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OSMOTIC DEHYDRATION OF *COCOS NUCIFERA L.*: EFFECTS OF PROCESS FACTORS, COMPARATIVE PROCESS MODELLING AND SENSITIVITY ANALYSIS

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Abstract

Osmotic Dehydration (OD) improves product quality and shortens subsequent drying time; leading to energy saving, reduced environmental impact and overall sustainable production. This study investigated the OD characteristics of *Cocos nucifera* at varied OD process factors; that is, temperature (30 and 50°C), sugar concentration (30, 40 and 50%w/w) and time (10, 20, 60, 80, 120, 140, 160, and 180 min). The OD process was indicated with moisture loss (ML (%)) and solid gain (SG (%)). Furthermore, uni-variate empirical (Azuara and Magee) models and multivariate statistical (regression) model were comparatively utilized to interpret the observed OD process characteristics. The mechanisms of ML (%) and SG (%) action were determined through their respective effective diffusivity (D_{eff}). Additionally, sensitivity analysis was used to rank the importance of the OD process factors to OD process indicators. Results showed that increment in OD process factors reduced ML (%) and increased SG (%). Azuara model had the highest efficiency ($R^2 = 0.998$) of the OD process representation followed by regression model ($R^2 = 0.989$) and Magee model ($R^2 = 0.890$). The average D_{eff} was 1.5945E-09 and 1.4803E-09 for ML(%) and SG (%), respectively. Sensitivity analysis showed that time, sugar concentration and temperature are responsible for 74.8, 23.7 and 1.5% variation in ML (%) and 75.1, 22.9 and 2.0% variation in SG (%), respectively. These results are important to standardizing *Cocos nucifera* OD processing prior to other required post-harvest operations such as drying.

Keywords: Osmotic Dehydration; Coefficient of Diffusivity; *Cocos nucifera*; Modeling; Moisture Loss; Solute Gain

Introduction

Coconut (*Cocos nucifera*) is rich in nutrients and offers a number of health benefits. It is a source of dietary fiber aiding digestion and regulation of blood sugar levels (Thakur *et al.,* 2020). *Cocos nucifera* also provides essential minerals such as potassium, manganese, copper, and magnesium, useful for various bodily functions such as maintaining healthy blood pressure and supporting healthy bones (Rethinam & Krishnakumar, 2022). Additionally, *Cocos nucifera* contains compounds that exhibit antimicrobial effects, potentially bolstering the immune system against infections (Sawo &Tukan, 2024).

Cocos nucifera flesh are eaten raw, processed into coconut milk, or oil that is widely used in various cuisines. Hence, coconut processing factory is vital for economies of many tropical countries giving financial freedom to millions of farmers (Wahab *et al.,* 2023). **However, the perishable nature of coconut after harvesting and shelling necessitates the utilization of specified post-harvest processing to ensure preservation and shelf stability.** Given the current global energy and environmental challenges, adopting an energy-saving post-harvest processing technique such as Osmotic Dehydration (OD) is enticing. Hence, OD is often used as a precursor to other post-harvest processes such as drying, for sustainable production.

OD has garnered significant attention due to its effectiveness in reducing the moisture content of fruits and vegetables while keeping sensory and nutritional qualities intact (Chavan & Amarowicz, 2012). Typically, hyper-tonic solution containing sugar, salt, or a combination thereof are employed for this purpose (Mari *et al.,* 2024), so far the hyper-tonic solution is edible, have low water activity, and pleasant in taste (Torreggiani, 1993). When the produce is immersed in a hyper-tonic solution, water molecules migrate from its intra-cellular spaces to the osmotic solution (that is, hyper-tonic). Concurrently, solutes from the osmotic solution diffuse into the produce. This uptake of solutes assists in maintaining the structural integrity and enhances flavor profile of the dehydrated produce (Bashir *et al.,* 2020). The efficiency and effectiveness of OD processing are influenced by several factors, such as type of hyper-tonic solution (osmotic agent) used, its concentration, temperature, solution-material ratio, agitation and speed, and the duration of immersion (Lewicki & Lenart, 2024), amongst others.

In processes development, utilization of representative model, analysis, optimization and control are basic requirements for scale up of experimental findings, design of more efficient and more effective equipment and processes (Akpan *et al.,* 2024). Hence, several models with uni-variate (that is, uni-dimensional) and multivariate (that is, multidimensional) structures have been applied (Adeyi *et al.,* 2024). Following model specification for a process, establishment of sensitivity analysis plays a critical role in understanding the relative influence of process factors on process indicators, ensuring optimal resource utilization for standardization and commercialization (Adeyi *et al.,* 2021).

