

## **Agricultural and Biological Engineering**

https://ph04.tci-thaijo.org/index.php/abe/index
Published by the Faculty of Engineering, Khon Kaen University, Thailand

# Development of an agricultural multi-zone solar dryer with airflow management using CFD and genetic algorithm

Jarinee Jongpluempiti, Metinan Kulanad, Nattida Nuankhamsing, Bunleab Chea and Ponthep Vengsungnle\*

Faculty of Engineering and Technology, Rajamangala University of Technology Isan, Nakhon Ratchasima, 30000, Thailand

\*Corresponding author. Email address: Ponthep.ve@rmuti.ac.th

> Received 24 Fabruary 2025 Accepted 12 April 2025

#### Abstract

This research focuses on the development of an agricultural drying house with multi-zone airflow management using Computational Fluid Dynamics (CFD) combined with Genetic Algorithm (GA) to enhance drying efficiency. The experiment compared the results of a conventional drying house with the improved version by analyzing drying time, energy consumption, average product moisture content, and drying uniformity. The results demonstrated that the drying house utilizing CFD and GA techniques reduced drying time by an average of  $30.0 \pm 2.6\%$ , decreased energy consumption by  $25.0 \pm 2.0\%$ , reduced the average product moisture content from  $15.5 \pm 1.0\%$  to  $10.5 \pm 0.6\%$ , and increased drying uniformity from  $70.0 \pm 3.5\%$  to  $90.1 \pm 2.4\%$ , all with statistical significance. These findings reflect the capability of CFD and GA technologies to improve efficiency, reduce production costs, and enhance the quality of products sustainably. This technology holds significant potential for advancing drying processes in agriculture and the food industry in the future.

Keywords: Airflow simulation, Genetic algorithm, Drying, Agricultural greenhouse, Airflow management in greenhouses

#### 1. Introduction

Drying is one of the most important technologies in the agriculture and food industry, playing a key role in extending the shelf life of produce, reducing transportation losses, and adding value to products [1-2]. The global agricultural drying market is currently valued at around USD 1.2 billion by 2023 and is expected to grow at a CAGR of 6.5% during 2023-2030 [3]. Over 1.8 billion tons of agricultural produce are used in drying processes, accounting for 20% of the total global agricultural production [4-5]. However, current drying systems often suffer from airflow inconsistency, moisture retention, and high energy consumption. Conventional drying systems typically consume 12-25% of the total energy consumed in food processing [6], which results in higher production costs. Furthermore, studies have shown that quality losses due to improper drying account for as much as 30-40% of all produce in some areas [7], which poses a significant challenge for value addition and long-term management of agricultural resources.

Air flow management in drying houses is one of the key factors that directly affect the drying process efficiency and quality of produce. Proper air flow enables efficient heat and moisture transfer from produce, reduces moisture retention in produce and reduces drying time. It also affects the uniformity of the drying process, which reduces the problem of drying non-uniformity, which is a major problem in traditional drying plants. In addition, improper air flow can also cause hot spots that adversely affect produce quality, such as loss of natural color, reduced nutritional value, or even partial deterioration of produce. One of the most effective ways to manage airflow in drying houses is through the design and optimization of airflow distribution systems. Researchers have developed various methods to ensure uniform airflow, including the use of air barriers, spoilers, and guide vanes. For instance, the integration of trapeze and straight air barriers in tunnel-type dryers has been shown to reduce drying time by 45% and 20%, respectively, while achieving significant energy savings [8]. Similarly, the strategic placement of spoilers in drying chambers, based on Computational fluid dynamics (CFD) simulations, has improved airflow uniformity, reducing the average velocity deviation ratio from 0.5124 - 0.2565% [9]. In the past, the design of air flow systems in drying plants often used the traditional trial-and-error approach, where designers had to build real prototypes to experiment and adjust the structure or settings of the system based on the results. This method is time-consuming and resource-intensive. There are also limitations in terms of improving the system at a complex level, such as designing a multi-zone airflow system, which requires a deep understanding of fluid dynamics and heat transfer. Currently, the application of modern technologies such as CFD allows for accurate simulation of airflow and heat distribution processes in a drying house in three

