Characterization of Greenhouse Parameters by Quasi Moment Method

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Abstract
This paper develops a theoretical model to study the greenhouse features and evaluate its state variables. The Quasi Moment Method (QMM) is employed for the analysis and design of the greenhouse. In this method, the unknown coefficients are determined, and then, the predicted results are obtained through the formulated expression. Based on the analytical results, MATLAB codes are developed for computational results. These results are compared with experimental and simulation results for validation's sake. The results obtained are consistent with the existing data available in the literature. Also, in terms of Mean Squared Error (MSE), the numerical values of least square method, and the developed model are 60.39, and 41.37, respectively. These results showed that the model outperformed the published data of the existing method.

Keywords: Greenhouse, quasi-moment method, Greenhouse parameters, mean squatted error, Climate Control

1.0 INTRODUCTION

A greenhouse is an enclosed environment for plant development and growth and waste management (Gürsu, 2024; Hu, Zhang, Huang, & Teng, 2017; Lammari, Bounaama, & Draoui, 2017). State variables, which include air temperature, humidity, velocity, and carbon dioxide (CO_2), as illustrated in Fig. 1, are constantly regulated due to the air exchange between the inside and outside for optimum control of crop cultivation and productivity. An extensive review of these control variables, through developed models, has been thoroughly discussed and presented by Albright, Arvanitis, and Drysdale (2001), and in addition, different stages of controlling the environment for effective plant production have been emphasized. The authors pointed out that climatic automation has evolved over the years, however, the control of the parameters has been computationally intensive, even with the various techniques that have been utilized to simplify the models up to date. Another explicit study of the environmental control of plant production has been reported in (Pasgianos, Arvanitis, Polycarpou, & Sigrimis, 2003), where, besides the control variables, the effect of changing solar loads on the greenhouse's performance has been examined. Figure 1 shows a schematic overview of the greenhouse climate control systems. It highlights the key variables and their interactions.

