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Prediction of Gestational Age: A Comparison of Regression Models

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Abstract

Aim: *The main objective is to incorporate the major foetal parameters – biparietal diameter, head circumference, abdominal circumference and femur length for prediction of gestational age through ultrasonography between 10th and 42nd weeks of gestation and try to do a simultaneous comparative study with gestational age predicted by last menstrual period.*

Methods: *The study has been conducted particularly on the population of Bangladesh. It has been done on 229 Bangladeshi women who had usual singleton foetuses, with evidence of menstrual dates by sonography before fourteen weeks of gestation. Foetal anatomical structures have been scanned and measured at the time of sonographic inspection. For each patient, in addition to the four foetal parameters such as Biparietal Diameter (BPD), Head Circumference (HC), Abdominal Circumference (AC) and Femur Length (FL), the other parameters like Gestational Age (GA) by Last Menstrual Period (LMP) as well as by Ultrasonography (USG) have been recorded. Here we have adopted non-linear regression models in order to predict the response on gestational age. Usually, different modelling methods have been used for this purpose.*

Results: *The logarithmic models normally presented better results if gestational age was predicted based on a single parameter than polynomial models whereas if all predictor variables were considered together, then Nernst model may turn out to be the best one. Also, it was seen that the accuracy level of gestational age predicted by ultrasonography was slightly more accurate than that determined by last menstrual period.*

Conclusions: *There is a high degree of association among the different foetal parameters. Further, there is a high degree of association between the gestational ages by LMP and that by USG. Prediction of gestational ages by USG technique gives a good degree of accuracy and hence can be a reliable technique for estimation of gestational ages.*

Keywords: *Gestational Age (GA), Biparietal Diameter (BPD), Head Circumference (HC), Abdominal Circumference (AC), Femur Length (FL), Last Menstrual Period (LMP), Ultrasonography (USG).*

1. Introduction

The prediction of gestational age with precision is an important component of obstetric sonography. It is more vital in order to provide proper treatment and to take care of the pregnant mothers. Accurate assignment of gestational age may reduce post-dates labour induction and may improve obstetric care through allowing the optimal timing of necessary interventions and to avoid the unnecessary ones[1]. Several sonographic foetal measurement parameters during the second and third trimesters may be proposed for this purpose. Some of them are the followings

i) Biparietal Diameter (BPD): The transverse distance between the parietal eminences on each side of the head[2].
ii) Head Circumference (HC): The distance from above the eyebrows and ears and around the back of the head[3].
iii) Abdominal Circumference (AC): The distance through the upper abdomen covering the stomach[4].
iv) Femur Length (FL): The distance from the head of the femur to its distal end or the length of the thighbone[5].

The length of other long bones and binocular distance are also often considered, but the main focus is laid on the measurement of these four parameters[6]. Ultrasonography foetal femur length measurements have been introduced recently as an alternative to biparietal diameter measurements[7]. In last few decades, most studies had made using the Last Menstrual Period (LMP) in women with regular cycles as the major standard for obtaining the true Gestational Age (GA). This criterion also had several potential sources of inaccuracy, such as, faulty memory, bleeding in early pregnancy and use of oral contraceptives[8]. Also early USG i.e. less than 20 weeks' of gestation, systematically underestimates the gestational age of smaller foetuses by approximation of 1-2 days; but this bias is sometimes relatively small in comparison with the large error introduced by LMP estimation[9].

