ZIBELINE INTERNATIONAL™ PUBLISHING

ISSN: 2576-6724 (Print)
ISSN: 2576-6732 (Online)
CODEN: ACMCCG

Acta Chemica Malaysia (ACMY)

DOI: http://doi.org/10.26480/acmy.01.2024.01.12

CrossMark

RESEARCH ARTICLE

MULTI-GENE GENETIC PROGRAMMING MODELING OF THERMODYNAMIC CHARACTERISTICS OF CONVECTIVELY DRIED COBRA 26 F1 TOMATO, GRAPHIC USER INTERFACE MODEL DEPLOYMENT, AND SENSITIVITY ANALYSIS

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ARTICLE DETAILS

Article History:

Received 17 January 2024
Revised 20 February 2024
Accepted 23 March 2024
Available online 28 March 2024

ABSTRACT

This study explores the thermodynamic characteristics of convectively dried Cobra 26 F1 tomatoes at various temperatures and after different thermal pre-treatments. Employing Multi-gene Genetic Programming (MGGP), the refined model accurately predicts energy utilization (EU), energy utilization ratio (EUR), exergy loss (ExLoss), and exergy efficiency (ExEff). The MGGP model, structured with 100 populations, 150 generations, and 4 trees, demonstrated superior performance, with R2 values of 0.9155, 0.9116, 0.9756, and 0.9736 for EU, EUR, ExLoss, and ExEff, respectively. The model was successfully deployed to a graphic user interface (GUI), achieving high accuracy rates of 99.97-99.99% when tested on randomly selected drying conditions. Monte Carlo simulation was employed to assess the sensitivity of thermodynamic characteristics to drying factors, revealing significant influences of temperature, time, and pre-treatment variations. The results indicate the EU, EUR, ExLoss, and ExEff responses to temperature, time, and pre-treatment changes, providing valuable insights for sustainable process design, management, control, and commercialization of dried Cobra 26 F1 tomato production. Overall, this research contributes essential knowledge for enhancing the efficiency and sustainability of dried food production processes.

KEYWORDS

Energy and exergy, sensitivity analysis, Cobra 26 F1 tomato, modelling, drying, multi-gene genetic programming

1. INTRODUCTION

Drying is an age long preservation technique that constitutes greatly to food industries as unit operation for product processing and storage (Golpour et al., 2020). Drying gives value to food and vegetables; reduces weight and makes stable for longer period. Therefore, drying can effectively deal with food insecurities resulting from the inability to store bountiful yields during peak harvest seasons. Variants of drying technologies with varied effectiveness exist; however, all drying technologies work towards minimizing water activity, enzymatic reaction and spoilage organisms' activity (Rahmawati et al., 2020).

Compared to convective drying technology, modern drying technologies (such as ultrasonic, microwave, infrared and others) have the advantages of considerably reducing the drying time and preserving the product quality, however, their adaptability for commercial purposes in the developing countries is still technically challenging, thereby making convective drying technology to remains a popular option (Kaveh et al., 2018). Convective drying technology has low investment cost, easy installation and maintenance, effectiveness, and operational simplicity. Convective drying technology can also close ranks with modern drying technologies (especially in drying time reduction and product quality preservation) if appropriate pre-treatment methods such as oil blanching, alkaline solution blanching, hot water blanching and others were applied (Ojediran et al., 2020; Adeyi et al., 2022). Previous studies by Inyang et al., Adeyi et al., and Rahmawati et al., applied convective drying technology to stabilize unripe plantain, fish cracker and indigenous cocktail yeast mold culture, while Anawe and Folayan, and Golpour et al., utilized convective drying technology to evaluate the energy and exergy characteristics of onion and potato (Inyang et al., 2018; Rahmawati et al., 2020; Adeyi et al., 2018; Anawe and Folayan, 2018; Golpour et al., 2020). It therefore implied that convective drying technology remains relevant and suitable amidst modern technologies. Hence, this study is also focused on the application of convective drying technology to investigate the energy and exergy characteristics of Cobra 26 F1 tomato.

Quick Response Code	Access this article online	
	Website: www.actachemicamalaysia.com	**DOI:** 10.26480/acmy.01.2024.01.12

Cite the Article: Hamdan Alanzi, Hamoud Alenezi, Oladayo Adeyi, Abiola J. Adeyi, Abogunrin-Olafisoye Oladunni Bola, Chee-Yuen Gan, Olusegun Abayomi Olalere, Osama Al-Qabandi (2024). Multi-Gene Genetic Programming Modeling of Thermodynamic Characteristics of Convectively Dried Cobra 26 F1 Tomato, Graphic User Interface Model Deployment, and Sensitivity Analysis. *Acta Chemica Malaysia, 8(1): 01-12.*

Energy is stated as the tendency to perform work (not the work done), while exergy is stated as the maximum work produced (the work done) in a system as its temperature reaches the environmental equilibrium state (Encarta, 2009; Zadhossien et al., 2021). In energy dependent systems, probing the effectiveness for energy conversion cannot be evaluated efficiently and precisely with energy analysis alone except with complimentary exergy analysis because exergy analysis is a means towards the achievement of sustainable development (Terzi, 2018; Dincer and Rosen, 2004). Apart from thermal systems analysis, exergy analysis is also essential for design and optimization of process and equipment by profiling the energy availability at different times and locations (Akpinar, 2005). Therefore, energy (usually analyzed with first law of thermodynamics) and exergy (usually analyzed with second law of thermodynamics) are co-joined analysis for thermal operations efficiency, troubleshooting and enhancement (Nikbakht et al., 2014). Usually, drying is an energy intensive process (Liu et al., 2019), hence, the need to reduce the associated expenses on energy utilization and assuring the efficiency of the drying equipment is paramount (Darvishi et al., 2014). To this end, the thermodynamic analysis (energy and exergy) becomes pivotal to the effective management of energy in thermal processes such as drying.

In the existing knowledge, Okunola et al., worked on energy and exergy analyses of okra drying process in a forced convection cabinet dryer (Okunola et al., 2021). A group researchers also worked on energetic and exergetic analysis of a convective drier using potato drying process as a case study (Golpour et al., 2020). These show that energy and exergy study is dependent on dryer type as much as it depends on the material or product subjected to drying. This is a clear indication of material-processing-property relationship. The Cobra 26 F1 tomato is an improved tomato breed that is gaining popularity amongst the citizenry due to its nutritional integrity and shelf stability. It is a crossbreed strain with distinctive attribute (physical and chemical). Therefore, it is save to hypothesis that the drying related knowledge of Cobra 26 F1 tomato will be distinct from other traditional tomatoes drying knowledge in the literature (Adeyi et al., 2022). Consequently, and to aid the industrial drying acceptability of Cobra 26 F1 tomato, a study focused on its thermodynamic analysis for thermal efficiency is necessary. Up until now, no literature had earlier reported the energy and exergy analysis specific to convectively dried Cobra 26 F1 tomato, and this could be considered as a study gap.

Modelling of phenomena plays an important role for in-depth understanding of mechanism, if-then analysis and control (Mbegbu et al., 2021). To this end, various modelling methods, including statistical, physics, empirical, artificial intelligence (AI) and others are used in science and engineering (Alenezi and Al-Qabandi, 2023; Alenezi et al., 2022; Olalere et al., 2022; Mokaizh et al., 2022). Since the performance of a particular modelling method is strongly dependent on the nature of the data, then, there is no cure all modelling method. This reason reinforces the need to investigate various modelling methods for specified application before making a choice for implementation of process control. Of all the modelling methods, AI methods are gaining popularity because of their capability for complex multi-variant modelling and accuracies (Okonkwo et al., 2022). Of all the presently available AI method, a scantly used one is the Multi-gene Genetic Programming (MGGP). MGGP is a machine learning technique with capability to infer statistical model as against networked architecture models that is customary to most AI modelling methods including artificial neural networks (ANN), fuzzy logic (FL), adaptive neuro fuzzy inference system (ANFIS), and support vector machine (SVM) amongst others (Olalere et al., 2022; Sharief and Sheta, 2014). MGGP is based on natural evolution theory where fitter solutions are derived from multi-generational simulation within a specified population. In previous AI modelling of thermodynamic analysis research, Liu et al., applied ANN to model the dependence of the energy and exergy characteristics of mushroom slices drying in hot air impingement dryer on the drying factors (Liu et al., 2019). Nikbakht et al., applied response surface methodology (RSM) and ANN to model the energy and exergy analysis of microwave assisted thin layer drying of pomegranate arils (Nikbakht et al., 2014). However, the application of MGGP AI to predict thermodynamic characteristics is scarce in the literature.

