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Prediction of Milk Production of Holstein Cattle Using Principal Component Analysis

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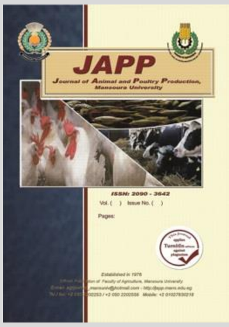

ABSTRACT

The aim of this research is to increase the accuracy of estimating environmental standards by starting to fix fixed effects by using Principal Component Analysis (PCA) as an alternative approach to analyzing the studied traits and solving the problem of multicollinearity, with the possibility of identifying an appropriate and more accurate model for predicting milk production and thus obtaining an increase in economic return. Number of records 2067 in Holstein Friesian (HF). Studied traits were Total milk yield (TMY, kg), lactation period (LP), Calving interval (CI), Dry period (DP) and Days open (DO); day. Methods: The factor program of SPSS statistical package was used for the principal component analysis (PCA). It was found that for all studied traits; the first 2 principal components(PC) explained more than 82% of the total variation . Multiple regression models were: TMY=2331.34+4.96LP+0.98CI+2.01DP+2.04DO. To predict the increase in the amount of TMY, the multiple regression (MR) model was used variables LP, CI and DP. The obtained equations for (PCA) were written as:PC1=0.533 LP+0.272 CI- 0.226DP+ 0.407 DO, PC2 = 0.019 LP+0.551 CI+ 0.581 DP- 0.035 DO. Regression equation for PCA scores as: TMY = 4726.12+433.30 PC1+ 179.83 PC2 ,(PC1& PC2) used as predictors with (TMY); increasing TMY would be expected to increase with increasing PC. The present results showed that instead of (MR) analysis use of (PCA) in (MR) analysis might offer a good opportunity without multicollinearity problem for predicting TMY of HF

Keywords **:**Holstein cattle, milk production, Principal Component Analysis (PCA).

INTRODUCTION

The application of (PCA) in animal breeding as a tool to reduce the dimensions by judging a large group of variables through a small group that represents them and gives more accurate results. However, Bhattacharjya (1996) predicted TMY in cattle from all lactation traits utilizing PCA and concluded that PCA was effective. Gandhi (2004) predicted TMY from (PC) scores derived from many early traits. The accuracy of prediction TMY production from PCA of cattle. The (PC) index developed from all the six (PCA) had the highest rank correlation with 305 DMY. Moreover, Kannan (2002) found that TMY in cattle based on 1st lactation traits using (PCA) and concluded that accuracy of prediction from (PCA) had marginal improvement compared with multiple analyses. Factor analysis is a statistical procedure to identify how suites of variables are related. It also can be used for confirmatory or an exploratory purposes. The main objective of this study answer the following questions: How much variation in trait is explained by other traits? and also are there any (PC) for traits that explain more variation than others? His impact of environmental factors is accurately measured with no overlap between the factors studied. To determine the overlapping relationships between a large number of variables, to determine how they relate and to determine the importance of each factor individually; it is represented in TMY, LP, CI, DP and DO. This leads to more accurate results due to the non-overlapping factors and to identify the specific factors for each worker individually and to know, the extent of its impact on selection and genetic improvement programs.

MATERIALS AND METHODS

Management and feeding

The records data was used as it included the following information (cow number, dam and sire in addition to the milk production traits (productive, reproductive). The feed provided to the animals included the Egyptian clover, concentrate feed mixture, and rice straw in the winter, while in the summer it contained Egyptian clover hay, concentrate feed mixture and rice straw or wheat straw. Animals were fed in groups feeding assigned according to live body weight, milk yield and reproductive status. Heifers were served when the size is appropriate and with age (weight 350 kg, age 18 months) using artificial insemination. After two months pregnancy was diagnosed using rectal palpation. The cows milked twice a day, drying the cows two months before birth. The study herd was supervised by veterinarians to conduct vaccinations against diseases.