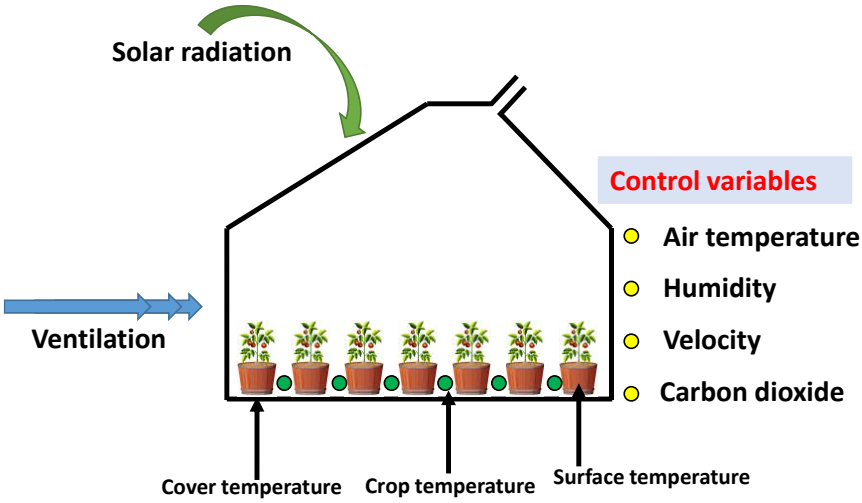


Figure 1: Schematic of a greenhouse climate control problem

As recorded in the extant literature, quite several models have been developed based on the energy and mass balance concept. For example, Seki, Komori, and Takada (1994) investigated the transport process of the plant using the heat and mass transfer equations, whilst (El Ghoumari, Tantau, & Serrano, 2005) employed the energy-mass concept in the climate study of the greenhouse. Also, Boulard and Baille (1993); (Liu, He, Zhang, & Miao, 2005; Vanthoor, Stanghellini, Van Henten, & De Visser, 2011) employed an energy-mass approach for the development of their models. Over the decades, dynamic models for closed environments have received attention, as reported and documented in the literature (Rezvani et al., 2021; Vanegas-Ayala, Barón-Velandia, & Leal-Lara, 2022). For such models, various numerical methods which include Runge-Kutta, Newton-Raphson (Boulard & Baille, 1993), the linear regression approach (Cole, Shehu, Abdullahi, & Bolarin, 2017; Mesmoudi, Bournet, Brima, & Benmoussa, 2017) have been applied as solutions to the system. Unfortunately, the convergence problem has received little attention, and also, methods, which can be used to reduce complex procedures, have not been reported. Recently, the quasi-moment method has been established as an efficient tool for path loss and energy forecasting modelling (Adekola, Ayorinde, Okewole, & Mowete, 2022; Adekola, Ayotunde, Muhammed, Okewole, & Mowete, 2023). Here, it will be used for the prediction of greenhouse parameters, to improve the efficient control and management of the greenhouse. Furthermore, the theory related to the solution of the greenhouse will be presented in section 2 and corresponding computational results alongside validation of the formulation are discussed in section 3. Then, concluding remarks are offered in section 4.

2.0 THEORETICAL BACKGROUND

The concept of the matrix method has been discussed elsewhere Adekola et al. (2022); (Adekola et al., 2023*)*, so it will be considered here for n-degree polynomials in the form

$$y = a + bx + cx^2 + dx^3 + ... + gx^n \tag{1a}$$

For the solution of eqn. (1a), the equation can be recast as follows

$$Y = \alpha_1\phi_1 + \alpha_2\phi_2 + \alpha_3\phi_3 + \alpha_4\phi_4 + ... + \alpha_n\phi_n \tag{1b}$$

The basis function can now be written as

$$\phi_b = \begin{bmatrix} 1 & x & x^2 & x^3 & ... & x^n \end{bmatrix}^T \tag{2}$$

and testing function, according to Galerkin's approach, is expressible as

$$\phi_t = \begin{bmatrix} 1 & x & x^2 & x^3 & ... & x^n \end{bmatrix}^T \tag{3}$$

Based on eqns. (1) to (3), the matrix formulation emerges as

$$\begin{bmatrix} \langle\phi_1,\phi_1\rangle & \langle\phi_1,\phi_2\rangle & \langle\phi_1,\phi_3\rangle & \langle\phi_1,\phi_4\rangle & ... & \langle\phi_1,\phi_n\rangle \\ \langle\phi_2,\phi_1\rangle & \langle\phi_2,\phi_2\rangle & \langle\phi_2,\phi_3\rangle & \langle\phi_2,\phi_4\rangle & ... & \langle\phi_2,\phi_n\rangle \\ \langle\phi_3,\phi_1\rangle & \langle\phi_3,\phi_2\rangle & \langle\phi_3,\phi_3\rangle & \langle\phi_3,\phi_4\rangle & ... & \langle\phi_3,\phi_n\rangle \\ \langle\phi_4,\phi_1\rangle & \langle\phi_4,\phi_2\rangle & \langle\phi_4,\phi_3\rangle & \langle\phi_4,\phi_4\rangle & ... & \langle\phi_4,\phi_n\rangle \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ \langle\phi_n,\phi_1\rangle & \langle\phi_n,\phi_2\rangle & \langle\phi_n,\phi_3\rangle & \langle\phi_n,\phi_4\rangle & ... & \langle\phi_n,\phi_n\rangle \end{bmatrix} \tag{4}$$

and the excitation matrix

$$\begin{bmatrix} \langle\phi_1,Y\rangle \\ \langle\phi_2,Y\rangle \\ \langle\phi_3,Y\rangle \\ \langle\phi_4,Y\rangle \\ . \\ . \\ . \\ \langle\phi_n,Y\rangle \end{bmatrix} \tag{5}$$

The unknown coefficients are:

$$\alpha_w = \begin{bmatrix} a \\ b \\ c \\ d \\ . \\ . \\ . \\ g \end{bmatrix} \tag{6}$$