In addition, the use of graphic user interface (GUI) to drive technical operations is useful in applied engineering practice. A unique attribute of GUI to process industry is the deployment of mathematical model (backend) with interactive user interface (frontend) application for easier process management. This simplifies processing and gives advantage to even non-technically inclined (without deep scientific background knowledge) operators to communicate or work with the process. This can seriously demystify process monitoring, control and decision-making. The application of GUI to wrap the MGGP predictive models of energy and exergy analysis of a drying process is scarce in the literature. Moreover, the evolution of present-day knowledge makes it a scientific dishonesty to carry out modelling without conducting the sensitivity analysis of the model because the choice of influencing factors parameters are risk incorporated (Rai et al., 1996). Therefore, it is important to quantify such risk or uncertainty in other to deepen the mechanistic understanding, standardization and control of the process. Although authors have conducted sensitivity analysis on conventional drying process using Monte Carlo simulation (MCS), such analysis on the energy and exergy characteristics is still a gap or scarce in the literature (Adeyi et al., 2021a; Adeyi et al., 2020; Adeyi et al., 2021b).

Based on our literature search, the investigation of the thermodynamic characteristics of convectively dried thermally pre-treated Cobra 26 F1 tomatoes, application of MGGP to model the experimental thermodynamic characteristics, implementation of GUI application for the thermodynamic characteristics and the investigation of the sensitivity analysis of the thermodynamic characteristics to the influencing drying factors are observable gaps in the literature. Attendant to these observed gaps are the novelty and objectives of this study because elucidation of the specific material - processing - properties relationship necessary for realistic specific process and equipment design, monitoring and control is an important consideration for product commercialization.

2. MATERIALS AND METHODS

2.1 Sample Preparation

Matured unblemished Cobra 26 F1 tomatoes were purchased from a local farm in Omu-Aran, Kwara State Nigeria. The Department of Biological Science (Botany unit) of Landmark University Omu-Aran Nigeria assisted to confirm the tomato to be of Cobra 26 F1 variety. The tomatoes samples are represented in Figure 1.

Figure 1: Cobra 26 F1 tomatoes

In accordance with the work of Ekissi et al., the physicochemical properties of Cobra 26 F1 tomato is characterized by water content level of 94.52, ash content of 10.63, oBrix of 4, hydrogen potential of 4.29, acidity level of 6, vitamin C level of 150.28 (Ekissi et al., 2021). In addition, Cobra 26 F1 has organoleptic property (acceptability) of 6.16 ± 1.83 compared to Kilélé (6.21 ± 1.73) and old tomato (5.05 ± 1.77) varieties, respectively (Ekissi et al., 2021).

The tomato samples were rinsed in drinkable water for 5 min, recovered by hand picking and wiped with soft cloth to remove excess water. Thereafter, tomato samples of equal thicknesses (6 mm) and diameter (approximately 45 mm) were cut out using knife. The sample dimensions were verified with vernier caliper. The samples were pre-treatment using steam and hot water blanching procedure in accordance with the method of (Adeyi et al., 2022). In brief, steam blanched samples were achieved through sample exposure to blancher's steam while hot water blanched samples were achieved through sample insertion into hot water (80 OC) for 5 min blanching time, respectively. After the specified blanching time, samples were recovered, and excess surface water removed with tissue paper. The blanched samples were left to air dry and attain room temperature before further studies were conducted. The initial moisture content of the un-blanched, steam-blanched, and hot-water-blanched Cobra 26 F1 samples in this study as determined with oven drying method at 105 OC for 5 h (AOAC, 1990) were 94.49%, 94.65% and 94.80% wet basis (wb g/g), respectively.

2.2 Drying Procedure and Data Analysis

The influence of temperature of drying (40, 50, 60 and 70OC) on the energy and exergy characteristics of un-blanched (UB), steam-blanched (SB) and hot-water-blanched (HWB) tomatoes samples were investigated in convective dryer equipment (Stangas SG-90526, Stangas Italy). The dryer was operated at an unchanged air-drying velocity of 1.2 m/s. Samples (approximately 7 g ± 0.50 g) of un-blanched Cobra 26 F1 tomatoes were spread un-stacked on the drying tray within the dryer after the dryer had initially worked unloaded for 30 min to allow for equal temperature distribution within the dryer. Sample weights consequent to the moisture loss were recorded at successive 10 min intervals when the drying experiment first started and 30 min interval towards the end of the drying investigation by weighing on a digital-scale balance (having ± 0.01 g accuracy). The weighing continued until samples reached a constant weight.

To obtain data for energy and exergy analysis, the dryer inlet/outlet temperatures and relative humidity values at drying sample's weighing intervals were measured and recorded with dryer attached sensors DS18B20 and DHT11, respectively, as also used (Okunola et al., 2021). The same drying procedures were repeated for the steam and hot-water-blanched samples. Possible errors during experimentation from human, machine, procedures and environment were envisaged; therefore, each specific drying experiment was performed twice, and the means of the results were used for the energy and exergy analysis. The equations utilized for energy and exergy analysis in this study are summarized in Table 1.

Table 1: Thermodynamic (energy and exergy) equations utilized.

Energy analysis Equation number Equation	Reference
EU = $\dot{m}_a(h_{ai} - h_{ao})$	Golpour et al., 2020
$\dot{m}_a = \rho_a\, v_a\, A_a$	Odewole et al., 2020
$h_a = C_a\,(T_a - T_e) + h_{fg}$w	Azadbakhtn et al., 2017
C_a = 1.004 + 1.88*w	Golpour et al., 2020
$w_a = \frac{0.622*\text{Ø}*P_{vs}}{P-\text{Ø}*P_{vs}}$	Akpinar, 2005
$w_{ao} = w_{ai} + \frac{\dot{m}_t}{\dot{m}_a}$	Golpour et al., 2020
$\dot{m}_t = \frac{We_t - We_{t+\Delta t}}{\Delta t}$	Nikbakht et al., 2014
EUR = $\frac{\dot{m}_a(h_{ai}-h_{ao})}{\dot{m}_a(h_{ai}-h_e)}$	Golpour et al., 2020
Exergy analysis **Equation number Equation**	**Reference**
Cp_{da} = 1.0029 + 5.4 * 10-5 T_{da}	Alenezi and Al-Qabandi, 2023
$Ex_i = Cp_{da}\,[(T_{dai} - T_\infty) - T_\infty Ln\frac{T_{dai}}{T_\infty}]$	Nikbakht et al., 2014
$Ex_o = Cp_{da}\,[(T_{dao} - T_\infty) - T_\infty Ln\frac{T_{dao}}{T_\infty}]$	Anawe and Folayan, 2018
$Ex_{loss} = Ex_i$ - Ex_o	Okunola et al., 2021
$\eta_{exergy} = 1 - \frac{Ex_{loss}}{Ex_i}$	Nikbakht et al., 2014

The equations (1 – 7) were applied for the energy analysis; where, EU (kJ/s) is the energy utilization, $\dot{m}_a$ (kg/s) is the mass flow rate of air, ρ_a (kg/m3) is the air density, v_a (m/s^2) is the air velocity, A_a (m^2) is the area of air inlet, h_a (kJ/kg) is the enthalpy of air, C_a (kJ/kg OC) is the specific heat of air, T_a (OC) is the temperature of air, T_e (OC) is the temperature of the ambient, h_{fg} (kJ/kg) is the latent heat of vaporization of water, and w (kg water/kg dry air) is the absolute humidity, w_a is the transformer of relative humidity to absolute humidity (kg/kg), Ø is the relative humidity (%), P is the atmospheric pressure (kPa), and P_{vs} is the saturated pressure (kPa), $\dot{m}_t$ is the mass transfer rate (kg/s), We_t (kg) is the initial weight of the product, $We_{t+\Delta t}$ (kg) is the weight at different drying times of the product and Δt (s) is the drying time, EUR is the energy utilization ratio and h_e (kJ/kg) is the specific enthalpy of the ambient. The subscript i and o are representation of inputs and outputs, respectively.

Likewise, the equations (8 – 12) were applied for the thermodynamics exergy analysis where Cp_{da} (kJ/kg OC) is the specific heat of drying air, T_{da} (OC) is the temperature of the drying air, Ex (kJ/s) is the exergy, T_∞ (OC) is the ambient temperature, T_{dao} is the temperature of the dryer measured at the inlet, Ex_{loss} is the exergy loss and η_{exergy} is the exergetic efficiency. The subscript i and o are representation of inputs and outputs, respectively.