In related OD studies, Yadav & Singh (2012) provided an overview of OD of fruits and vegetables and highlighted the effectiveness of combining different hypertonic osmotic agents, such as sucrose and salt, to improve the dehydration process. Chavan & Amarowicz (2012) explored the economic benefits of OD compared to conventional drying methods and found out that OD significantly reduces energy consumption and costs, while also improving the shelf life and quality of the farm produces. Despite the extensive studies on OD for fruits and vegetables, research on OD of *Cocos nucifera*, including comparative uni-variate empirical and multivariate statistical models with the establishment of sensitivity analysis remained scarce in the literature. Hence, addressing this gap forms the focus of the present study with the ultimate intention to enhance OD process efficiency and sustainability.

Materials and Methods

Table salt (NaCl), table sugar and distill water were used for constituting the OD hypertonic solutions used in this study. Convective oven (SG-9052G, Stangas Luxury Modern Appliances, Italy) and weighing balance (0.001 accuracy) were used for drying and weighing purposes, respectively. The initial moisture content of fresh *Cocos nucifera* used in this study was 53.04% (wet basis) as determined by using the oven-drying method (Oranusi *et al.,* 2014). This was done in a convective oven at 105°C for 24 hours.

OD hypertonic Solution Constitution

The hypertonic solutions for OD were prepared following the method of Singh & Gangwar (2022) with slight modifications. Three different hypertonic solution were prepared, each containing varying sugar concentrations (30% w/w, 40% w/w, and 50% w/w) in 300 ml of distilled water. The three solutions were used for experimentation at two different temperatures (30°C and 50°C). This resulted in a total of six hypertonic solutions for the OD kinetics analysis at varying times (10, 20, 60, 80, 120, 140, 160, and 180 min).

Experimental Procedure for *Cocos nucifera* OD Kinetics

Ripe *Cocos nucifera* fruits were shelled after a 10-day post-harvest period. The shelled *Cocos nucifera* were washed in distilled water and air-dried at room temperature (28 – 32°C) for 30 min to remove surface water. Thereafter, air-dried *Cocos nucifera* cube samples of approximately 5 × 5 × 5 mm, each weighing ~20 g, were cut-out with the aid of knife and vernier caliper.

The OD experiments were done, such that, a set of eight prepared air-dried samples of *Cocos nucifera* fruit were immersed in each of the earlier prepared six hypertonic solutions. Samples were sequentially removed one after the other at 10, 20, 60, 80, 120, 140, 160, and 180 min, blotted dry with paper towel and weighed. The final samples' moisture content after OD was determined by drying the samples in a convective oven at 105°C for 5 h. Thereafter, moisture loss (ML) and solid gain (SG) were calculated using Eqn. (1) and (2), as described by Deshmukh *et al.,* (2021).

$$\text{ML}\ (\%) = \frac{M_i X_i - M_f X_f}{M_i} \text{ X } 100 \qquad (1)$$

$$\text{SG}\ (\%) = \frac{M_f(1-X_f) - M_i(1-X_i)}{M_i} \text{ X } 100 \qquad (2)$$

Where; M_i is the sample's initial weight before OD, X_i is the sample's moisture content before OD, M_f is the sample's final weight after OD and X_f is the sample's final moisture content after OD.

Empirical Modelling of *Cocos nucifera* OD Kinetics

Uni-variate modelling involves mathematical representation and analysis of data based on a single variable (Sohil *et al.,* 2021). Empirical models are example of uni-variate model, and offer the advantage of reduced computational complexity, making them particularly suitable for scenarios with limited datasets (Venables *et al.,* 2002).

In this study, two univariate empirical models; Azuara and Magee, were employed, each characterized by time (*t*) as the independent variable and incorporated specific parameters/constants. The mathematical structures of Azuara and Magee models are represented by Eqn. (3) (Bera & Roy, 2015) and Eqn. (4) (Deshmukh *et al.,* 2021).

$$ML_t \text{ or } SG_t = \frac{S*t*ML_\infty \text{ or } S*t*SG_\infty}{1+S*t} \qquad (3)$$

$$ML_t \text{ or } SG_t = A + k*\sqrt{t} \qquad (4)$$

Where; ML_t is the moisture/water loss at any time, SG_t is the solute/solid gain at any time, S and k are the parameter representing the rate of solute and water diffusion in and out of the material undergoing OD processing, ML_∞ is the moisture or water loss at equilibrium, SG_∞ is the solute or solid gain at equilibrium. A is the contribution of the hydrodynamic mechanism due to the action of capillary pressures at very short times, for mass transfer of water or solids.