Reviewed literature reveals that different mathematical models has a wide use for the purpose of prediction of gestational ages and observed that most of these models are linear in nature[10]. In this paper our main objective is to better understand and characterize the misclassification found with gestational ages determined by using LMP[9]. This study is focused to determine the accuracy of gestational ages (measured in weeks) predicted by foetal measurements (measured in millimeters) through USG with the help of non-linear regression models. Often it is observed that the linear regression can give good fits, still it might not be able to model the specific curve that exists in our data. We may get a high correlation value if we give a closer look. We also observed that the regression line systematically over-predicts and under-predicts the data at different points in the curve. In this paper, we have fitted the same data using non-linear models where the regression line follows the data to a large extent with negligible systematic deviations. Again, in the case of linear modelling, the result yields a non-random residual plot. In the present study we have gone for non-linear models where the residual plot exhibits a random behaviour which is a key indication of the better understanding than the former. In the case of any modelling techniques, generally two or more variables, say, two or more foetal parameters in our paper may be combined for analysing the extent of association between the different independent variables. In the analysis, very high correlation values are obtained for all the possible pairs. The best performing formula used for a single foetal parameter at a time is demonstrated by Mul et al. which showed that FL served as the most crucial predictor for determination of gestational age by USG in the late second trimester[10]. Also for the case of early second trimester, Chitty and Altman showed that FL is the best predictor for predicting GA[11] while Hadlock et al. combined both BPD and FL to get more accurate results[12].

2. Methods and materials

We have considered a cross-sectional study collected in a prospective nature where considered 229 singleton pregnant mothers enrolled during December 2015 to November 2016 in Ibn Sina Diagnostic and Imaging Center and Ad-din Hospital in Dhaka, Bangladesh. Verbal communication with consent was taken from all participants. Participants who could recall last normal menstrual period and had regular menstrual cycles before pregnancy, they had an ultrasonogrphic assessment before 14 weeks indicates a crown-rump length which matched with the time length of LMP by one week also included in the study. Besides, the mothers who had the criteria of multiple gestation, maternal complications such as maternal diabetes or abnormal glucose tolerance test, pregnancy-induced hypertension, chronic hypertension, pre-eclampsia, eclampsia, placental abruption, Rh isoimmunization, drug abuse, severe oligohydramnios or polyhydramnios, abnormal fetal karyotyping, fetal congenital abnormalities were excluded from our study.

Four fetal parameters namely biparietal diameter (BPD), head circumference (HC), abdominal circumference (AC), and femur length (FL) were measured through ultrasonographic process. The thalamic view was used to measure BPD and HC. In thalamic view, it was displayed the thalamus, third ventricle, falx cerebri and cavum septum pellucidum (CSP) or the fornices anteriorly. As we know there are several methods to measure BPD, but the common established method was used for measurement from outer-toinner. In our study, the calipers for BPD measurement have been placed at the widest distance vertical to the midline on the leading edges of the near and far parietal bones (Figure 1).

To measure the HC accurately, the elliptical measurement cursor is placed at the outer edge of the of the skull bones without including the skin tissue. The calipers for occipito-frontal diameter measurement is placed on a plane perpendicular to the biparietal diameter at the midpoint of the frontal and occipital bones. The cephalic index is calculated as the ratio of biparietal diameter to occipitofrontal diameter (Figure1).

Figure 1: Bi-parietal diameter (BPD) and head circumference (HC)

Figure 2: Abdominal circumference (AC)

Figure 3: Femur length (FL)

Abdominal circumference (AC) is measured through a particular plane of section where fetal abdomen appeared round or nearly round. Sonographic marker for the correct AC level included the fetal spine, stomach and portal vein. The AC can predict gestational age better in the second trimester with declining precision about to term. Similarly, biological variation and risk factors may cause the factual error of AC measurements. However it should be noted that the abdominal circumference shown in Figure 2 is the gestational growth parameter that is widely affected during pregnancies affected by weird fetal growth behaviour.

The fetal femur is measured as early as 12 weeks of gestation. The proper plane of section is the long axis of the bone when the femur is horizontal and shadows uniformly- at least from end to end. One example of measuring FL has been shown in Figure 3.