2.3 MGGP Modeling

Genetic programming (GP), created by J. Kozais in the year 1992 biologically inspired machine learning process (Sharief and Sheta, 2014; Morrison et al., 2010). The GP is useful for model representation of systems and processes. GP is also useful for solution development for regression problems. Typically, GP applies the principles of genetic algorithms (GA) to solve a problem by evolving probable solutions represented as computer programs. The computer programs consist of tree structure, made up of incremental units as represented in Fig. 2 (where a_1 and a_2 are the input factors of an historical data being modelled). The trees are also called genes.

In its solution procedure, GP creates initial population of probable solutions amongst which the best performing individuals are selected and recombined (using mutation, elitism, and cross over rules) to create a new stronger population of probable solutions. This new population of solutions forms the next generation. The solution procedure continues until GP attains the population that contains program or solution that best solved the task. Compared to some intelligent methods like decision trees and ANN, GP can determine models that have equal or improved performance (Jabeen and Baig, 2010). When GP algorithm creates more than one gene (components of a solution), it is termed a multigene genetic algorithm (MGGP). The multi gene solution is the linear combinations of low order non-linear transformation of the non-dependent variables and consists of several individual GP trees. The multi gene GP often derives efficient solution than single gene GP (Abhishek et al., 2014). The genes are made up of predefined functions set and terminals and are incrementally built to strengthen their stiffness through minimizing of the model error that result in a model characterized with weights and bias that depicts the intrinsic characteristics of a process. A typical MGGP solution model is represented Eqn (13).

$$y = k_o + k_1 * tree\ 1 + \cdots + k_b * tree\ b \tag{13}$$

where k_o is the model constant or bias term, k_1, … , k_b are the weights of the gene, subscript b is the number of genes in the ith set of input.

In MGGP, the mathematical model development from dataset is termed symbolic data mining. The symbolic data mining has advantage over empirical model because the coefficients of the model are established alongside the model structure. More also, MGGP can establish concise and accurate models even for complex multi-dimensional problems (Adeyi et al., 2021). Another important consideration for MGGP is the structural transparency of the model, which is a great advantage when compared with networked architectural models that are associated with ANN, ANFIS and other intelligent methods (Searson et al., 2010). Transparent models are easily deployable for process, monitoring, and control. In this study, the MGGP structure was refined to model the observed experimental thermodynamic characteristics. The refinement was done around the optimum population size and number of generations. Observed experimental data were divided into training (70%) and testing data (30%). The MGGP parameter settings used in this study are represented in Table 2.

Other variables in the table were kept constant while population size (300 and 500) and number of generation (100 and 200) were varied. The MGGP solution procedure was implemented in Matlab R2010a software. The efficiency of the developed MGGP model and prediction was determined using the coefficient of determination and root mean square error statistical measures.

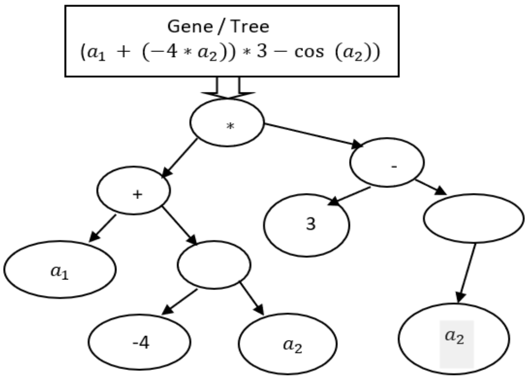


Figure 2: Representation of a typical MGGP structure

Table 2: MGGP parameter setting.		
Variable	**Characteristics**	**Value**
Population size	varied	300 and 500
Number of generations	varied	100 and 200
Tournament size	fixed	4
Elitism fraction	fixed	0.02
Termination value	fixed	0.001
Maximum gene	fixed	4
Node Functions	*fixed*	*times, minus, plus, rdivide, psqroot, plog, square, tanh, pdivide, iflte, sin, cos, exp*

2.4 GUI Application Implementation

In this study, the models developed by MGGP for EU, EUR, Ex_{Loss} and Ex_{Eff} were regarded as estimators. The estimators were deployed for GUI application development. The stages involved are represented in Figure 3. Matlab 2021 software was utilized to build the backend and the frontend application for the GUI application. Once built, the efficiency of the GUI application was statistically validated with mean estimation accuracy.

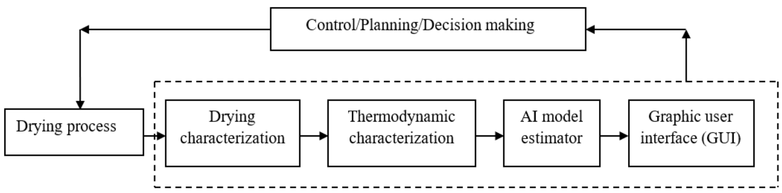


Figure 3: GUI application development

2.5 Performance Efficiency

The statistical measure employed in this study for determine the performance efficiency of the MGGP and soft sensor are represented in Eqns (14) - (16), respectively.

$$\text{Coefficient of determination } (R^2) = 1 - \left[\sum_{i=1}^{n} \frac{(\text{Pred,i} - \text{Exp,i})^2}{(\text{Pred,i} - \text{AverageExp})^2}\right] \quad (14)$$

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{n}(\text{Exp,i} - \text{Pred,i})^2}{N}} \quad (15)$$

$$\text{Accuracy} = \left[100 - \sqrt{\frac{\sum_{i=1}^{n}(\text{Exp,i} - \text{Pred,i})^2}{N}}\right] \quad (16)$$

Where $Pred_{,i}$ is the i^{th} predicted value, Exp,i is the i^{th} experimental value. $Average_{Exp}$ is the mean experimental value. N is observation number.

2.6 Sensitivity Analysis

The investigation of the level of contribution of each drying factor to the energy and exergy characteristics (EU, EUR, Ex_{Loss} and Ex_{Eff}) of convectively dried Cobra 26 F1 tomato is crucial for making operational decision for the process. Such investigation represents the sensitivity of a process characteristic or performance indicator to the process factors. In this study, the sensitivity analyses were determined using Monte Carlo Simulation (MCS).

3. Results

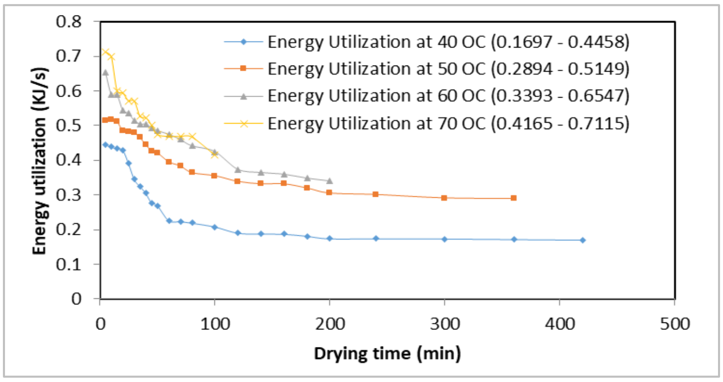
3.1 Drying factors effect on energy utilization

The background of energy analysis is the energy balance or energy conservation relationship which implied that energy given to a system is equal to the energy coming out of the system and the energy accumulated within the system (Golpour et al., 2020; Terzi, 2018). Energy accumulated within the system is the energy available to do work. Bearing this in mind, the energy utilization at different temperature and pre-treatment in this study is represented in Figure 3 (a – c). The figure showed that energy utilization (i.e., energy accumulation) amplifies with increased temperature from 40 to 70°C. This observation can be explained by changes in thermodynamic parameters (such as enthalpy and humidity ratio increase, air density decreases and other) that accompanied temperature increase (Golpour et al., 2020). The figure also showed that the energy utilization at all the temperature considered reduced as the drying time increased; this is related to the decreasing mass transfer rate as drying progressed. A group researchers also made an identical observation when the energy and exergy analysis of mushroom slices dried in hot air impingement dryer was investigated (Liu et al., 2019).