Statistical Modelling of *Cocos nucifera* OD Kinetics

Multivariate statistical model is an indispensable tool to analyse complex datasets with multiple interacting variables (Zeitler, 2015 & Fabrigar *et al.,* 1999). Compared to uni-variate approach that focuses on single variable, multivariate statistical regression model offer understanding of factors interaction that deepens relationship understanding and identification of latent variables (Cohen *et al.,* 2002; Hair *et al.,* 2019). In this study, multivariate statistical modelling was implemented in Microsoft Excel 2007 Package. A usual multivariate statistical model is represented by Eqn. (5).

$$Y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \dots . + \beta_n X_n + \varepsilon \quad (5)$$

Where; the dependent variable (Y) is expressed as a linear combination of the independent variables (X_1 to X_n) along with error term (ε). The error term (ε) accounts for unexplained variance in the data, which could be due to random error, measurement inaccuracies, or the influence of other variables not included in the model (Hair *et al.,* 2019). The coefficients (β) represent the regression coefficients, which quantify the individual effect of each independent variable on the dependent variable, holding all other variables constant (Zeitler, 2015).

Effective Moisture and Solute Diffusivity of *Cocos nucifera*

Crank built on Fick's law to propose an expression for a one-dimensional diffusion observation in a flat sheet that is in contact with an infinite solution (Bera & Roy, 2015). The proposed expression in its simplified form (when '*t*' is small) is given by Eqn. (6).

$$\frac{ML_t}{ML_\infty} = 2 * \left(\frac{D*t}{3.142*l^2}\right)^{\frac{1}{2}} \quad (6)$$

When the interpolation of relevant variable from Azuara empirical model are incorporated into Eqn (6), the instantaneous or time-dependent effective moisture diffusivity is derived for moisture and solute diffusion in the sample, as represented by Eqn. (7) and (8). The respective average effective diffusivity (either for ML or SG) is depicted in Eqn. (9).

$$D_{eff_{ML}} = \frac{3.142}{4*t^{\frac{1}{3}}}\left[\left(\frac{S_1*L^3}{1+S_1*t}\right) * \left(\frac{ML_\infty^{model}}{ML_\infty^{experiment}}\right)\right]^{\frac{2}{3}} \quad (7)$$

$$D_{eff_{SG}} = \frac{3.142}{4 * t^{\frac{1}{3}}} \left[\left(\frac{S_2 * L^3}{1 + S_2 * t} \right) * \left(\frac{SG_{\infty}^{model}}{SG_{\infty}^{experiment}} \right) \right]^{\frac{2}{3}} \quad (8)$$

$$D_{eff_{Avg}} = \frac{\sum_{i=1}^{n} (D_{eff})i}{N} \quad (9)$$

Where; D_{eff} is the instantaneous effective moisture diffusivity coefficient for ML or SG, $D_{eff_{Avg}}$ is the average effective moisture diffusivity coefficient for ML or SG. N is the number of observations for ML or SG.

Modelling Efficiency

The efficiencies of the utilized models were determined using performance metrics that includes sum of squared error (SSE), coefficient of determination (R^2), and root mean square error (RMSE). A lower SSE and RMSE with a higher R^2 (usually ranged from 0 to 1) indicated a better fit and their respective mathematical representations are depicted in Eqn. (10) – (12) (Adewale *et al.,* 2015; Adeyi *et al.,* 2021).

$$SSE = \sum_{i=1}^{n} (Pred,i - Exp,i)^2 \quad (10)$$

$$R^2 = 1 - \left(\sum_{i=1}^{n} \frac{(Pred,i - Exp,i)^2}{(Pred,i - AverageExp)^2} \right) \quad (11)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Exp,i - Pred,i)^2}{N}} \quad (12)$$

Where; Pred,i is the ith predicted value, Exp,i is the ith experimental value, Averaged Exp is the average of all the experimental value, N represents the number of observations.

Results and Discussion

Experimental Data Exploration

The descriptive statistics of the experimental data of *Cocos nucifera* OD is presented in Table 1.

Table 1: Descriptive Statistics of the Experimental Data

ID	Time (min)	Temperature (^{O}C)	Sugar Concentration (%)	ML (%)	SG (%)
Minimum	0	30	30	0	0
Maximum	180	50	50	44.13	6.21
Kurtosis	-1.13	-2.07	-1.52	-0.84	-0.60
Skewness	0.42	3.04E-17	-8.70E-18	-0.16	-0.17

The observed ML (%) in Table 1 ranged from 0% (indicating no dehydration) to a maximum of 44.13% (indicating maximum dehydration), while the observed SG (%) ranged from 0% (indicating no solute absorption) to 6.21% (indicating maximum solute absorption). These changes demonstrated dynamism that is typically associate with OD process.