dimensions. CFD reduces the need for initial prototype construction, allowing for rapid and cost-effective system analysis and improvement. Examples of CFD applications include the analysis of air velocity, temperature distribution, and moisture transfer in a drying house, which allows for clear identification of areas for improvement. Furthermore, the use of Genetic algorithm (GA) as the optimization method in this research was strategically selected due to its robustness in exploring complex solution spaces and its independence from derivative-based formulations. GA is particularly effective for multi-objective optimization, such as balancing airflow uniformity and temperature consistency in a multi-zone drying house. Its population-based search strategy enables efficient convergence to global optima, especially when coupled with CFD simulations, where the objective function is computationally expensive and non-linear. Compared to methods like PSO, ANN, or gradient-based techniques, GA offers superior flexibility, interpretability, and integration with simulation-based workflows, making it well-suited for solving the engineering challenges addressed in this study.

In addition, the use of GA in conjunction with CFD can enhance the potential of drying system design. GA is an evolutionary algorithm that mimics natural processes such as selection, breeding, and mutation to find the optimal solution in a highly complex system. An example of GA application is the optimization of the position of fans and vents to reduce drying time and energy consumption. Combining these two technologies allows for a more accurate and efficient design of airflow systems in a drying house. As a result, the drying house can meet the requirements of energy cost reduction, product quality improvement, and sustainability development in the agricultural sector. The use of CFD and GA technologies also opens up opportunities for "predictive design" systems, which can use simulation data to analyze air flow characteristics under different environmental conditions, such as changes in temperature or humidity outside the greenhouse. These technologies not only help in the design process, but also help in the development of smart drying systems that can automatically adjust their operation according to the actual conditions in the greenhouse. Therefore, the application of such modern technologies is an important step in elevating the design and development of agricultural drying houses to meet the current demands for efficiency, cost-effectiveness, and sustainability in the agricultural production process. This research focuses on the development of a multi-zone agricultural drying house with appropriate air flow management, using CFD to simulate air flow and GA to increase design efficiency. The system's functionality will be evaluated based on drying consistency, energy consumption, and product quality. The innovations resulting from this research will help increase drying efficiency, reduce costs, and improve product quality in the agricultural sector sustainably.

#### 2. Methodology

#### 2.1 Drying of agricultural products

Drying is an important process used in the processing and preservation of agricultural products to extend their shelf life, reduce post-harvest losses, and add value to the products. The drying process focuses on reducing the water content of the products to a safe level, which inhibits the growth of microorganisms such as bacteria, mold, and yeast, as well as inhibiting biochemical reactions that cause deterioration. Drying also reduces the weight and volume of the products, making them easier to transport and store. Examples of products that are popularly processed include fruits (e.g. mangoes, bananas, and longans), vegetables (e.g. lemongrass and chilies), grains (e.g. rice and beans), and herbs (e.g. kaffir lime leaves and ginger). The drying methods can be divided into two main types: natural drying and mechanical drying or active drying [1, 10]. In the natural drying process, sunlight and natural wind are often used as energy sources. This process is simple, economical, and suitable for small-scale farmers, but has limitations such as uncontrollable weather conditions, contamination from dust and insects. Including the uniformity of drying that is lower than other methods. In contrast, drying with machinery or supplementary energy, such as using hot air ovens or solar dryers, allows for efficient control of temperature, humidity, and drying time, resulting in higher quality and more consistent produce. However, this type of drying is expensive and requires appropriate technology. The choice of drying method depends on the type of produce, production scale, and available resources. This process is also important for creating food security in the community and the country, as well as promoting the development of agricultural products that can compete sustainably in the global market. This model will be a greenhouse with dimensions W x L x H of 3.00 m x 2.90 m, as shown in Figure 1.