Structure of data

Data were collected from the commercial farm located in the northern part of the Nile Delta. The number of records of the data analyzed for HF in presented in (Table 1). Studied traits were: TMY (kg), LP, CI, DP and DO (days).

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Table 1. number of records of the data analyzed for herd (HF)

Items	Number
Record	2067
Sire	80
Dam	439
Year	10
Parity	6
Season	4

Statistical analysis:

The relationship of these principal components with milk production traits was analyzed using the general linear model in the GLM procedure of (IBM) SPSS.

$$Y_{xz} = \mu + F_x + e_{xz}$$

Where:

Y_{xz} = adjusted value of total milk yield (kg)/ of z^{th} animal of i^{th} factor; μ = overall mean; F_x = effect of i^{th} factor; e_{xz}= residual error NID (0, σ^2_e).

Data of Linear Measures (LP, CI, DP and DO) as predictors TMY were analyzed according to the following regression model of SPSS 16 (2007).

$$Y = a+b_1X_1+b_2X_2+ ... +b_pX_p+ e$$

Where:

Y= the dependent variable (TMY); a= intercept/constant;
X_p= the p^{th} independent variable LP, CI, DP and DO.
$b_1, b_2, ..., b_P$ = the p^{th} partial regression coefficients of Y on Xp's; and e = error term and is assumed to be normally independently distributed with mean = 0 and variance = σ^2_e.

Principal components

To select the number of PC that explained the highest percentage of variance only those PC with greater than one eigen values. The linear correlations of traits with each PC were estimated, also significant. This analysis was conducted using command PCA, Factor Mine library (Husson *et al.,* 2014). The PC factor program of (SPSS 16, 2007) statistical package was used for the (PC) analysis.

$$Y = a + B_iPC_i + ………… + B_K PC_K …….$$

Where:

Y is the TMY, a is the regression intercept, Bi is the i^{th} partial regression coefficient of the i^{th} LP, CI, DP and DO, Xi, or the i^{th} (PC), and determining the number of PC to extract by using cumulative proportion of variance criterion.

RESULTS AND DISCUSSION

Overall means (Mean) and standard errors (SE) of TMY, LP, CI, DP and DO are shown in Table 2. These estimates were 4726.1kg, 307.0 day, 408.1day, 104.5day and 128.5day, respectively. The overall mean for TMY was higher than found by Chongkasikit (2002), Koonawootrittriron *et al*., (2009), and Endris *et al.* (2012), while it were lower than those found by Hashemi *et al.* (2009). were while it within the range reported by Konig *et al.* (2005).

Table 2. Overall means and standard errors of TMY, LP, CI, DP and DO

Traits	Mean	SD	CV%
TMY	4726.12	1897.67	40.2
LP	307.01	69.57	22.5
CI	408.71	77.90	19.1
DP	104.53	68.57	65.1
DO	128.48	94.57	73.6

The mean for LP in the present study is higher than that found by Haftu, (2015) as 252.3 days, while it was lower than that found by Ayalew and Asefa, (2013) as 333.9 days for HF. The shorter LP may be due to factors such as dry period, feeding system and management practices. The mean CI in this study was similar to results obtained by (Ansari-Lari *et al.,* 2010) as 403±8.6 days for HF, while it was lower than that reported by Haftu (2015) 462.9±19.5 days and Fekadu *et al.,* (2011) as 561.3±18.9 days for HF. This longer CI might be related to housing, poor nutrition and non-genetic factors such as weather. The mean for DP in this study was similar to results reported by Ansari-Lari *et al.,* (2010). The mean of DO was higher than those reported by Lopez *et al.,* (2019) and Oyama *et al.,* (2002).