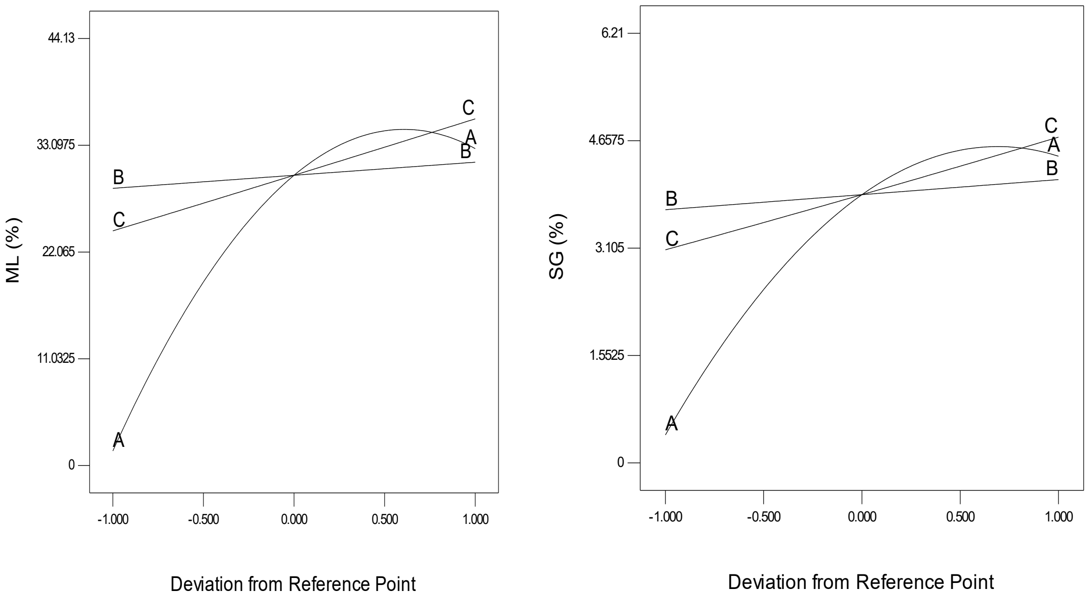
All factors (both dependent and independent) exhibited negative kurtosis, indicating flatter distributions than a normal distribution, and with associated lighter tails. These means that the data distribution is broad and has fewer outliers. Such broad data distribution is desirable for accurate modeling since model performance relies heavily on quality and quantity of data (Adeyi, 2024).

The slight positive Time factor's skewness (that is, 0.42) suggested that the distribution of time values is slightly right-skewed, meaning that the majority of dehydration effects occur early in the process, with diminishing returns at longer duration, implying decreased potential difference as OD progressed. The skewness values of Temperature (that is, 3.04E-17) and Sugar Concentration (that is, -8.70E-18) that near zero indicated that their distributions are almost symmetric, with no significant skew in either direction. Symmetry distribution implied an evenly distributed experimental data that ensured balanced representation across the entire range. This provided a dependable framework for evaluating their effects on ML (%) and SG (%). In addition, both response variables have slight negative skewness (that is, ML (%) = -0.16 and SG (%) = -0.17), indicating a minor skew towards lower values. These implied that the OD process efficiently facilitated water loss and solute uptake, as influenced by the concentration gradient and process duration.

This descriptive statistical exploration of the observed experimental data enabled familiarity, transparency and reliability of data for further exploration, interpretation and utilization (Adeyi *et al.,* 2023).

Effect of Process Factors on Osmotic Characteristics of *Cocos nucifera*

The observed relationship between ML (%) and SG (%) against the process factors (A:Time, B: Temperature and C: Sugar Concentration) for the OD process of *Cocos nucifera* are represented in Fig. 1 (a) and (b).



1. (a) (b)

Fig. 1: Effect of A: Time, B:Temperature and C:Sugar Concentration on (a) ML (%) and (b) SG (%)

The trends in the two figures are close, increment in process factors (A:Time, B:Temperature and D:Sugar Concentration) lead to increment in process responses (that us, ML (%) and (b) SG (%)). The shape of the 'Time trend' showed that the incremental effect peaked at a point and thereafter decreased. The peak is the point of equilibrium moisture uptake or solute gain as the case may be, after which the *Cocos nucifera* sample could not lose more moisture or gain more solute. Therefore, any attempt after equilibrium points for further stretch became counter beneficial. This conforms to the observation of Ponting (1973), that, when the processing time is quite high, considerable diffusion of the osmotic solute from the solution in the reverse direction is likely to happen.