### 2.2 Statistical data analysis

Statistical data analysis is an important process in managing data to gain insights, patterns, or relationships in the data. This process involves collecting data, summarizing the data in numbers (such as mean, median, or standard deviation), and displaying the data in an easy-to-understand format such as graphs, tables, or charts. Statistical data analysis plays an important role in many fields, such as science, medicine, marketing, economics, and agriculture. Especially in the era of big data being created every day, the use of statistics as a tool to help synthesize data has become increasingly important. Statistical data analysis has various purposes, such as understanding the basic characteristics of the data, predicting future behavior, testing hypotheses, and making strategic decisions. The process of statistical data analysis often begins with preliminary data exploration (Exploratory data analysis: EDA) to understand the data, such as examining the frequency distribution of the data, finding patterns or basic relationships in the data, and identifying outliers. The next step is to use appropriate analysis techniques, such as descriptive statistics, to summarize the data in a concise and easy-to-understand format. And inferential statistics such as hypothesis testing or ANOVA to understand the relationship or difference in the data. In addition, statistical data analysis also covers the use of mathematical models such as linear regression or cluster analysis to assist in forecasting or segmenting data. Effective statistical data analysis enables users to make accurate decisions and provide clear supporting data for solving problems or developing strategies in various aspects of research or business. This research will analyze the mean and standard deviation as in Equations (1) and (2), respectively, to examine the results of the product drying experiment to see how much they differ.

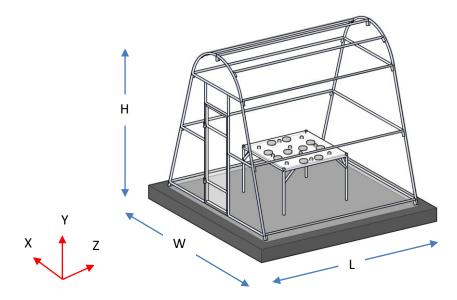


Figure 1 Greenhouse 3D Model

$$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{n} \tag{1}$$

$$s = \sqrt{\frac{\sum_{i=1}^{n} (xi - \overline{x})^2}{n-1}}$$
(2)

#### 2.3 Computational fluid dynamics

Computational fluid dynamics (CFD) is a branch of engineering that uses computational techniques to analyze the flow of fluids (both liquids and gases) and energy transfer in complex systems. CFD uses mathematical equations that represent the laws of physics, such as the Navier-Stokes equations, which are fundamental equations that describe the flow, motion, and behavior of fluids. Using CFD, complex phenomena such as turbulent flow, laminar flow, heat transfer, and mass transfer can be studied without the need for expensive laboratory experiments. CFD has important steps that enable efficient system simulation and analysis, including: Geometry modeling, using CAD software to design the fluid flow domain in the system to be studied; Meshing, which divides the domain into smaller units, such as structured or unstructured meshes, to prepare the data for calculation. The next step is: Setting up simulation parameters (Simulation Setup) such as defining boundary conditions and related equations. Finally, the analysis of the results (Postprocessing) is a graphical display, such as showing streamlines or pressure and temperature distributions, to understand the behavior of the fluid in the studied system. In this research, the equations used in the study start from the analysis of the continuity equation or the mass conservation equation (Continuity equation) is one of the basic equations in fluid dynamics that describes the conservation of mass (Mass conservation) of fluids, whether liquids or gases. This equation states that in a closed system or any area, the mass of the fluid will not increase or decrease as in Equation (3). Then it will be the momentum conservation equation (Momentum conservation equation), which is an important equation in fluid dynamics and is part of the Navier-stokes equations that describes the change of momentum in a fluid system under various forces acting on the fluid. This equation comes from Newton's second law of motion (F = ma) and is used in the context of fluids as Equation (4). The last equation is the Energy conservation equation, which in the context of CFD considers the total energy in the system, which includes kinetic, potential and internal energy. The energy equation can be written in conservative form as Equation (5).

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \vec{v}) = 0 \tag{3}$$

$$\rho \frac{\partial \vec{v}}{\partial t} + \rho (\vec{v} \cdot \nabla) \vec{v} = -\nabla \rho + \mu \nabla^2 \vec{v} + \vec{f}$$
(4)

$$\rho \frac{\partial e}{\partial t} + \rho \vec{v} \cdot \nabla e = -\rho (\nabla \cdot \vec{v}) + k \nabla^2 \tau + \phi$$
 (5)

Computational fluid dynamics is used in a variety of industries, such as aircraft design, engine development, building environmental control, and energy production system design, as well as agricultural systems development, such as agricultural drying facilities or greenhouse airflow management. CFD also plays an important role in environmental research, such as predicting the spread of air pollution or simulating changes in aquatic ecosystems. This technology enables researchers and engineers to understand fluid behavior in complex systems and improve designs for efficiency and sustainability.