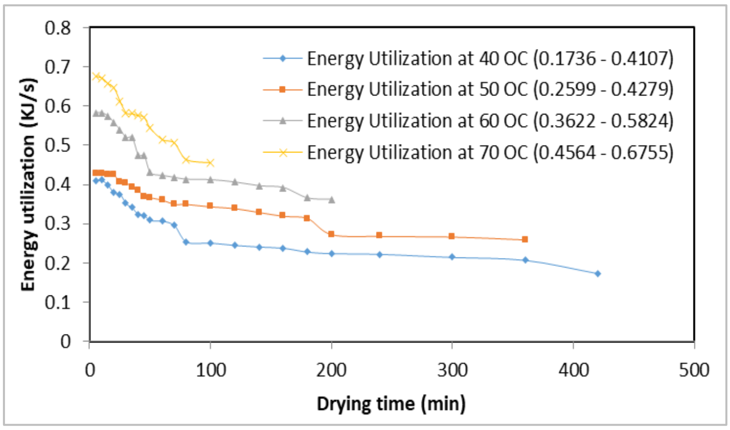
In addition, Figure 4 (a – c) showed that energy utilization decreased from un-blanched sample to steam-blanched sample and to hot-water-blanched sample, successively. This observation resulted from increased energy output that led to lowered energy accumulation in the successive samples. The increased energy output is attributed to increased initial moisture content and weakened capsule/tissue microstructure of the successive samples because of the applied blanching pre-treatment. The ranges of the minimum and maximum energy utilizations at different drying temperatures were also depicted on Figure 4 (a – c).

3.2 Effect of Drying Factors on Energy Utilization Ratio

Considering the relationship for energy utilization ratio stated in Eqn. 7, it could be established that energy utilization ratio implied the energy accumulated with respect to the dryer in relation to the energy accumulated with respect to the ambient condition. This means the dryers' accumulated energy from a total possible energy. The energy utilization ratio results in this study are represented in Figure 5 (a –c). The figure showed that energy utilization ratio decreased with increased drying temperature from 40 – 70 OC. This observation reinforced the observation noticed for the energy utilization result in section 3.1, because considering Eqn. 7, the higher the energy utilization the lower the energy utilization ratio could be. A close observation was also reported by Nikbakht et al., drying of pomegranate arils (Nikbakht et al., 2014). Furthermore, Figure 5 (a – c) showed that energy utilization ratio decreased from un-blanched sample to steam-blanched sample and to hot-water-blanched sample, successively. This observation resulted from increased energy output that led to lowered energy accumulation in the successive samples. The increased energy output is attributed to increased initial moisture content and weakened capsule/tissue microstructure of the successive samples because of the applied blanching pre-treatment. The ranges of the minimum and maximum energy utilization ratios at different drying temperatures were also depicted on Figure 5 (a – c).



(a)



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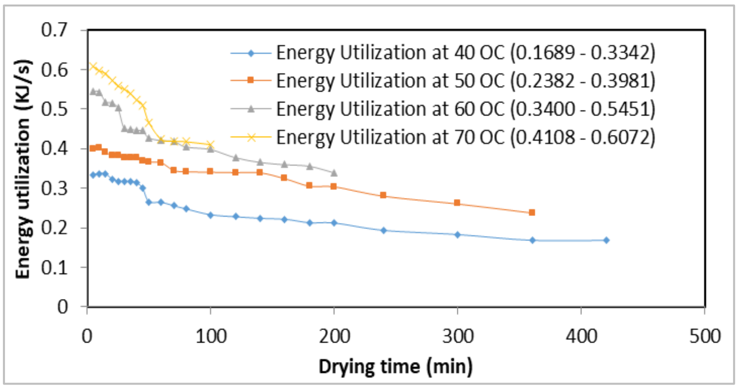
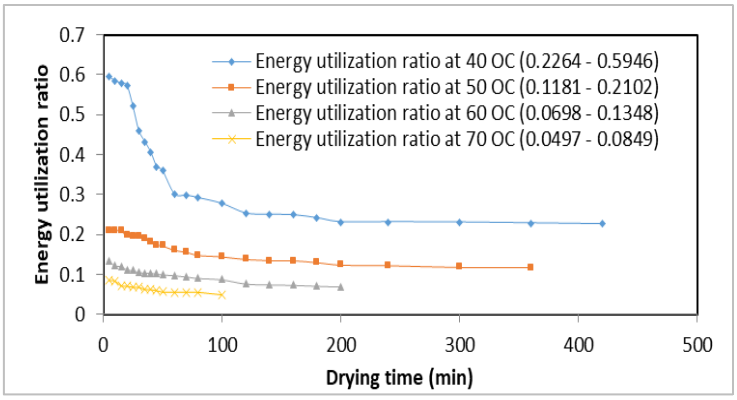
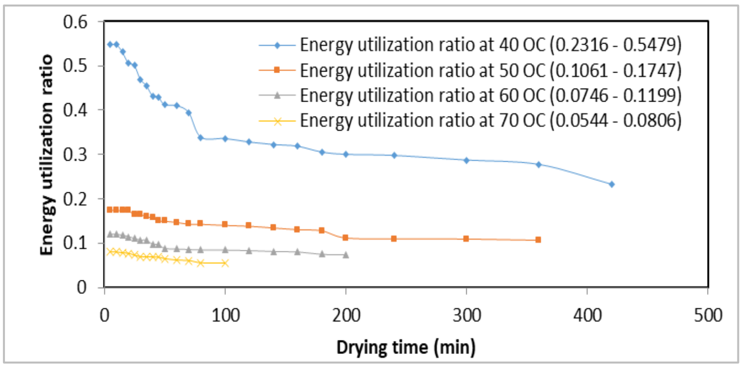


(c)

Figure 4: Energy utilization for (a) un-blanched (b) steam-blanched and (c) hot-water-blanched sample



(a)



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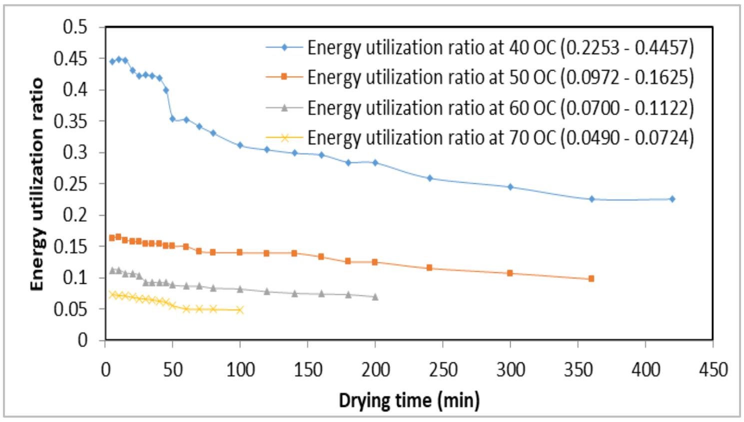


(c)

Figure 5: Energy utilization ratio for (a) un-blanched (b) steam-blanched and (c) hot-water-blanched sample

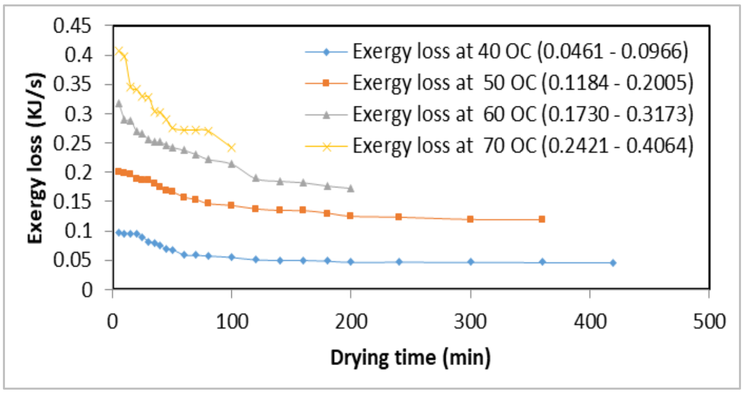
3.3 Effect of Drying Factors on Exergy Loss

The background of exergy analysis is the exergy balance which states that exergy input must be equal to the summation of exergy accumulation, exergy consumption and exergy output (Akpinar, 2005). Relying on this principle, it therefore means that exergy loss is the combination of exergy accumulation and consumption. The accumulated exergy is consumed due to irreversibility (Nikbakht et al., 2014). The exergy loss at different drying temperature and pre-treatment variation in this study is represented in Figure 6 (a – c). The figure showed that exergy loss increased with increased drying temperature from 40 to 70 °C, meaning that amplified temperature amplified the energy accumulated and consumed. In addition, the exergy loss for all temperature considered reduced as the drying time increased. Golpour et al., [1] in energy and exergy analysis of convectively dried potato also reported a similar observation (Golpour et al., 2020).