The increment in ML (%) and SG (%) due to Temperature and Sugar Concentration factors did not abate. This is as a result of increased osmotic pressure gradient, that improved the movement of solute and water in and out of *Cocos nucifera* samples. This effect is more noticeable in Temperature than Sugar Concentration; and it is attributed to the fact that increased temperature increased rate of OD reaction which will increase water and solute migration or diffusivity, while increased sugar concentration increased the viscosity of the hypertonic solution which may restraint diffusivity of water and solute.

Similar observation were reported by Deshmukh *et al.,* (2021).

Univariate Empirical Modeling of *Cocos nucifera* OD

Mathematical models are desirable for data and observation representation, analysis, investigation, optimization and control. The result of the utilization, analysis and performance of univariate empirical Azuara and Magee model to *Cocos nucifera* OD experimental data under varying conditions of temperature and sugar concentration is represented in Table 2. These metrics are critical for evaluating model reliability in food engineering applications.

Table 2: Analysis and Performance of Univariate Empirical Azuara and Magee Model

(a) ML (%)

Model	Model	ML Process Factors (Temp. ^{O}C/Sugar Conc. % w/w)					
Name	Parameter	30/30	30/40	30/50	50/30	50/40	50/50
Azuara	ML_∞	33.52	45.24	54.18	39.79	50.91	62.25
	S_1	0.017	0.015	0.017	0.014	0.015	0.016
	SSE	3.98	7.53	15.56	5.309	7.989	19.89
	R^2	0.993	0.992	0.990	0.993	0.993	0.990
	RMSE	0.754	1.037	1.491	0.870	1.068	1.686
Magee	A	6.064	7.701	10.2	6.443	8.708	10.76
	k	0.251	0.336	0.407	0.292	0.376	0.463
	SSE	104.4	174.4	302.1	117.3	201.5	345.9
	R^2	0.825	0.835	0.811	0.850	0.846	0.828
	RMSE	3.861	4.991	6.57	4.094	5.365	7.030

(b) SG (%)

Model Name	Model Parameter	SG Process Factors (Temp. ^{O}C/Sugar Conc. % w/w)					
		30/30	30/40	30/50	50/30	50/40	50/50
Azuara	SG_{∞}	4.557	5.203	6.055	5.71	7.133	8.021
	S_2	0.015	0.021	0.029	0.011	0.014	0.018
	SSE	0.037	0.053	0.033	0.064	0.037	0.067
	R^2	0.996	0.996	0.998	0.995	0.998	0.998
	RMSE	0.073	0.087	0.069	0.096	0.073	0.098
Magee	A	0.781	1.175	1.685	0.733	1.138	1.591
	k	0.033	0.039	0.046	0.040	0.052	0.060
	SSE	1.241	2.736	5.173	1.566	2.938	5.017
	R^2	0.878	0.818	0.767	0.890	0.879	0.851
	RMSE	0.421	0.625	0.859	0.473	0.647	0.846

In both Azuara and Magee model, the values of equilibrium points ($ML_{\infty}$and SG_{∞}) increased consistently with increased temperature and sugar concentration (Chavan & Amarowicz, 2012), attributed to increased rate of reaction as temperature increased. The value of parameters $S_1$and S_2 showed slight variation across different process conditions, with higher values at 30 ^{O}C than 50 ^{O}C (Singh & Gangwar, 2020). The diffusion of solutes and moisture tends to decrease as the viscosity of the hypertonic solution increases, which is caused by higher sugar concentrations. In Azuara model, the low SSE and RMSE values across all conditions indicated a good fit to the experimental data of ML (%) and SG (%). The high R^2 values (ranging from 0.990 to 0.993) also suggested that the model explained variability in the response variable well, demonstrating strong predictive accuracy. In addition, the R^2-values decreased as sugar concentration increased while RMSE values increased showing stron accuracy dependence on sugar. According to Oke *et al.,* (2017), the closer R^2 value is to 1 and RMSE is to 0 the more efficient the modeling and prediction endeavor.

In Magee model, value of parameter A and k increased with temperature and sugar concentration, similar to ML_{∞} and SG_{∞} in the Azuara model, indicating a rate-dependent behavior. The Magee model showed significantly higher SSE values compared to the Azuara model, indicating a less accurate fit to the experimental data. Its R^2-values are lower than those for the Azuara model (ranging from 0.811 to 0.850), suggesting that the Magee model does not explain as much of the variance in the data. In addition, RMSE values are consistently higher than those for the Azuara model, reinforcing the conclusion that the Magee model's predictions are less precise. A close observation was made by Deshmukh *et al.,* (2021).

Therefore, both models showed a consistent trend of increasing the predicted parameter values with increased temperature and sugar concentration; however, the Azuara model demonstrated improved predictive accuracy over the Magee model, as evidenced by lower SSE and RMSE values, and higher R^2 values.