#### 2.4. Genetic algorithm

Genetic algorithm (GA) is an evolutionary computing technique developed from the natural processes of natural selection and genetics. This algorithm is used to solve optimization problems by finding the most suitable solution in a highly complex problem. GA works by creating an initial set of solutions called a population, where each solution in the population is called an individual member or chromosome. These members are evaluated according to an objective function to measure the efficiency or fitness of each solution. The GA procedure through the following main steps (Figure 2): Selection of members with the highest fitness to act as parents to create new solutions, crossover or mixing data between two parents to create new members (offspring) with dominant characteristics from both parents, mutation or random modification of values in the chromosomes of some members to increase the diversity in the population and prevent the algorithm from being stuck in the most inappropriate solution (Local optimum), and then creating a new population (Generation). The new members are combined with the old population. And this process will continue until a certain criterion is reached, such as a specified number of iterations or when no improvement in fitness is found. The application of GA is diverse, for example, design improvement in engineering, logistics planning, financial model development, resource management, or even machine learning to find the most suitable parameter values. The advantage of GA is that it can work well with problems with large and complex answer spaces without having to know the structure of the target function in advance. However, GA requires careful parameter settings, such as the mutation rate and crossover rate, to make the algorithm work efficiently. In research and industry, GA has been used in conjunction with other techniques, such as CFD, to improve engineering systems, such as designing air flow in drying houses or modifying building structures to increase cooling efficiency and energy use. GA is therefore an important tool to help solve problems in highly complex tasks that require the most suitable answers in multiple dimensions. In this research, GA is used to increase temperature uniformity and reduce the occurrence of hot spots and dead zones by checking the wind speed at each point to be consistent throughout the greenhouse. The function used for checking can be shown as Equations (6) and (7).

$$\min \boldsymbol{\sigma}_{\tau} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( \tau_{i} - \overline{\tau} \right)^{2}}$$
 (6)

$$\min \sigma_{\upsilon} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\upsilon_{i} - \overline{\upsilon}\right)^{2}}$$
 (7)

The two targets are combined using weighting to balance temperature and air flow, where  $w_1$ ,  $w_2$  = the weights, initially set to 0.5 for both, as shown in Equation 8. In this study, three primary design variables were selected for optimization: the height of the air inlet, the height of the air outlet, and the airflow rate governed by the exhaust fan. To ensure that all solutions generated by the Genetic algorithm were physically feasible and applicable within the greenhouse configuration, appropriate boundary constraints were defined for each variable. Specifically, the inlet height was restricted to a range between 0.3 and 1.5 m, while the outlet height was allowed to vary between 0.3 and 2.4 m. The fan-controlled airflow rate was constrained within a range of 60 - 80 cfm. These boundaries were imposed throughout the GA optimization process to maintain structural compatibility, promote thermal efficiency, and ensure the practicality of the design outcomes.