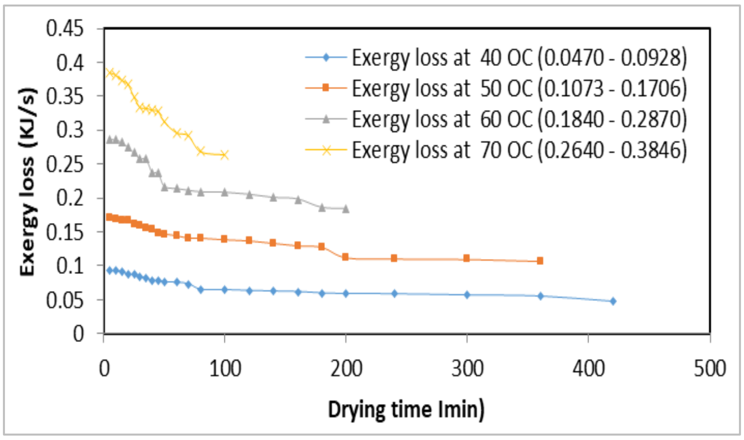
Furthermore, Figure 6 (a – c) showed that exergy loss decreased from un-blanched sample to steam-blanched sample and to hot-water-blanched sample, successively. This observation resulted from increased exergy output that led to lowered summation of accumulated and consumed exergy in the successive samples. The increased exergy output is attributed to increased initial moisture content and weakened capsule/tissue microstructure of the successive samples because of the applied blanching pre-treatment. The ranges of the minimum and maximum exergy losses at different drying temperatures were also depicted on Figure 6 (a – c).

3.4 Exergy Efficiency

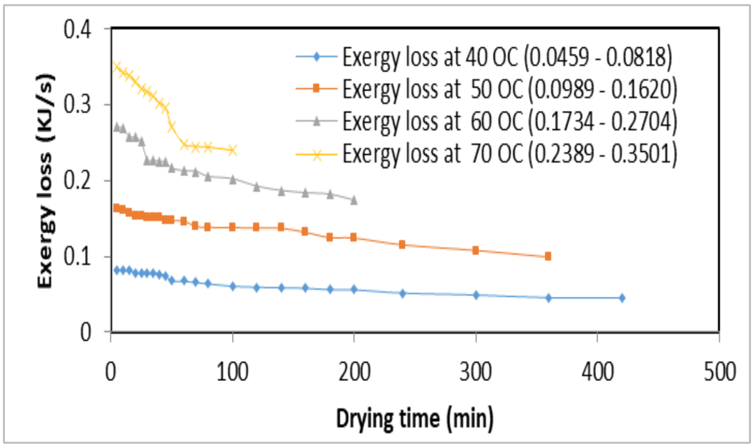
In thermodynamic analysis, the exergy efficiency gives a verifiable measure of the performance of drying operations; therefore, higher exergy efficiency is desirable (Goulpour et al., 2020). The exergy efficiency result in this study is represented in Figure 7 (a – c). The figure showed that exergy efficiency increased with increased drying temperature from 40 to 70 °C. This result is true because going by Eqn. 11, higher exergy loss signifies the summation of higher exergy accumulation and exergy utilization with lower exergy output. Therefore, higher exergy loss implied lower or minimized exergy wastages, which also means higher exergy efficiency. Buttressing furthermore, Eqn. 12 signifies that higher exergy loss is a prerequisite for higher exergy efficiency. Therefore, the result in Figure 7 (a - c) implied that the drying process of thermally pre-treated Cobra 26 F1 tomato is most exergetically efficient at 70 °C at all pre-treatment variations in this study. This observation is attributed to the higher mass transfer rate occurring at higher temperature. More also, the effect of pre-treatment on the exergy efficiency in Figure 7 (a - c) showed that hot-water-blanched pre-treated samples were most exergetically efficient. This can be attributed to the change in the microstructure of the samples from un-blanches, steam-blanched and hot-water-blanches samples. Akpinar and Nikbakht et al., reported a close observation in their respective thermodynamic studies on eggplant and pomegranate arils drying (Akpinar, 2005; Nikbakht et al., 2014).



(a)

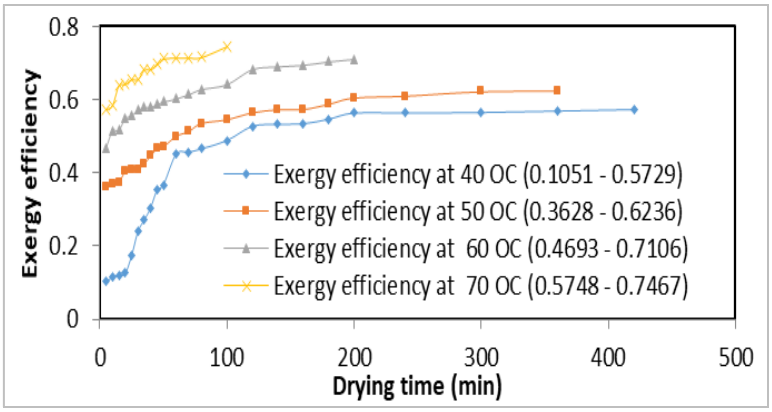


(b)

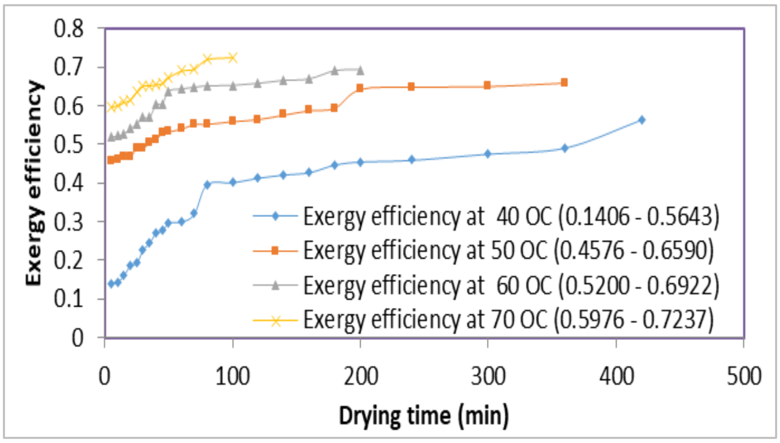


(c)

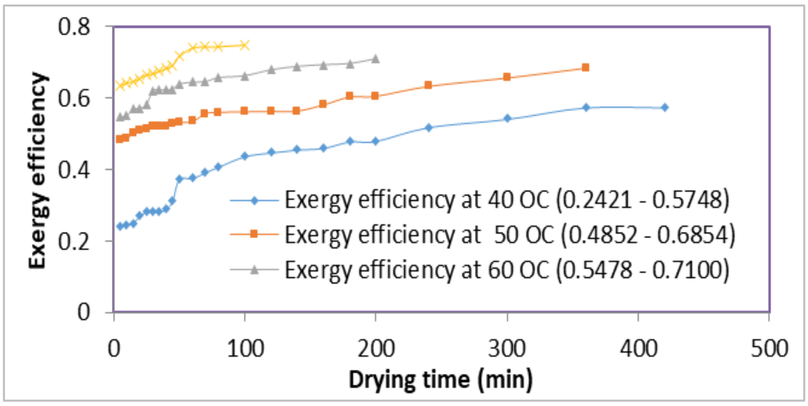
Figure 6: Exergy loss for (a) un-blanched (b) steam-blanched and (c) hot-water-blanched sample



(a)



(b)



(c)

Figure 7: Exergy efficiency for (a) un-blanched (b) steam-blanched and (c) hot-water-blanched sample

3.5 Energy and Exergy Data Description

The description of the energy and exergy data intended for statistical predictive model development using RSM in this study is represented in Table 3. The descriptive statistics enables familiarity and understanding of the data.

Table 3: Description of the experimental data

Descriptive statistics	EU	EUR	Ex_{Loss}	Ex_{Eff}
Mean	0.3931	0.1842	0.1733	0.5315
Standard error	0.0080	0.0087	0.0060	0.0095
Median	0.3845	0.1351	0.1588	0.5638
Standard deviation	0.1231	0.1341	0.0930	0.1457
Sample variance	0.0151	0.0179	0.0086	0.0212
Kurtosis	-0.5177	0.7690	0.4340	0.9999
Skewness	0.2009	1.2990	0.4340	0.9999
Range	0.5426	0.5455	0.3604	0.6449
Sum	**91.9951**	**43.1230**	**40.5688**	**124.3713**

Amongst other data description given in Table 3, the skewness represents the measure of data inequality around its mean value. The skewness can be positive, negative, or undefined; and in a normal distribution, the tail on either side of the m s the exact mirror image of one another. In addition, the Kurtosis measures the profusion or lack of outliers in relation to a normal data distribution. The kurtosis is regarded as heavily tailed or light tailed depending on the quantity of outliers in a data. It should be noted that the Kurtosis is distinct from standard deviation, which quantifies the amount by which data differs from the arithmetic mean. The types of kurtosis include meso, lepto and platykurtic. The other data descriptors including mean, median, mode, standard error, samples variance, standard deviation and others are literal.