Multivariate Statistical Modeling of OD

The multivariate statistical models derived for the process responses (ML (%) and SG (%)) are represented in Eqn. (13) and (14), respectively. The two models have information regarding linear, non-linear and interaction terms, respectively.

$$ML\ (\%) = 0.004177*A + 0.102138*C - 4.4E\text{-}07*A^2 - 0.00052*B^2 + 0.000439*C^2 + 1.9E\text{-}05*A*B + 6.8E\text{-}05*A*C + 0.00185*B*C - 5.35971 \qquad (13)$$

$$SG\ (\%) = 0.000453*A + 0.005915*C - 5E\text{-}08*A^2 - 0.00034*B^2 + 0.000175*C^2 + 4.59E\text{-}06*A*B + 6.93E\text{-}06*A*C + 0.000603*B*C - 0.50132 \qquad (14)$$

In the linear terms, the positive values of Time and Sugar Concentration term in both equations implied incremental effect and justified the observations in ML (%) and SG (%) that was depicted in Fig. 1.

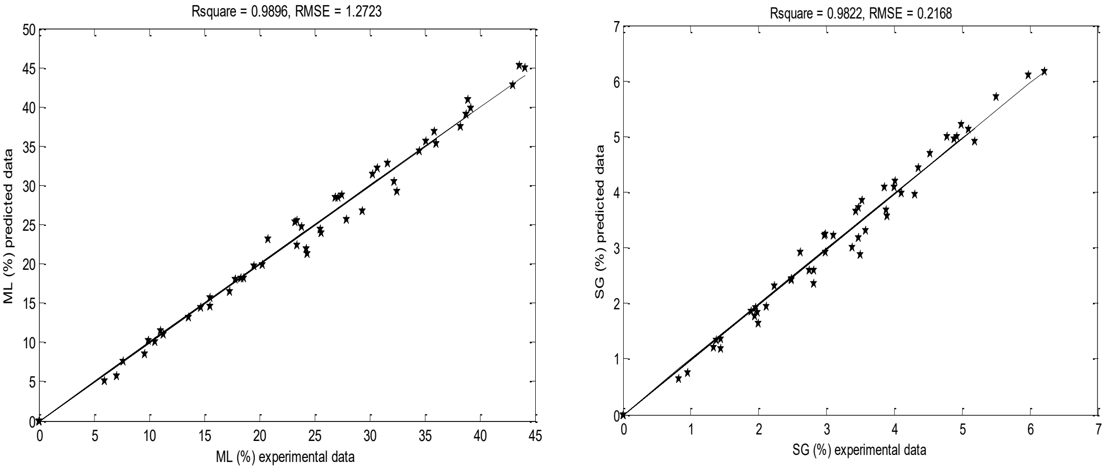
In the non-linear terms, the negative values of Time and Temperature, implied that while increasing Time and Temperature increased moisture loss, a point existed beyond which further increment yielded diminishing returns. This point of diminishing return indicated an optimum processing point beyond which further increment is no longer effective in promoting ML (%) and SG (%). The slight positive coefficient increase for the effect of Sugar Concentration term on ML (%) and SG (%) suggested that applied high Sugar Concentrations are increasingly effective throughout its observed range.

In the interaction term, the positive coefficient of the combined effect of Time, Temperature and Sugar Concentration implied synergy, meaning that the interaction between these three terms or factors increased ML (%) and SG (%)

more than would be expected from their individual effects alone.

The constant term in the Eqns (13) and (14) serves as a baseline or intercept to adjust the model to fit the observed data accurately. These values were -5.35971 and -0.50132 for ML (%) and SG (%), respectively. In a related studies, multivariate statistical model also served as a veritable tool that complement the observed experimental effects in adsorption characteristics of dried *Nauclea latifolia* medicinal leaves (Adeyi, 2024) and rehydration of *Hailanthus annuus* leaves (Adeyi, 2024).

The efficiencies of the prediction capability of the models (Eqns. (13) - (14)) are represented in Fig 2 (a) and (b).



(a) (b)

Fig. 2: Performance Efficiency of the Multivariate Statistical Models (a) ML (%) and (b) SG (%)