$$Obj = W_1 \cdot \sigma_T + W_2 \cdot \sigma_D \tag{8}$$

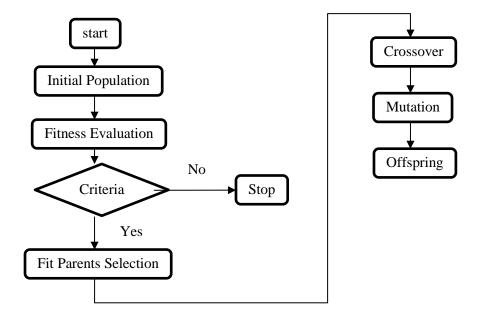


Figure 2 Genetic algorithm procedure

The three graphs in Figure 3 show the relationship between the main parameters, outlet height, inlet height, and fan flow rate, and the fitness function value, which is an indicator of the fitness of the system designed by the GA to reduce the variability of temperature and air flow in the drying plant. The first graph shows that the outlet height tends to have a clear effect on fitness in 2.150 m, with fitness near the minimum in this area, meaning that the height of the outlet port plays an important role in determining the balance of the air flow system. The second graph shows the inlet height, with fitness near the minimum in the range of approximately 1.25 m, indicating that at this level, the air entering the system is evenly distributed and has good variability. Considering the last graph, fan flow rate, which 77 cfm, the fitness value is stable and the lowest in this range. It indicates that the optimal fan flow rate enhances heat transfer and reduces dead zones in the system. Overall, all three graphs show the point where all parameters result in the lowest Fitness, reflecting the optimum value for the system design. The outlet height should be approximately 2.15 m, the inlet height is 1.25 m, and the fan flow rate is close to 77 cfm. This combination of parameters provides the most balanced temperature and airflow distribution in the system. Furthermore, the variation in fitness in each graph reflects the effectiveness of the GA in finding the optimal solution, highlighting its sensitivity to changes in outlet height and fan flow rate rather than inlet height.

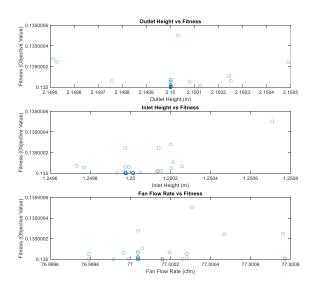


Figure 3 Relationship between physical parameters and fitness value in airflow and temperature optimization

From the analysis of the two graphs obtained from the operation of the GA in Figure 4, it can be concluded that the algorithm is effective in finding the most suitable answer in the early stage. The best fitness and mean fitness values decrease rapidly in the first 10 generations, reflecting the ability of GA to improve the parameter values in the early stage. However, after the 30<sup>th</sup> generation onwards, the two values begin to stabilize and do not improve further, indicating that the most suitable answer has been found. It is important to note that the Fitness values in this final period have very little difference between the populations, indicating the consistency and stability of the obtained answers. However, the stability of the Fitness values after the 30<sup>th</sup> generation may be a limitation of the algorithm or a factor in the objective function that prevents the algorithm from finding a better answer. In addition, the Score histogram

graph indicates that the fitness values are distributed in a very narrow range, indicating the clustering of close populations at the most suitable value. This is a good result because it shows the accuracy of GA in adjusting the parameters.

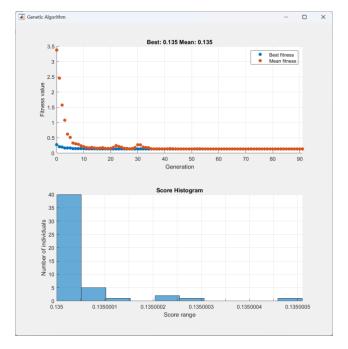


Figure 4 Fitness convergence and score distribution in genetic algorithm optimization

After determining the optimal parameters using the GA, the derived configuration was physically implemented in the experimental greenhouse. The same data collection procedure was applied to this optimized system, and the resulting performance indicators were compared against those of a conventional greenhouse. This comparative analysis allowed for a direct evaluation of the improvements achieved through the integration of CFD modeling and GA-based optimization. To support the optimization and validation processes, environmental data—including air temperature and humidity—were continuously collected using THS01 sensors manufactured by Sonoff. These sensors were strategically installed at three vertical positions within the greenhouse: 20 cm, 100 cm, and 150 cm above ground level, in order to capture stratified variations in microclimatic conditions. Data logging was performed at one-hour intervals throughout the test period. The collected data were subsequently used to calculate four key performance indicators (KPIs) for evaluating the system's effectiveness: drying time (h), power consumption (kWh/batch), final product moisture content (% wb), and uniformity of drying (%). These indicators provided a quantitative basis for comparing the optimized system with the conventional setup and for assessing the accuracy of the simulation-based optimization process.

#### 3. Results and discussion

The results of the computational fluid dynamics analysis are presented in the form of temperature color shades with the observed planes XYZ = 1.5 m, YZX = 1.5 m, and XZY = 1.0 m as shown in Figure 5.