The skewnesses in the data category (energy utilization, energy utilization ratio, exergy loss and exergy efficiency) are low and positive meaning that the data are normally distributed and has symmetry about its mean in a frequency distribution. Furthermore, the Kurtosis values in the factors are also low. This shows that a larger portion of the data fits to a specific distribution while very few portion deviates. The observations in the data descriptive statistics therefore implied that the data is uniformly organized and reliable.

3.6 MGGP Modeling and Prediction

The summary of different MGGP structures that were investigated for modeling and prediction of the thermodynamic characteristics in this study are depicted in Table 4.

The optimization of the MGGP structure was based on the number of population and number of generations. The best structure was selected using coefficient of determination (measure of prediction accuracy of the developed model) value. A high coefficient of determination value (close to unity) is desirable because it is an implication of high prediction accuracy (Oke et al., 2017; Olalere and Gan, 2023). The coefficient of determination of all the tested structures were high (> 0.9000), however, Table 6 showed that higher coefficient of determination was generally achieved in all the MGGP structure that comprised of 100 number of population with 150 number of generation. A minimal number of population or generation is desirable in AI model building to preserve the memory utilization of the computer during development, deployment, and utilization of models. The training process for the best MGGP structure applicable to EU, EUR, Ex_{Loss} and Ex_{Eff}, respectively is represented in Figure 8.

Table 4: Refining/optimization of MGGP structure

College	Number of population	Number of population	R^2
EU	100	100	0.91202
	100	150	0.93047
	200	100	0.92120
	200	150	0.92295
EUR	100	100	0.90684
	100	150	0.94341
	200	100	0.94156
	200	150	0.94188
ExLoss	100	100	0.96826
	100	150	0.97702
	200	100	0.96241
	200	150	0.97362
ExEff	100	100	0.90893
	100	150	0.93490
	200	100	0.92557
	200	**150**	**0.93111**

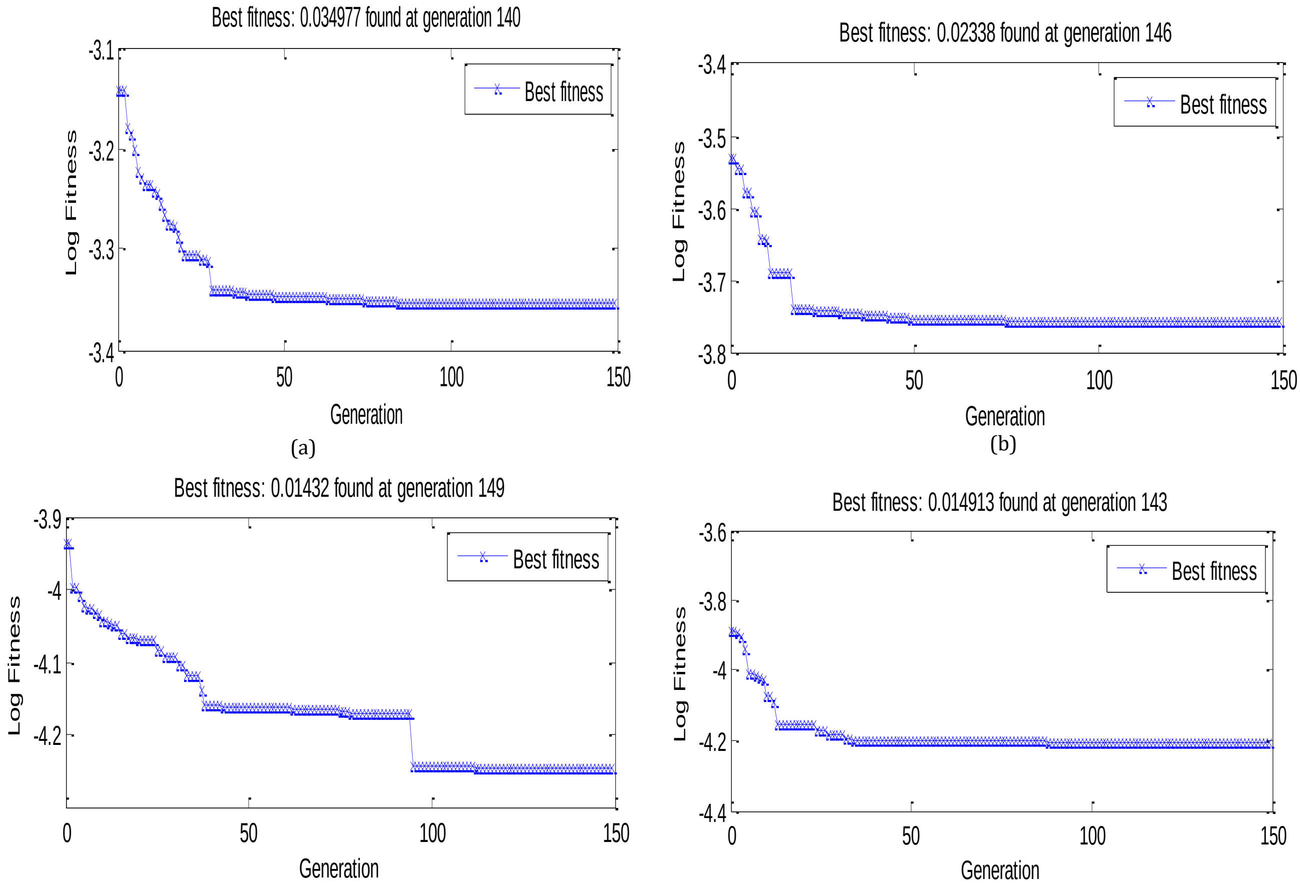


Figure 8: MGGP model development of (a) EU, (b) EUR, (c) Ex_{Loss} and (d) Ex_{Eff}

The Fig. 8 showed that Ex_{Loss} utilized the maximum number of generations of 149 and have the least root mean square error of 0.0143 while EU utilized the least number of generations of 140 and have the maximum root mean square error of 0.0349 during structure training and model inference before a solution was found. This observation showed that there is likelihood of improved accuracy at the choice of higher generation than the selected 150 maximum number of generation.

The MGGP structured models that gave the highest coefficient of determination reported in Table 6 are presented in Eqns. (17) – (20) for EU, EUR, Ex_{Loss} and Ex_{Eff}, respectively.

$$\text{EU}= 0.01373 * x_2 - 0.0008257 * x_3\,(x_2 + 5.705) + \frac{3.947*(x_1^2+x_2)*(x_2-x_3)*(x_3+x_3-x_2)}{10^7} - 0.1024 \quad (17)$$

$$\text{EUR}= 0.007891 * x_2 - 0.03551 * x_3 - \frac{2.445*(x_2-9.87)*(x_2-6.714*x_3)*(x_1-x_2)}{10^7} - 0.002596 \quad (18)$$

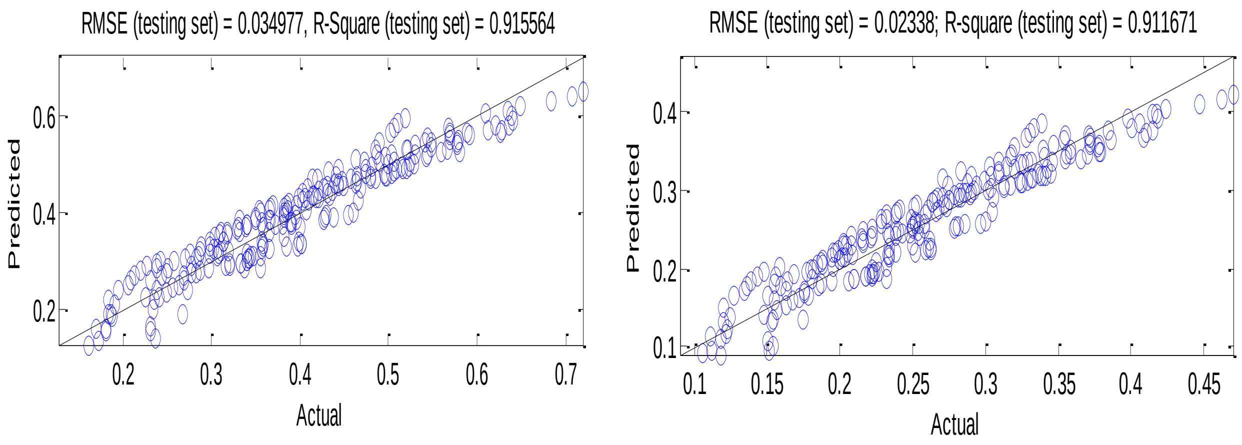
$$\text{ExLoss} = 0.00912 * x_2 - 0.01992 * x_3 + \frac{5.328*x_1*x_2*(x_2-9.122)*(7.706*x_3-x_2+9.147)}{10^9} - 0.2413 \quad (19)$$

$$\text{ExEff} = 0.0005016 * (x_2 + 27.8) * (x_3 + 20.43) + \frac{5.613*x_1*x_2\,(x_2-29.52)*(x_2-x_3)}{10^9} - 1.031 \quad (20)$$

Where, x_1, x_2 and x_3 are the drying time, drying temperature and the pretreatment type.