Hadlock et al. (1982) combined many measurements to increase the accuracy of gestational age assessment with the rationale when two or more parameters estimated the same end point where the chance of predicting the end point with accuracy was improved. The BPD, HC, AC, and FL measurements were found as described before and the gestational ages corresponding to these parameters were averaged to get a standard gestational age. However, if gestational age measurements under various parameters were quite dissimilar then averaging several parameters decreased the accuracy of the predictors. But while certain anomalies, as example, fetal macrosomia, intrauterine growth retardation and congenital anomalies when traced, then averaging of fetal growth parameters appeared may be inappropriate (Butt et al. 2014). In the present research, to increase accuracy of determination of gestational age, multiple linear regression models have been fitted for GA by LMP and GA by USG with BPD, FL, AC, and HC.

2.1 Polynomial regression

If the data is correlated, but the relationship doesn't look linear then the researchers can do a polynomial regression on the data to fit a polynomial equation to it. In statistics, polynomial regression is a form of regression in which the relationship between the independent variable (or vector of independent variables) X and the dependent variable Y is modelled as a 2^{t} degree polynomial in X[21,22]. We might propose a quadratic model of the form-

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \varepsilon \qquad (1)$$

In this model, when the predictor variable is increased from X to X+1 units, the expected changes of response variable by $\beta_1 + \beta_2(2X + 1)$ (*e.g*. this can be seen by replacing X in this equation with X+1 and subtracting the equation in X from the equation in X+1). The fact that the change in response variables (GA) depends on X is what makes the relationship between X and Y nonlinear even through the model is linear in the parameters to be estimated.

In general, the model of expected value of Y (GA) as an n^{t} degree polynomial regression model as-

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3 + \cdots + \beta_n X^n + \varepsilon \quad . \qquad (2)$$

The regression equation (2) is linear in terms of the unknown parameters $\beta_0, \beta_1, \cdots, \beta_n$. That's why least squares analysis, the computational and inferential problems of polynomial regression can be completely addressed using the techniques of multiple regressions[23].

2.2 Ridge regression

Ridge regression is a technique for analysing multiple regression data that suffer from multicollinearity. When multicollinearity occurs, least square estimates are unbiased, but their variances are large so they may be far from the true value. By adding a bias to the regression estimates, ridge regression reduces the standard errors[13]. It is already evident from the above models considering one independent variable at a time, that the data at our disposal is highly multicollinearity in nature, which implies that near-perfect relationship exists among all the variables.

Ridge regression is a technique for analysing multiple regression data that suffer from multicollinearity[24]. Suppose the regression equation is written in matrix form as-

$$Y = X\beta + \varepsilon. \qquad (3)$$

where Y is a $n \times 1$ vector of observations on a response variable.$\beta$is a $p \times 1$ vector of unknown regression coefficients, X is a matrix of order $(n \times p)$ of observations on 'p' predictor (or regressor) variables and ε is an $n \times 1$ vector of errors with $E(\varepsilon) = 0$ and $V(\varepsilon) = \sigma^2 I_n$. For the sake of convenience, we assume that the matrix X and response variable Y are standardized in such a way that $X'X$ is a non-singular correlation matrix and $X'Y$ is the correlation between X and Y [24, 25]. The ordinary least squared estimate in equation (3) is

$$\hat{\beta}_{ls} = (X'X)^{-1}X'Y. \qquad (4)$$

But this estimator could be improved by adding a small constant value λ to the diagonal entries of the matrix $X'X$ before taking its inverse.

$$\hat{\beta}_{ridge} = \left(X'X + \lambda I_p\right)^{-1} X'Y. \qquad (5)$$

$\hat{\beta}_{ls}$ is an unbiased estimator of β ; $\hat{\beta}_{ridge}$ is a biased estimator of β . For orthogonal covariates, $X'X = nI_p$,$\hat{\beta}_{ridge} = \frac{n}{n+\lambda}\hat{\beta}_{ls}$. Hence, in this case, the ridge estimator always produces shrinkage towards 0. λ controls the amount of shrinkage. An important concept in shrinkage is the "effective" degrees of freedom associated with a set of parameters. In a ridge regression setting:

i) If we choose $\lambda = 0$, we have □ parameters (since there is no penalization).

ii) If λ is large, the parameters are heavily constrained and the degrees of freedom will effectively be lower, tending to 0 as $\lambda \to \infty$.