From eqns.(1-5), the unknown parameters are determined as

$$\begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ . \\ . \\ . \\ \alpha_n \end{bmatrix} = \begin{bmatrix} \langle \phi_1, \phi_1 \rangle & \langle \phi_1, \phi_2 \rangle & \langle \phi_1, \phi_3 \rangle & \langle \phi_1, \phi_4 \rangle & \dots & \langle \phi_1, \phi_n \rangle \\ \langle \phi_2, \phi_1 \rangle & \langle \phi_2, \phi_2 \rangle & \langle \phi_2, \phi_3 \rangle & \langle \phi_2, \phi_4 \rangle & \dots & \langle \phi_2, \phi_n \rangle \\ \langle \phi_3, \phi_1 \rangle & \langle \phi_3, \phi_2 \rangle & \langle \phi_3, \phi_3 \rangle & \langle \phi_3, \phi_4 \rangle & \dots & \langle \phi_3, \phi_n \rangle \\ \langle \phi_4, \phi_1 \rangle & \langle \phi_4, \phi_2 \rangle & \langle \phi_4, \phi_3 \rangle & \langle \phi_4, \phi_4 \rangle & \dots & \langle \phi_4, \phi_n \rangle \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ \langle \phi_n, \phi_1 \rangle & \langle \phi_n, \phi_2 \rangle & \langle \phi_n, \phi_3 \rangle & \langle \phi_n, \phi_4 \rangle & \dots & \langle \phi_n, \phi_n \rangle \end{bmatrix}^{-1} \begin{bmatrix} \langle \phi_1, Y \rangle \\ \langle \phi_2, Y \rangle \\ \langle \phi_3, Y \rangle \\ \langle \phi_4, Y \rangle \\ . \\ . \\ . \\ \langle \phi_n, Y \rangle \end{bmatrix} \tag{7}$$

It should be noted that subscripts b, or t, or w ranges from 1to n. ~~And~~

$$\langle \phi_t, \phi_b \rangle = \sum_{n=i}^{N} \phi_t(n) \phi_b(n) \tag{7a}$$

$$\langle \phi_t, Y \rangle = \sum_{n=i}^{N} \phi_t(n) Y \tag{7b}$$

3.0 RESULTS AND DISCUSSION

3.1 Validation with measurement data from (Mesmoudi et al., 2017)-Fig. 4]

The developed code, based on eqn. (7), is used to determine the unknown coefficients. In the case of (Mesmoudi et al., 2017), second-degree polynomials were considered. Consequently, incorporating their data in the MATLAB code yielded

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0.0209 \\ 0.9618 \\ 0.0010 \end{bmatrix} \tag{8}$$

And upon substitution of (8) in (1), the latter emerges as

$$y = 0.0209 + 0.9618x + 0.0010x^2 \tag{9}$$

Eqn. (9) has been utilized to plot the graph of Fig. 1. The result of the model is compared with the measured result from (Mesmoudi et al., 2017)-Fig. 5 in Fig. 2. Clearly, it is evidence that our result is in agreement with measured data. Furthermore, the inside air temperature T_i, in comparison with (Mesmoudi et al., 2017), can be computed as:

$$T_i = T_o + \left(\frac{0.0209\tau R}{0.9618U_e + 0.0010} \right) \qquad (9a)$$

where τ represents greenhouse cover transmissivity to solar radiation, R denotes solar radiation flux outside the greenhouse and its unit is W/m^2. $U_e\,(m/s)$ stands for the outside airspeed, and $T_o\,(K)$ is the temperature of the surrounding air.