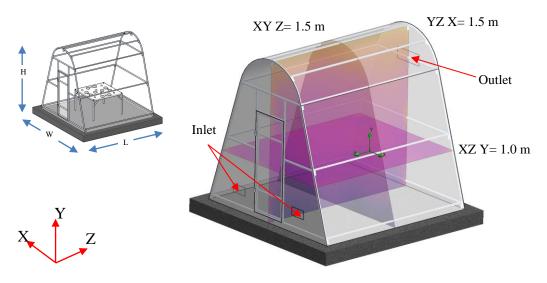


Figure 5 Plane reference

Computational fluid dynamics analysis of the temperature distribution characteristics inside the greenhouse and air flow can model the temperature distribution and air displacement direction. The plane XYZ=1.5 m in Figure 6 shows that the air will circulate at the area offset from the top of the greenhouse or at a level Y=1.8 m from the greenhouse layout. The warmer air will accumulate on the top, with some of it flowing out of the greenhouse through the ventilation fan vents.

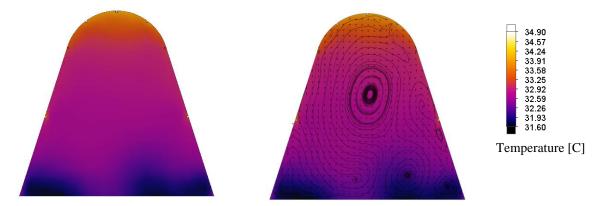
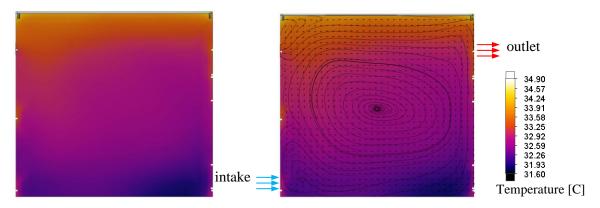


Figure 6 Temperature contour of the XY Z= 1.5 m plane

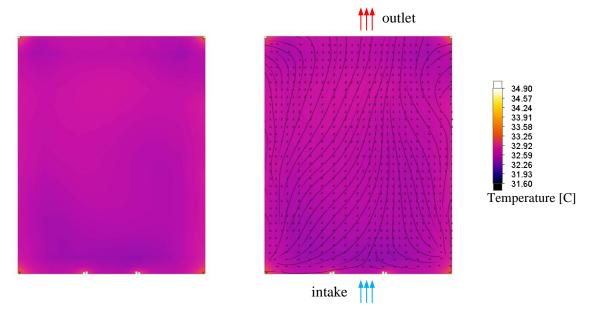
When considering the side of the greenhouse at plane YZ X = 1.5 m, a similar trend is observed as in the front plane where the air vortex in the center of the greenhouse is seen towards the top or at a distance Y = 1.8 m. The air flows from the bottom to the top and some of it exits through the exhaust fan. The analysis also shows that heat is accumulated at the side of the greenhouse while the bottom tends to have a lower temperature as shown in Figure 7.



**Figure 7** Temperature contour of the YZ X= 1.5 m plane

If we consider the XZ plane Y = 1.0 m, it can be seen that it is uniform because the temperature distribution at different heights Y is approximately the same due to the gravity of the earth. The temperature distribution can be shown as in Figure 8.

By using sensors to collect data on average temperature values throughout the test period, it was found that the greenhouses that used multi-zone air flow management with CFD techniques combined with GA had higher average temperatures throughout the test period than the normal type and were also able to reduce humidity in the air more than the normal type, resulting in the drying results in the said greenhouses being more efficient than the normal greenhouses. An example of data collection can be shown in Figure 9. In addition to the air temperature data, humidity levels were also continuously recorded using sensors installed in both greenhouse models, as well as the ambient air humidity outside the structures. Figure 10 illustrates the experimental results of air humidity measurements during the same test period. The data illustrate that Greenhouse 2 achieved a consistently lower humidity level during peak drying periods, particularly between 09:00 and 15:00, indicating more efficient moisture removal due to optimized airflow distribution. This supports the conclusion that the developed system enhances drying efficiency not only through improved temperature control but also through effective humidity management, which contributes to higher overall performance in agricultural drying applications.