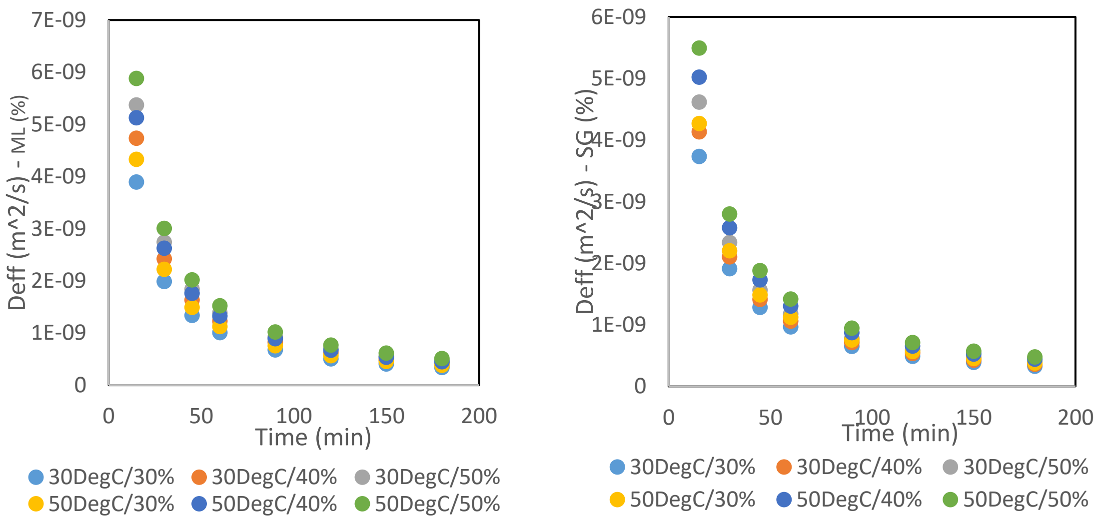
The models' R^2 and RMSE values for ML (%) (that is, 0.989 and 1.273) and SG (%) (that is, 0.982 and 0.216) showed that the models are accurate and reliable (Adewale *et al.,* 2015).

Model Performance Comparison

The comparison of the selected modelling methods that were utilized to represent and interpret the experimentally observed *Cocos nucifera* OD data in this study showed strong performances across all methods, as indicated by their respective predictive accuracy metrics (R^2, SSE, and RMSE). The univariate Azuara empirical model exhibited the highest predictive accuracy, outperforming both multivariate statistical and univariate Magee empirical model. However, the multivariate statistical model presented a significant advantage over the empirical univariate models (Azuara and Magee) due to its compact and multi-dimensional mathematical structure (Adeyi, 2024). Furthermore, unlike the one-dimensional structured univariate models, the multivariate approach incorporated both the individual and interactive (that is, combined) effects of OD process factors (Sohil *et al.,* 2021). This comprehensive framework made the multivariate statistical model particularly valuable for advanced applications, in process optimization, control design, and overall management (Kourti, 2020).

OD Effective Diffusivity of *Cocos nucifera*

The instantaneous effective diffusivity regarding ML (%) and SG (%) in this study was calculated at varied experimental composition (Temperature - Sugar Concentration combination). The results are represented in Fig. 3.



(a) (b)

Fig. 3: Effective Diffusivity of (a) ML (%) and (b) SG (%)

The figure demonstrated a decrease in effective diffusivity over time for both ML(%) and SG (%). As anticipated, the initial period exhibited a rapid effective diffusivity compared to later stages, driven by the significant partial pressure difference between the hyper-tonic solution and the samples (Pessoa *et al.,* 2020). The figure also showed that effective diffusivity slightly increased with increment in temperature (Dehghannya *et al.,* 2015), higher temperature increased kinetic energy of molecules, making them move faster and facilitating diffusion (Giannakourou *et al.,* 2020).

Furthermore, Table 3 presented the average effective diffusivities for each experimental composition (that is, Temperature - Sugar Concentration combination), showing average diffusivity based on the interaction between increment in solute (that is, sugar) and temperature of the hypertonic solution.