Principal component analysis

Result of Kaiser-Meyer Olkin (KMO) Measure of Sampling Adequacy (0.294) is suitable for the data evaluated statistically. Also, Chi-square = 9094.8 and significant (P≤0.001) of factor analysis application on the data in (Table, 3). The same model reported by many authors (Tolenkhomba *et al.,* 2013; Shah *et al.,* 2018; Romero *et al.,* 2018 and Mujibi *et al.,* 2019) studying different productive traits in cattle.

Table 3. KMO and Bartlett's Test for studied traits.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	Bartlett's Test of Sphericity		
	Approx. Chi-Square	Df	Sig.
.249	9094.836	6	.000

Principal Components Analysis (PCA) converts a group of large variables into a relatively small (PC) without losing information. In this study, when all the four studied traits (LP, CI, DO and DP) were included 4 PC were extracted. The percent variance explained by each of the first four PC were 44.0%, 38.3%, 17.6% and 0.2%, respectively. Also, together with the two PC explained more than 82% of the total variance of the explanatory variables was explained (Table, 4). The same model was used by Barbosa *et al.,* 2006.

Santos *et al.,* (2010) used principal component analysis (PCA) to evaluate the formation of productive the purpose to discriminate the traits most important for milk yield. The obtained three components accounted for 82.3% of the total variation. These results show that most of the variations are explained by the first 3 principal components (PC) for all traits, whereas more than 90% (90.8%) of the total variations were explained by Mello *et al.,* (2020).

Furthermore, Khan *et al.,* 2013 observed that the first PC showed 61.9% variation followed by second PC (26.1%), whereas more than 90% (90.8) of the total variations were explained.

Table 4. Eigen values, variance and cumulative % by different PC with four studied traits

PC	Total Eigen values	Variance%	Cumulative %
1	1.76	44.020	44.020
2	1.531	38.267	82.287
3	.703	17.549	99.836
4	.007	.167	100.000

***Explanatory variable set: LP, CI, DO & DP while dependent variable: (TMY)**

Figure (1). noticed again investigation of scree plots and cumulative explanation of principal components showed that the first 2 principal components were informative enough, found smaller (Karacaoren *et al.*, 2006) and (Karacaoren and Kadarmideen, 2008).

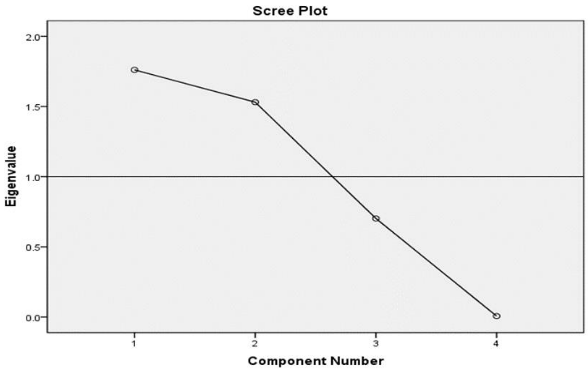

Figure 1. Eigenvalues and cumulative percent of variance with four studied traits

Estimation of principal components (PC)

The principal components (PC) factor score coefficients of LP, CI, DO and DP, prediction of TMY (kg), from independent of LP, CI, DO and DP and their independent PCA scores. While estimated the correlation between (PC) extracted and the original variables in (Table 5 & 6).

Table 5. Coefficients for the prediction of the of TMY.

Traits	PC_1	PC_2	Communality
LP	0.533	0.019	0.868
CI	0.272	0.551	0.980
DO	-0.226	0.581	0.940
DP	0.407	-0.035	0.440

Table 6. Predict of TMY through correlation between (PC) and optimal original variables.

Traits	PC_1	PC_2
LP	0.927^{***}	0.070^{***}
CI	0.508^{***}	0.877^{***}
DO	0.508^{***}	0.877^{***}
DP	0.705^{***}	-0.023^{ns}

*****=significant ($P \leq 0.001$) and ns= non-significant**

The principal components (PC) showed that traits such as : LP, CI and DO were found to ($P \leq 0.001$) with the first PC and ranged from (moderates 0.356 to high 0 927). Similarly, traits such as CI and DP were found to have a highly significant correlation ($P \leq 0.001$) with the second PC and ranged from (low 0.07 to high 0.885). While DP (-0.023) was found to have a negative correlation with the second PC. These results agree for some researchers (Karacaoren *et al.*, 2006; Karacaoren and Kadarmideen, 2008 and Mello *et al.,* 2020).