The effective degrees of freedom associated with $\beta_1, \beta_2, \cdots, \beta_p$ is defined as-

$$df(\lambda) = tr\left(X\left(X'X + \lambda I_p\right)^{-1}X'\right) = \sum_{j=1}^{p} \frac{d_j^{\,2}}{d_j^{\,2} + \lambda}. \quad (6)$$

where, d_j are the singular vectors of X.

3. Results

3.1 Analysis of regression models with a single variable

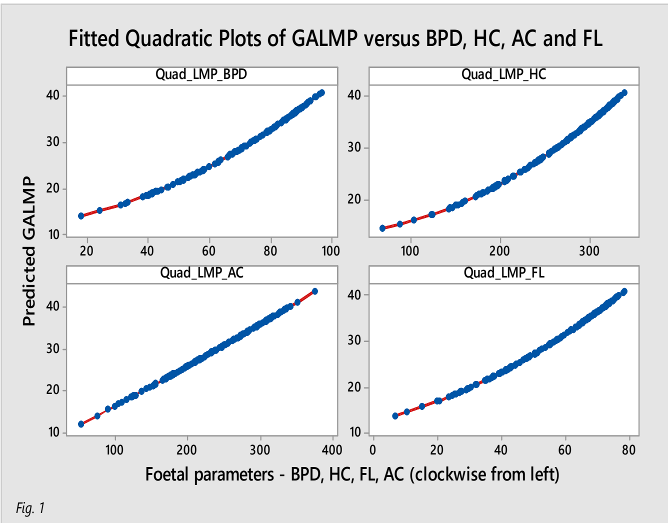
Let us consider a polynomial regression model of order 2 or higher. We have implemented the regression models of order 2 and 3 which serve our purpose and not required to proceed with further higher order models these are likely to give more accurate estimates. For our analysis purpose, we have chosen y_1 and y_2 to denotethe two response or dependent variables i.e. gestational ages by LMP and USG respectively. Also let, x_1, x_2, x_3 and x_4 denote the four predictor or independent variables i.e. BPD, HC, AC and FL respectively.

3.1.1 Dynamical behaviour of quadratic model

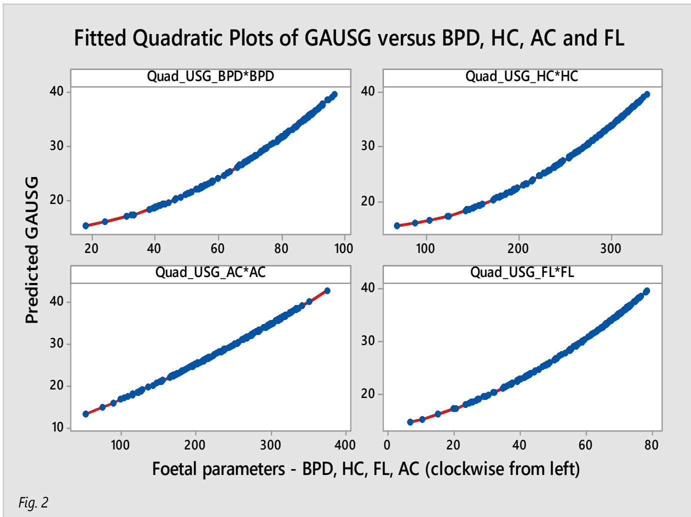
We have predicted the responses GA by LMP as well as by USG individually for each of the independent variables through quadratic and cubic models. We have fitted a regression in each case and determined which parameter best describes the output. Cubic model is being a degree higher almost than the quadratic models which yields better prediction results.

