optimization solutions and the physical dynamics of the control object.

Although the described model allows us to form accurate strategies for regulating microclimate parameters, its practical application has a number of limitations. First, constant adjustment of rational parameters in real time is difficult due to the variability of conditions and high computational load. Second, at different phenological stages of crop growth, the target values of the parameters change significantly, which requires an adaptive approach. Therefore, replacing continuous adjustment with discrete updating of rational values (for example, once every 6 hours) is a reasonable compromise that facilitates practical implementation and increases the reliability of the system.

The main limitation of our study relates to the crop grown under greenhouse conditions. This model is also suitable only for annual crops. The model does not take into account the full biological dynamics of plants, in particular the development of diseases.

The disadvantage is that the collected dataset [21] has a limited volume. It would be advisable to conduct modeling on a larger dataset and take into account several crops although the acquired dataset completely covers the entire process of strawberry cultivation from flowering to harvest, which makes it possible to draw reasonable conclusions.

Further research should be aimed at improving the economic efficiency of automated control systems. In particular, an important area is the optimization of the costs of electricity, water, fertilizers, taking into account variable tariffs, weather conditions, and crop type. There is a need to integrate a multi-criteria model that would make it possible not only to maximize yield but also minimize the total costs per unit of production. In addition, it is necessary to conduct more in-depth economic research, including an analysis of the payback period for the implementation of intelligent control systems, an assessment of the scaling effect on large greenhouse complexes. It is also necessary to investigate the impact of external market factors on the operational efficiency of such systems.

## 7. Conclusions

1. A random Markov decision-making process has been defined for the greenhouse operation improvement problem. A two-level optimization was chosen to solve the problem. The first level concerns strategic and long-term parameters, in particular, the system configuration, the total budget. The second level determines the operational climate control in the greenhouse through the formed strategies, which are determined from the random Markov decision-making process within specific strategic boundaries.

2. A model of the dynamics of temperature, humidity, and $CO_2$ concentration changes under the influence of external factors and control actions has been proposed, which describes how external and control factors affect the microclimate parameters inside the greenhouse. This is important for ensuring rational conditions for growing crops and obtaining high yield indicators. The described model is the basis for building a decision-making model in the activities of a greenhouse agricultural enterprise taking into account climate-oriented agricultural practices.

3. To validate the proposed model for greenhouse control, data from a real experiment on strawberry cultivation conducted in a greenhouse complex were used. In order to preliminary analyze the stability of the system input parameters and justify the feasibility of using adaptive scaling methods, basic statistical characteristics, mean value, and variance, were calculated for key physical and technological indicators recorded during the experiment. The proposed approach to greenhouse control based on the Markov decision-making process model demonstrates high practical feasibility, especially in the context of growing sensitive crops such as strawberries. The results of experimental validation confirm that taking into account the dynamics of microclimatic parameters and timely activation of controlling mechanisms makes it possible to enable stable growth conditions with minimal resource consumption. The use of the model has made it possible to reduce electricity consumption by 12%, water consumption by 8.9%. The total cost savings amounted to about 10%. The average yield increased by 7%, which led to a significant increase in revenue and profit. The overall financial result improved by more than 30%.

## Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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## Data availability

Vatskel, V., Kuchanskyi, O., & Andrashko, Y. (2025). Strawberry Greenhouse Environmental Control Dataset. Zendo, https://doi.org/10.5281/zenodo.16268298.

## Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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