Phenotypic variability in the traits associated with the PC_1 or PC_2, thus can be selected by numerical scores generated by PC_1 & PC_2 to increase of improving TMY (Table, 5). The same trend was reported by Mello *et al.,* (2020).

Varimax rotation, the widely used and accepted method was applied as it maximizes the sum of the variances of the squared loadings (squared correlations between variables and components). The coefficients of the PCA of the rotated component matrix of the two extracted principal components are given in (Table, 7). The component weights varied from -0.432 to 0.926 for first component for DP to LP, respectively. While, the second component weights varied from -0.072 to 0.892 for DO and CI, respectively. The same trend found that by Campos *et al.,* (2015) and Sinha *et al.,* (2020).

Table 7. Estimates of principal component for studied traits using varimax rotation

Traits	Principal component	
	1	2
LP	.926	.103
DO	.661	-.072-
CI	.429	.892
DP	-.432-	.868

Prediction of TMY using production and reproduction traits

Multiple regression analysis VIF values greater than 3, VIF were 47.6, 57.6, 48.9 and 1.2 for LP, CI, and DP and DO; respectively. Meaning that there was a problem (multicollinearity). Found that prediction equation of

$$\mathbf{TMY = 2331.34+4.96\ LP+0.98\ CI+2.01\ DP+2.04\ DO}.$$

Similar results were noticed by Gul *et al.,* (2005) and Eyduran *et al,. (*2013). However, VIF can be estimated as an indicator of multicollinearity problem, the results obtained for multiple regression analysis will be accuracy. Also, VIF values peculiar to the coefficient values must be less than 3. The same trend was found by Kannan (2002); Katneni (2003), Karacaoren *et al.,* (2006) and Taggar *et al,.* (2012). PCA, two new PC score variables, with the explanation proportion of 82.3%. The standardized (TMY, kg) two principal components (PC) score, PC regression revealed that VIF = 1 for both PC_1& PC_2. The 1st PC had a variance of 1.76 (eigen value) of 44.02%. The proportion was 38.27 % for the 2nd PC with a variance of 1.53. This means that the first two components explained 82.30%. The equations to calculate PC_1 & PC_2 were reported by Kannan, (2002); Katneni, (2003) ;Taggar *et al.,* (2012) and Karacaoren *et al.,* (2006).

The multiple regression equation for PC scores:

$$\mathbf{TMY = 4726.12+433.30\ PC_1+ 179.83\ PC_2}$$

Equations for (PC) are :

$$\mathbf{PC_1 = 0.533\ LP + 0.272\ CI - 0.226\ DP + 0.407\ DO}\&$$

$$\mathbf{PC_2 = 0.019\ LP + 0.551\ CI + 0.581\ DP - 0.035\ DO.}$$

The factor (PC) was conducted using the genetic values which would explain most; increasing TMY would be expected to increase with increasing PC_1&PC_2.

In this study, the multicollinearity problem can be solved with the prediction of TMY through other independent variables. This study is in agreement Kannan, (2002), Katneni, (2003) and Taggar *et al*., (2012).

Furthermore Bhatacharya and Gandhi (2005) compared multiple regression analysis (MRA) and principal components analysis (PCA) to predict lifetime milk production (LTMY) and found that total variance was lower from the model having PCs as compared to original variables in the regression model. This showed the importance of principal component regression analysis (PCRA) in the estimation of longevity. So, it is concluded that the prediction model LTMY4 = 32.61 (PC_1) 0.67 and LTMY5 = 103.77 (PC_1) 0.57, may be helpful in the early selection of cattle based on initial part lactation records.