Table 1. Correlation between GA and foetal parameters for quadratic and cubic models

Models	Predictors		BPD	HC	AC	FL
Quadratic	Gestational age	By LMP	0.959	0.942	0.939	0.958
		By USG	0.996	0.951	0.958	0.964
Cubic		By LMP	0.960	0.943	0.942	0.958
		By USG	0.968	0.953	0.968	0.969

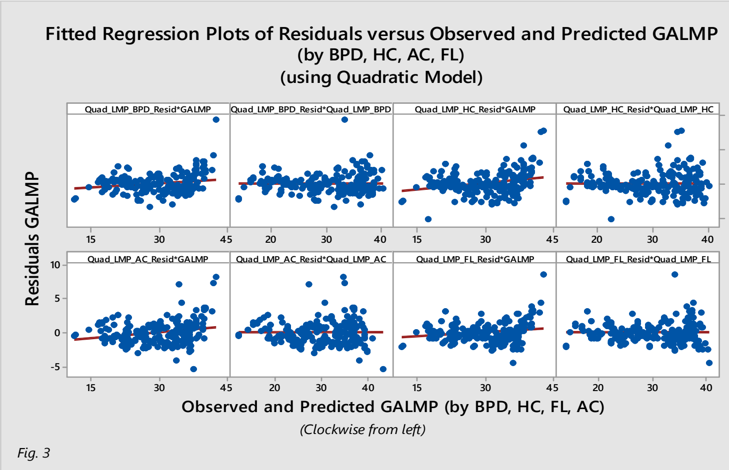


a) Quadratic modelling of GA by LMP for respected variables

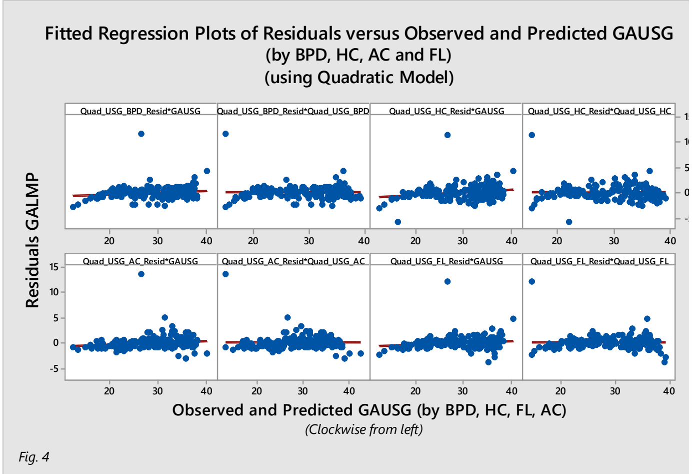


b) Quadratic modelling of GA by USG for respected variables

Fig. 4. Quadratic modelling of GA by LMP and USG for BPD, HC, AC and FL separately