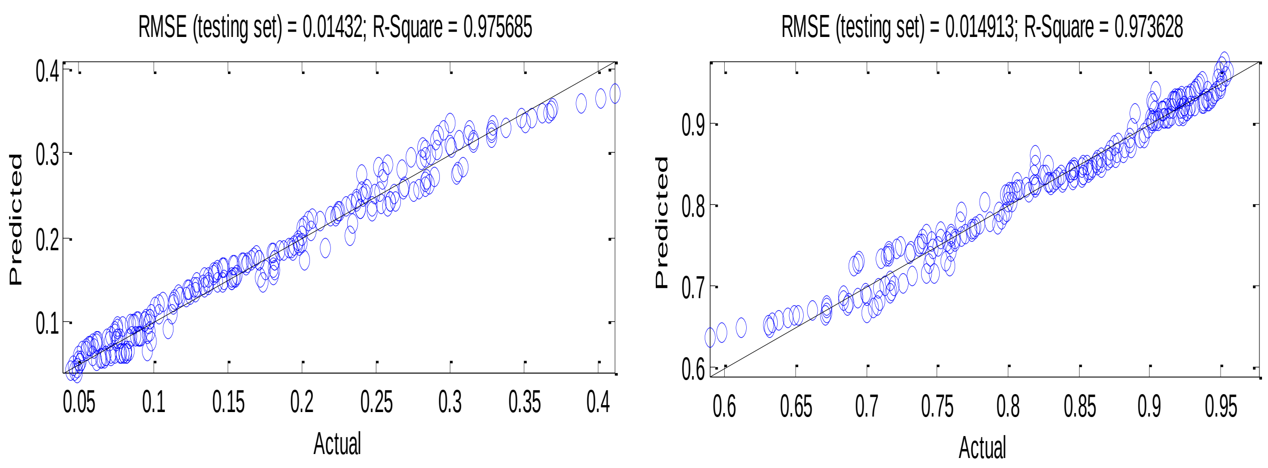
Eqns. (17) – (20) had four genes (tree structure) and one bias each. These is based on the initial MGGP setting and verifies that the GP was truly multi-gene in nature. The multi-gene has capability for delivering accurate models. In the study of Adeyi et al., multi-gene genetic programming applied to polymer composite modeling also yielded model with high accuracies (> 0.9000) and therefore confirmed its proficiency (Okonkwo et al., 2023).

The performance evaluation in form of parity plot of the Eqns. (17) – (20) are shown graphically in Figure 9.



(a)

(b)



(c) (d)

Figure 9: Parity plot for (a) EU, (b) EUR, (c) ExLoss and (d) ExEff

The cluster of data around the straight regression line vindicates the observed coefficient values observed in Table 7.

3.7 GUI Application Wrapping

GUI wrapping is a technique used to create a graphical user interface for a command line interface programming. It combines robust model evaluation with graphical buttons to allow users to interact with a program using mouse and keyboard, rather than having to type in the command line this makes programs more accessible to users who are not familiar with command line and it is believed to have capability to hasten or assist process management in the industry. The GUI application developed for the energy and exergy characteristics in this study is represented in Figure 10.

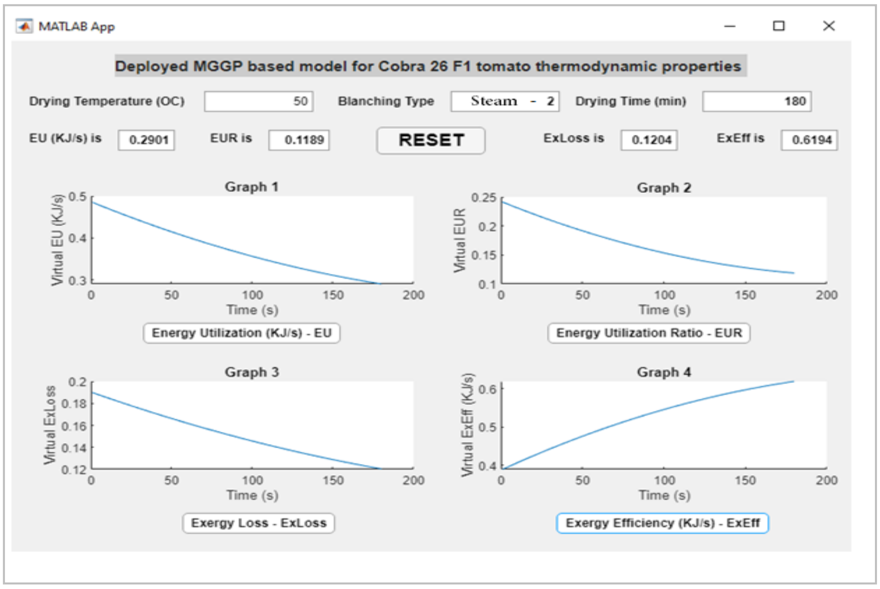


Figure 10: Deployed MGGP based model to graphic user interface (GUI) application.

The GUI application in Figure 10 represents the functional coupling of the backend (MGGP model) and frontend (graphical user interface) for user interaction with the process thermodynamic characterization. The GUI was designed to composed of input components where the user is expected to state the drying temperature, blanching type, and drying time of interest for estimation, decision making and monitoring. It also composed of displays for the thermodynamic characteristics (EU, EUR, Ex_{Loss} and Ex_{Eff}) ones the respective designated action buttons are pressed for the individual characteristics.

In addition, graphs in the GUI also plotted for visual understanding ones the respective action button is pressed. The GUI also has of a reset button needed to return it to a refreshed stage to begin another round of estimation. This GUI application that couples the backend and frontend programming for characteristic estimation is interactive, flexible, and simple to use for both technically and non-technically inclined process operators or personnels. The performance evaluation of the GUI application is validated with randomly selected process operational parameters as depicted in Table 5.

The result of the validation in Table 4 showed that the GUI application had an accuracy of 99.9700, 99.9800, 99.9900 and 99.9700 for EU, EUR, Ex_{Loss} and Ex_{Eff}, respectively. These result show that the GUI application's performance is reliable for the specific process' thermodynamic characteristics for which it was developed.

3.8 Sensitivity Analysis

The sensitivity analysis of the thermodynamic characteristics to the drying factors (time, temperature and pretreatment) are represented in Figure 11 (a - d). EU and EUR are cause and effect scenario where the EU is the cause and EUR is the effect. EU quantifies the amount of energy used per unit of time to carry out the drying operation and it's an indication of the effectiveness of the energy input in achieving the desired outcome, which, in this case, is the successful removal of moisture from the tomatoes. Generally, higher energy utilization values suggest that the drying process is more efficient in utilizing energy, and less energy is wasted during the operation. On the other hand, lower energy utilization values indicate that the drying process might be less efficient, and there could be potential areas for improvement to optimize energy usage. The sensitivity of energy utilization to the drying factors is represented in Figure 11 (a). The figure showed that drying time contributed a - 53.40% (i.e., reduced contribution) to EU. This means that as drying progressed, lesser energy is utilized because of lesser moisture availability in the sample as drying progressed. The Figure 11 (a) also showed that drying temperature contributed a +46.6% (i.e. increased contribution) to the EU during the drying of Cobra 26 F1 tomato. This means that higher temperature is utilized because of higher moisture vapor removal potential at higher temperature. In addition, the pretreatment type does not have any contribution to the EU. Although it was observed in section 3.1 that the energy utilization decreased with pretreatment variation from unblanched samples to steam-blanched samples and to hot-water blanched samples, however, the sensitivity analysis result showed that the observation in section 3.1 is not statistically significant.