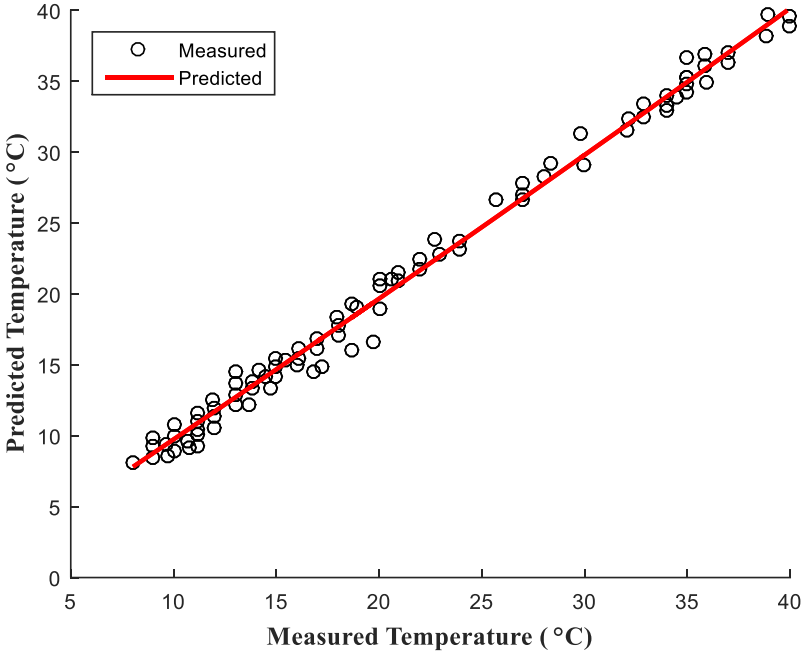


Figure 2: Comparison between predicted and measured inside air temperature T (°C)

3.2 Emission of CO_2 gas (Cole et al., 2017)

Another example is presented to validate the matrix formulation of the derived expression published in the work of (Cole et al., 2017). Following a similar procedure, as described in the previous sub-section, the generated parameters are

$$\begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} -0.2068 \\ 1.1726 \\ 0.3058 \\ -0.0123 \end{bmatrix} \qquad (10)$$

so that $$y = -0.2068 + 1.1726x + 0.3058x^2 - 0.0123x^3 \qquad (11)$$

The result of eqn. (11) is shown in table 1. It is obvious from Tables 1 and 2 that the developed model outperformed the simulated result in (Cole et al., 2017) and is consistent with the measurement data. The discrepancy is due to a round-off error.

Table 1: Comparison of result with the published result

Year	Measurement of emission of CO_2 from gaseous fuel	Result Data from Model (Cole et al., 2017)	Result of the Present Model	Error
1994	4.24	4.12	1.26	2.98
1995	5.25	6.66	3.26	1.99
1996	7.22	9.2	5.73	1.49
1997	7.59	11.75	8.59	-1
1998	9.29	14.3	11.76	-2.47
1999	12.59	16.85	15.17	-2.58
2000	18.84	19.41	18.75	0.09
2001	21.17	21.97	22.43	-1.26
2002	26.8	24.53	26.12	0.66
2003	30.04	27.1	29.76	0.28
2004	41.46	29.67	33.27	8.19
2005	39.34	32.24	36.58	2.76
2006	36.12	34.81	39.61	-3.49
2007	30.61	37.39	42.3	-11.69
2008	43.11	39.98	44.55	-1.44
2009	50.5	42.56	46.31	4.19
2010	63.98	45.15	47.5	16.48
2011	37.86	47.74	48.04	-10.18
2012	41.54	50.34	47.86	-6.32
2013	50.61	52.94	46.88	3.73
2014	45.52	55.54	45.04	0.48

Table 2: Performance Metrics

Model	Standard error of Residuals	MSE
(Cole et al., 2017)	2.57	60.39
Present Model	1.26	41.37

3.3 Greenhouse Parameters

To verify our analytical approach to the greenhouse climate problem, eqn. (9a) is utilized to compute the greenhouse characteristics as a function of solar radiation and wind speed which are illustrated in Figs. 3 and 4, respectively.