CONCLUSION

Principal Component (PC) used for all TMY traits and would be useful in both reduction and solving collinearity problems, for analysis functional traits such as : LP or CI, DO, and DP. Where, it became clear through this study that LP and CI traits represent the most important variables that contribute a great deal to total variance. Also, the use of (PC_1&PC_2) was more appropriate than the use of the linear type traits for predicting the TMY traits. This is because multicollinearity of 2 or more TMY traits could It may cause erroneous inference; this may be due unstable regression coefficients. Define an appropriate model for predicting (MY) thus we expect a higher degree of accuracy for the estimates obtained and thus increase the effectiveness of genetic improvement and economic return, this is by exploring the relationship between functional traits. PCA is an approach for analyzing traits used for an alternative and reduces the dimension of these traits.

RECOMMENDATION

To complement this study, we are recommending studying the genetic evaluation and principal components of predicted breeding value for productive and reproductive traits in Holstein cattle.

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التنبؤ بإنتاج اللبن لأبقار الهولشتاين باستخدام تحليل المكونات الرئيسية

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الهدف من هذا البحث: هو زيادة دقة تقدير المعايير البيئية من خلال البدء في إصلاح التأثيرات الثابتة باستخدام تحليل المكونات الرئيسية (PCA) كنهج بديل لتحليل الصفات وحل مشكلة التعددية الخطية مع أمكانية تحديد نموذج مناسب وأكثر دقة للتنبؤ بإنتاج اللبن وبالتالي الحصول على زيادة العائد الاقتصادي . الطريقة المستخدمة للتحليل : تم إجراء التحليل باستخدام برنامج SPSS لتحليل المكونات الرئيسية (PCA) حيث اشتملت الدراسة علي 2067 سجلا لأبقار الهولشتاين فريزيان (HF) في احدي المحطات التجارية بشمال مصر. وتضمنت الصفات التي تم داستها : إنتاج الحليب الكلي (TMY،كجم) وفترة الحليب (LP) والفترة بين ولادتين (CI) وفترة الجفاف (DP) وفترة الايام المفتوحة (DO). وتتلخص النتائج المتحصل عليها كالاتي: بالنسبة لجميع صفات الدراسة وجد ان المكونان الأساسيان الأول والثاني كانا يمثلان أكثر من 82٪ من التباين الكلي. وتم استنتاج نموذج الانحدار المتعدد للمتغيرات LP و CI و DP. كالتالي: $TMY = 2331.34 + 4.96\ LP + 0.98\ CI + 2.01DP + 2.04DO$ بهدف التنبؤ بكمية انتاج اللبن الكلي TMY وتم استخدام نموذج الانحدار المتعدد (MR) للمتغيرات LP و CI و DP. تمت كتابة المعادلات التي تم الحصول عليها لتحليل المكونات الرئيسية على النحو التالي (PCA) : $PC_1 = 0.533\ LP + 0.272\ CI - 0.226\ DP + 0.407\ DO$ & $PC_2 = 0.019\ LP + 0.551\ CI + 0.581\ DP - 0.035\ DO$. بينما كانت معادلة الانحدارباستخدام PCAعلى النحو التالي: $TMY = 4726.12 + 433.30\ PC_1 + 179.83\ PC_2$ (PC_1 & PC_2) تستخدم كمتنبئات لإنتاج اللبن الكلي (TMY) ومن المتوقع ان تزداد كمية اللبن الكلي TMYمع زيادة المكونات الرئيسية (PC). كما أظهرت النتائج أنه بدلاً من تحليل الانحدار المتعدد ، فإن استخدام تحليل المكون الرئيسي في تحليل الانحدار المتعدد قد يوفر فرصة جيدة بدون مشكلة الخطية المتعددة للتنبؤ بإجمالي إنتاج الحليب من الهو لشتاين فريزيان.