Energy utilization ratio (EUR) is a metric that quantifies the efficiency of energy utilization during a specific process. It is a dimensionless value that represents the ratio of the useful energy output to the energy input. A higher EUR value indicates that a greater proportion of the input energy is effectively contributing to the drying process, resulting in a more efficient use of energy. On the other hand, a lower EUR value suggests that a significant portion of the input energy is lost or not directly contributing to the desired drying outcome, indicating less efficient energy utilization. The sensitivity of energy utilization ratio to the drying factors is represented in Figure 11 (b). The figure showed that EUR is -57.4% (i.e. reduced contribution) sensitive to the drying temperature, +41.9% (i.e. increased contribution) sensitive to drying time and +0.7% sensitive to pretreatment (i.e. increment contribution).

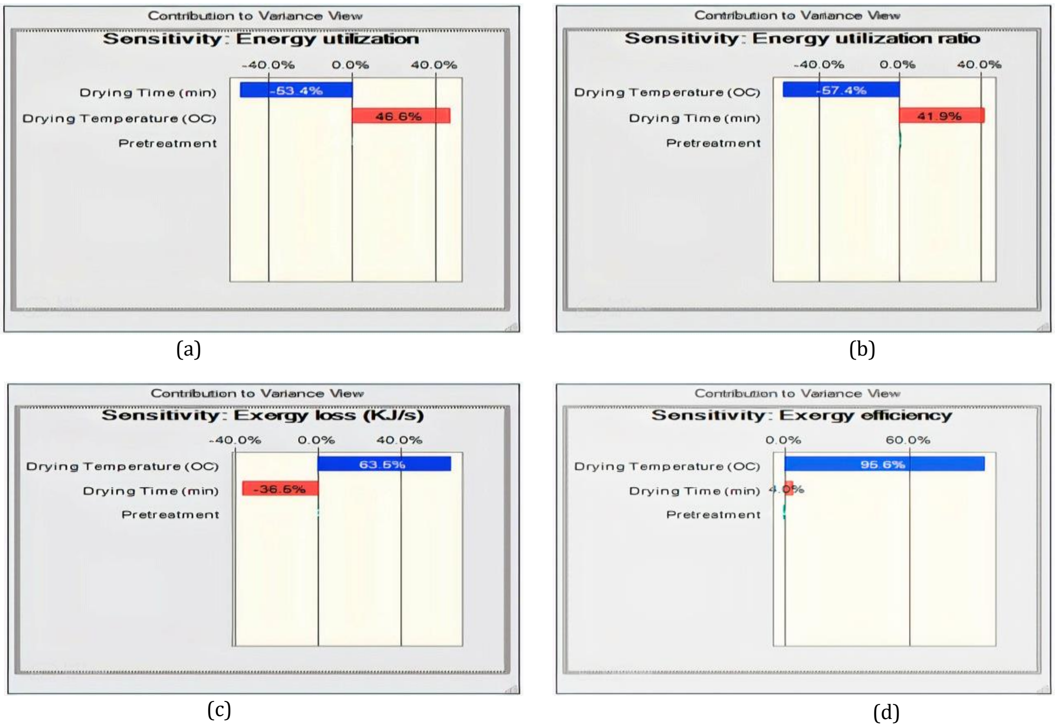
Table 5: Deployed GUI model performance

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
20	50	1	0.485	0.465	4E-04	0.198	0.222	6E-04	0.188	0.182	3E-05	0.404	0.421	3E-04
40	60	2	0.474	0.503	8E-04	0.098	0.085	2E-04	0.238	0.25	2E-04	0.603	0.587	3E-04
60	70	3	0.424	0.49	0.004	0.051	0.068	3E-04	0.247	0.286	0.002	0.741	0.708	0.001
80	50	1	0.364	0.38	2E-04	0.149	0.164	2E-04	0.146	0.154	5E-05	0.536	0.523	1E-04
120	60	2	0.406	0.403	9E-06	0.084	0.064	4E-04	0.205	0.204	3E-06	0.657	0.666	9E-05
140	70	3	0.524	0.518	3E-05	0.063	0.065	5E-06	0.302	0.302	5E-07	0.684	0.694	1E-04
160	40	1	0.187	0.209	5E-04	0.249	0.287	0.001	0.05	0.052	2E-06	0.534	0.48	0.003
180	50	2	0.314	0.29	6E-04	0.128	0.119	9E-05	0.128	0.12	5E-05	0.594	0.619	6E-04
200	40	3	0.212	0.18	0.001	0.283	0.253	9E-04	0.056	0.047	8E-05	0.481	0.524	0.002
RMSE					0.0300			0.0210			0.0140			0.0290
Accuracy					99.9700			99.9800			99.9900			99.9700

A= Drying time, B = drying temperature, C = Pretreatment type, D = Experimental EU, E = GUI app EU, F = EU Error, G = Experimental EUR, H = GUI EUR, I = EUR Error, J = Experimental Ex_{Loss}, K = GUI app Ex_{Loss}, L = Ex_{Loss} Error, M = Experimental Ex_{Eff}, N = GUI app Ex_{Eff}, O = Ex_{Eff} Error

This means that increased temperature reduced the efficiency of the process while increased time and varied pretreatment increased the efficiency of the drying process. The sensitivity of exergy loss to the drying factors is represented in Figure 11 (c). The figure showed that drying temperature contributed +63.5% (i.e., increased contribution). This means that more of the input energy were utilized as drying temperature increased and is attributed to increased drying potential as the drying temperature increased. The drying time contributed -36.5% (i.e., decreased contribution) to exergy utilization ratio. This means that more energy is not utilized as drying time increased and is attributed reducing moisture availability in the sample. Pretreatment showed no contribution, which means it is not statistically significant in the drying process. This result conforms to the observation made regarding the energy utilization. Therefore, the drying time should be optimized and kept realistically short.

The sensitivity of ExEff to the drying factors is represented in Figure 11 (d). The figure showed that drying temperature contributed a decisive +95.6% (i.e., increased contribution to efficiency) to the exergy efficiency while drying time contributed a considerable +4.0% (i.e. increased contribution to efficiency) to the exergy efficiency of the dryer. The pretreatment contributed a -0.4% (i.e., decreased contribution to efficiency) to the exergy efficiency. The extremely small value credited to the sensitivity of exergy efficiency to the pretreatment factor means statistical insignificance. The sensitivity analysis result is particularly useful in operation planning and for technoeconomic management of the drying process with respect to exergy and energy implications.



(a) (b) (c) (d)

Figure 11: Sensitivity of energy utilization to drying factors.

4. Conclusion

The thermodynamic characteristics of convectively dried thermally pre-treated Cobra 26 F1 tomato were investigated. The observed thermodynamic characteristics (energy utilization, energy utilization ratio, exergy loss and exergy efficiency) were intelligently modelled with MGGP and the MGGP model based graphic user interface (GUI) for quick and easy predictions was deployed. The sensitivity analysis of the thermodynamic characteristics to the drying factors was also determined. It was observed that variation of drying factors (drying temperature, drying time and blanching pre-treatment) affected the thermodynamic characteristics of the convectively dried Cobra 26 F1 tomato. The energy utilization increased with increase in temperature but decreased with increase in time, energy utilization ratio decreased with increase in temperature and time, exergy loss increased with increase in temperature but decreased with increase in time while exergy efficiency increased with increase in temperature and time. These results implied the need for the optimization of the drying factors for the thermodynamic characteristics that were investigated for adequate process planning and control. The optimized MGGP model was efficient (having high R2 values) in modelling the thermodynamic characteristics of the thermally pre-treated convectively dried Cobra 26 F1 tomato. This implies that MGGP based model is adequate for the present application and can be practically deployed. Complementarily, the high accuracies of the GUI based on deployed MGGP model also implied that it could be utilized for interactive and non-technical process design and planning, what-if analysis, and real-time prediction for plant control (Suparta and Pruto et al., 2014). Lastly, the sensitivity analysis result implied that the thermodynamic characteristics are most sensitive to the temperature and least sensitive to pre-treatment, implying that the temperature control must be taken most seriously during processing for best performances. On the overall, the results are useful for dryer and process management for sustainability. The results also give important consideration for commercialization of the Cobra 26 F1 tomato drying production especially in developing contries. Further exergo-economic analysis of this specifc process is recommended.

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