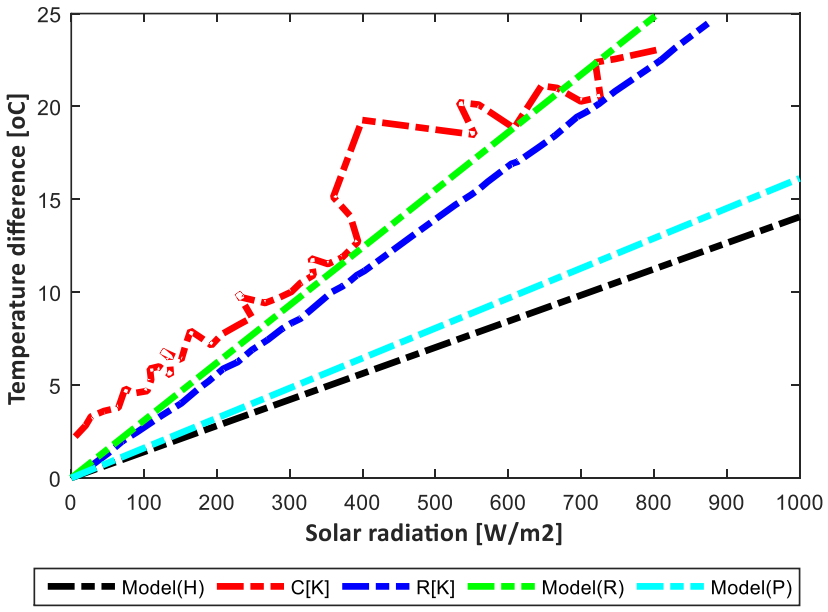


Figure 3: Temperature profile against solar radiation models

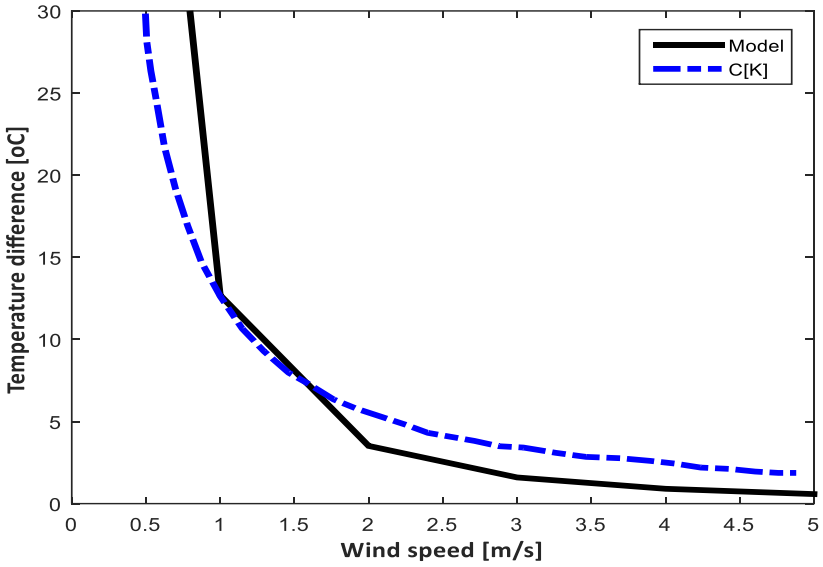
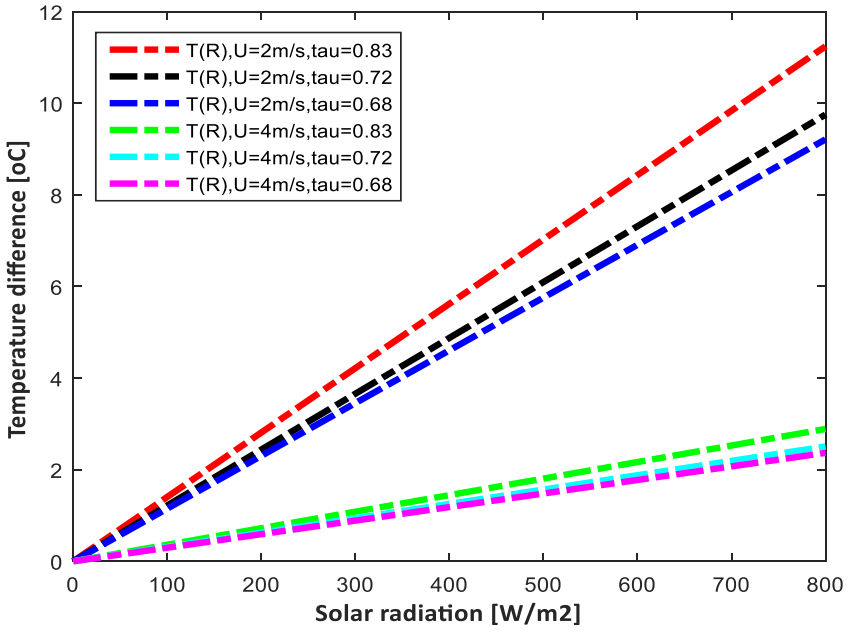
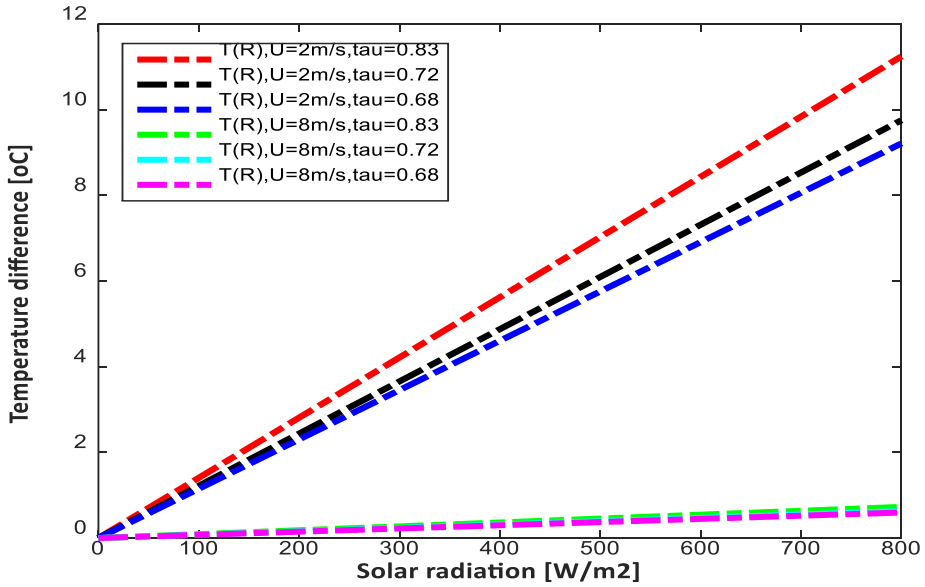


Figure 4: Temperature difference as a function of wind speed models

From these figures, there is fair conformity between the reference patterns Mesmoudi et al. (2017) and the computed patterns. Conclusively, figures 3 and 4, to a large extent, support the correctness of the formulation in this paper, which revealed that the magnitude of the solar radiation varies linearly with the magnitude of temperature difference while the variation of wind speed is nonlinear with the intensity of the temperature profile.



(a)



(b)

Figure 5: (a) Temperature profile versus solar radiation for two values of wind speed and covers (tau); **(b)**Temperature profile versus solar radiation for two values of wind speed and covers (tau)

As depicted in Fig. 5, the temperature profile intensity increases linearly with the solar radiation level, and concerning wind speed, the temperature difference decreases with every increment in solar radiation value. However, the greenhouse temperature increases as the cover increases in tandem with the solar radiation intensity.

4. CONCLUSION

A theoretical model has been developed in this paper, and utilized to determine the characteristics of a general greenhouse, as a function of parameters such as the wind speed for different system's attributes, including greenhouse cover transmittivity. Computational results obtained from the model have been demonstrated, through graphical comparisons, to align closely with published results in existing literature using other models. This strong agreement validates the model in this paper. Notably, the model provides a valuable tool for investigating additional greenhouse parameters, offering practical insights for engineers and researchers in greenhouse design and analysis.

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