**Figure 8** Temperature contour of the XZ Y= 1.0 m plane

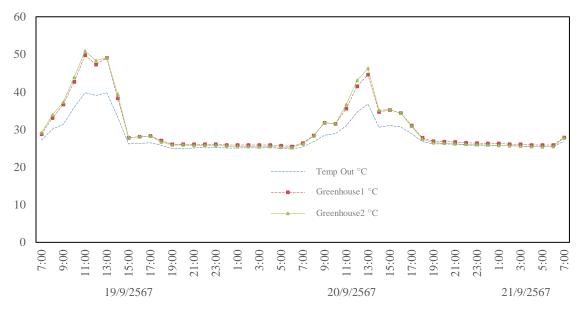


Figure 9 Experimental air temperature

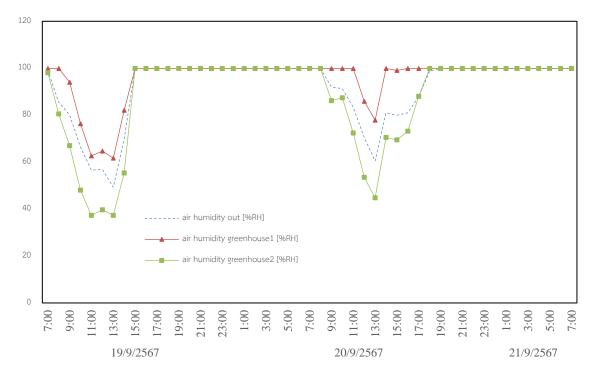


Figure 10 Experimental air humidity

Under optimal operating conditions, the greenhouse system was experimentally validated and benchmarked against a conventional drying setup. The results revealed that the integration of CFD and GA significantly enhanced the overall drying performance. Specifically, the optimized system achieved a reduction in drying time by  $30.0 \pm 2.6\%$ , a decrease in energy consumption by  $25.0 \pm 2.0\%$ , and a reduction in average product moisture content from  $15.5 \pm 1.0\%$  to  $10.5 \pm 0.6\%$ , all of which satisfied standard quality criteria. Moreover, drying uniformity improved markedly from  $70.0 \pm 3.5\%$  to  $90.1 \pm 2.4\%$ , indicating superior heat and airflow distribution across the drying zones. All reported values include standard deviations, and statistical analyses were performed using a 95% confidence level to ensure the robustness and significance of the results. These findings underscore the practical value and technical efficacy of applying CFD and GA techniques in advancing the design and performance of agricultural drying systems.

Table 1 Comparison of greenhouses using GA for analysis

Topic	Traditional drying house	Drying house developed with CFD+GA	% Improvement
Drying time (h)	$10.0 \pm 0.5$	$7.0 \pm 0.3$	decrease $30.0 \pm 2.6\%$
Power consumption (kWh/batch)	$500.0 \pm 10.0$	$375.0 \pm 8.0$	decrease $25.0 \pm 2.0\%$
Moisture content (%wb)	$15.5 \pm 1.0$	$10.5 \pm 0.6$	decrease $32.3 \pm 4.5\%$
uniformity of drying (%)	$70.0 \pm 3.5$	$90.1 \pm 2.4$	increase $28.7 \pm 4.9\%$

#### 4. Conclusions

The drying process is an important step in the agricultural and food industries, aiming to remove moisture from products to an appropriate level. However, inefficient drying process may cause energy consumption, long processing time, and affect the quality of the resulting products, such as moisture retention, inconsistency in drying, or product damage. To solve these problems, this research developed a drying house using multi-zone airflow management with Computational Fluid Dynamics technique and parameter tuning with GA, which is a technology that helps to increase the accuracy and efficiency of the drying process. The experiment compared the results between the conventional and the improved greenhouses by analyzing the main indicators: drying time, energy consumption, average product moisture, and drying uniformity to evaluate the efficiency of the developed technology. The results of this research can be summarized as follows:

- 1. Drying time The CFD + GA greenhouse reduced the drying time by an average of  $30.0 \pm 2.6\%$  from the conventional system ( $10.0 \pm 0.5$  h to  $7.0 \pm 0.3$  h), resulting in increased production efficiency and reduced working time.
- 2. Energy used for drying energy consumption was reduced by an average of  $25.0 \pm 2.0\%$  compared to the original system (500.0  $\pm$  10.0 kWh/cycle to only  $375.0 \pm 8.0$  kWh/cycle), reducing costs and increasing sustainability in the process.
- 3. Product moisture the average product moisture content was reduced by  $32.3 \pm 4.5\%$  wb from  $15.5 \pm 1.0\%$  wb to  $10.5 \pm 0.6\%$  wb, which is in line with the clearly defined quality criteria.
- 4. Drying uniformity the drying uniformity was increased by  $28.7 \pm 4.9\%$  (from  $70.0 \pm 3.5\%$  in the original greenhouse to  $90.1 \pm 2.4\%$  in the CFD + GA greenhouse), resulting in consistent product quality and reduced damage.

#### 5. Acknowledgements

We would like to thank the Smart Agricultural Engineering Program, Faculty of Engineering and Technology, Rajamangala University of Technology Isan, for providing the equipment, tools, and space for development and testing.

#### 6. References

- [1] Mujumdar AS [editor]. Handbook of industrial drying. 3<sup>rd</sup> ed. Boca Raton, Florida, United States: CRC Press; 2006. doi: 10.1201/9781420017618/HANDBOOK-INDUSTRIAL-DRYING-ARUN-MUJUMDAR.
- [2] Mujumdar AS [editor]. Principles, classification, and selection of dryers; Handbook of industrial drying. 3<sup>rd</sup> ed. Boca Raton, Florida, United States: CRC Press; 2006. doi: 10.1201/9781420017618-11/PRINCIPLES-CLASSIFICATION-SELECTION-DRYERS-ARUN-MUJUMDAR.
- [3] Zion market research. Agricultural dryer market size, share, growth report, 2030 [Internet]. 2022 [cited 2025 Jan 07]. Available from: https://www.zionmarketresearch.com/report/agricultural-dryer-market.
- [4] FAO. In brief to the state of food and agriculture 2024 [Internet]. 2024 [cited 2024 Nov 15]. Available from: https://openknowledge.fao.org/items/d287ef86-214b-4f25-a635-98c8f2751035.
- [5] FAO. The state of food and agriculture 2023 [Internet]. 2023 [cited 2024 Nov 15]. Available from: https://openknowledge.fao.org/items/1516eb79-8b43-400e-b3cb-130fd70853b0.
- [6] Dincer I, Sahin AZ. A new model for thermodynamic analysis of a drying process. Int J Heat Mass Transf. 2004;47(4);645–652. doi: 10.1016/J.IJHEATMASSTRANSFER.2003.08.013.
- [7] Ajuebor F, Aworanti OA, Agbede OO, Agarry SE, Afolabi TJ, Ogunleye OO. Drying process optimization and modelling the drying kinetics and quality attributes of dried chili pepper (Capsicum frutescens L.). Trends in Sciences. 2022;19(17):5752. doi: 10.48048/tis.2022.5752.
- [8] Catalkaya M, Akay O, Daş M, Akpinar EK. Application of experimental, numerical, and machine learning methods to improve drying performance and decrease energy consumption of tunnel-type food dryer. Drying Technology. 2023:1–20. doi: 10.1080/ 07373937.2023.2216781.
- [9] Zhu L, Xie Y, Li M, Zhang X, Zhang X, Zhu H, Gu J, Zhang Q, Yang X. Design and optimization of heat pump with infrared drying for Glycyrrhiza uralensis (Licorice) processing. Frontiers in Nutrition. 2024;11:1-14. doi.org/10.3389/fnut.2024.1382296
- [10] Babu AK, Kumaresan G, Raj VAA, Velraj R. Review of leaf drying: Mechanism and influencing parameters, drying methods, nutrient preservation, and mathematical models. Renewable and Sustainable Energy Reviews. 2018;90:536–556. doi: 10.1016/ J.RSER.2018.04.002.