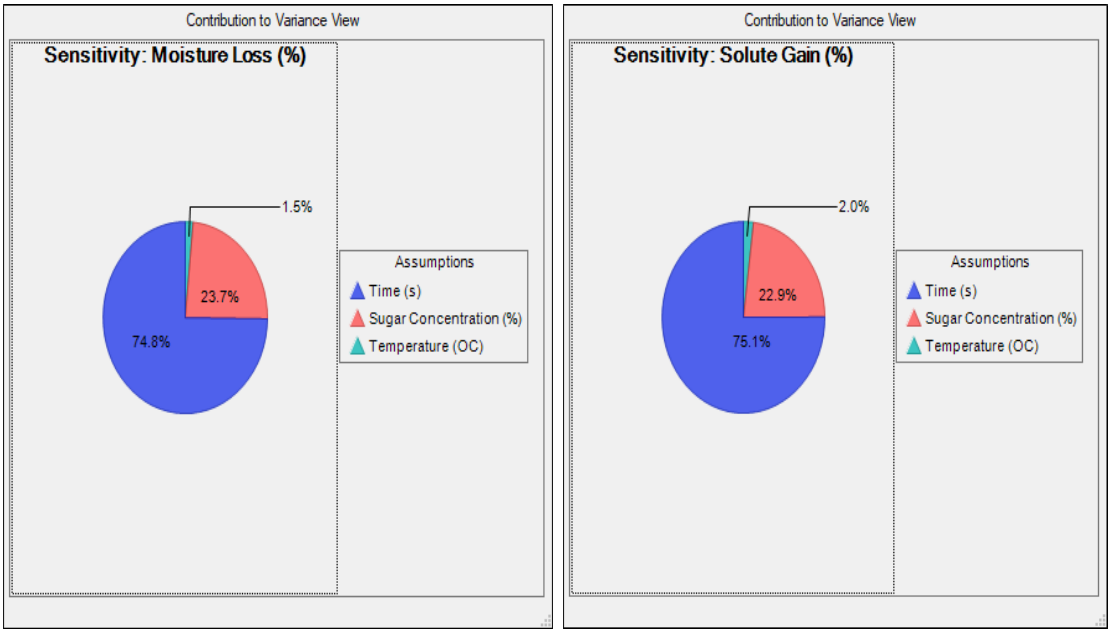
Table 3: Average Effective Diffusivity

S/N	Exp ID (^{O}C / %w/w)	$D_{eff_{Avg}}$ ML (%)	$D_{eff_{Avg}}$ SG (%)
1	30/30	1.26805E-09	1.2177E-09
2	30/40	1.54526E-09	1.3411E-09
3	30/50	1.74926E-09	1.4927E-09
4	50/30	1.4152E-09	1.4027E-09
5	50/40	1.67247E-09	1.6409E-09
6	50/50	1.91693E-09	1.7865E-09

The table implied that increment in both sugar and temperature increased the diffusivities of solute and moisture in the samples. This is due to increase in the kinetic energy of molecules and increased concentration gradient (Giannakourou *et al.,* 2020). These results are close to the observation of Pessoa *et al.,* (2020) for cassava cubes OD.

Sensitivity Analysis

The sensitivity of ML (%) and SG (%) to Time, Sugar Concentration and Temperature concerning the *Cocos nucifera* OD processing in this study are depicted in Fig. 4. This illustrated the relative importance of different OD process factors.



(a) (b)

Fig. 4: Sensitivity Analysis: (a) ML (%) and SG (%)

The percentages associated with each slice of the pie chart indicated the contribution of each factor to the overall variances in ML% and SG (%), respectively. As observed from the figure, Time has the most significant impact on ML (%) and SG (%), contributing 74.8% and 75.1%, respectively to their total variances. This suggested that changes in time have the greatest influence on the amount of water removed from the sample or solute gained into the sample during OD process. The second most influential variable is Sugar Concentration, contributing 23.7% and 22.9% to ML (%) and SG (%) variances, respectively. This indicated that the Sugar Concentration in the osmotic solution also contributed a substantial role. The least influential variable is Temperature, contributing only 1.5% to the ML (%) and 2.0% to the SG (%) variances.

Based on this analysis, Time is the primary factor affecting the measured characteristics (ML (%) and SG (%)) during the *Cocos nucifera* OD process. This information can be valuable for optimizing the OD process by focusing on controlling the highly significant process factors to achieve desired levels of moisture removal or solute gain. A number of authors including Oke *et al.,* (2021) and Adeyi (2024), successfully utilized and reported sensitivity analysis for drying, extraction, and re-hydration processes.

Conclusion

This study examined the osmotic dehydration (OD) process of *Cocos nucifera L.* by investigating the effects of Time, Temperature, and Sugar Concentration on moisture loss and solid gain, with process comparative modeling and sensitivity analysis. The results revealed that increment in Time, Temperature, and Sugar Concentration generally led to enhanced moisture loss and solid gain, with Time emerging as the most influential factor. The Azuara model, in particular, outperformed the Magee model, as indicated by its higher R^2 values and RMSE values metrics. The multivariate regression model provided further details on the synergistic interactions among the variables, which together govern the overall kinetics of the process. The investigation of effective diffusivity demonstrated that higher Temperatures and Sugar Concentrations facilitated increased effective diffusivity, especially during the initial stages of dehydration, emphasizing the dynamic nature of the mass transfer involved. Sensitivity analysis confirmed that Time is the critical factor influencing both moisture loss and solute gain, emphasizing its central role in guiding the process. These results provide a basis for optimizing, controlling and standardizing the OD process of *Cocos nucifera L.* Further investigations into alternative osmotic agents or process modifications may also offer additional enhancements in efficiency, extending the practical applications of the optimized osmotic dehydration process for *Cocos nucifera L.*

Declaration of Conflict of Interest

The author declares no conflict of interest on this article.

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