a) Residual plots for original vs. fitted GALMP for quadratic model

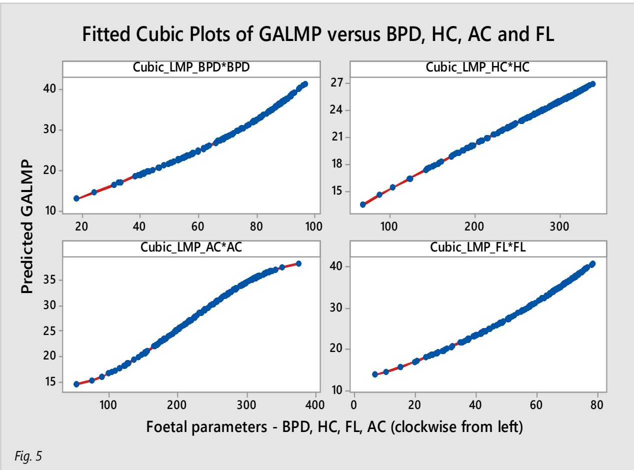


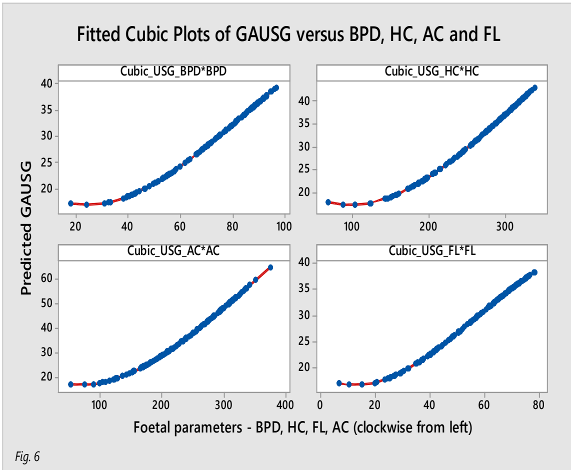
b) Residual plots for original vs. fitted GAUSG for quadratic model

Fig. 5. Plots of residual versus original and fitted GALMP and GAUSG for quadratic models

3.1.2 Dynamical behaviour of cubic models

The four regression plots for predicting GA by LMP and the other four for predicting the GA through USG have been shown below.

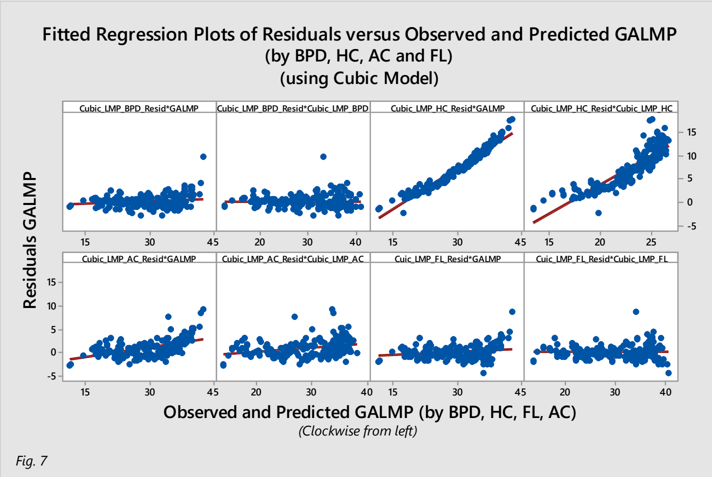




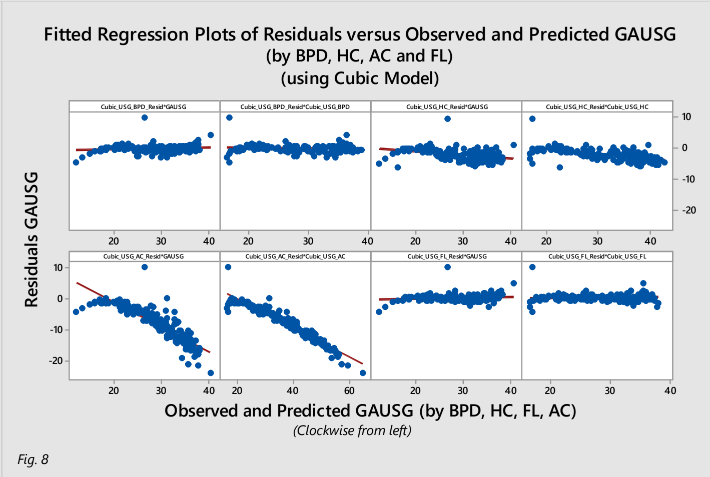
a) Cubic modelling of GA by LMP for BPD, HC, AC and FL separately

b) Cubic modelling of GA by USG for BPD, HC, AC and FL separately

Fig. 6. Cubic modelling of GA by LMP and USG for BPD, HC, AC and FL separately



a) Residual plots for original vs. fitted GALMP for cubic model



b) Residual plots for original vs. fitted GAUSG for cubic model

Fig. 7. Plots of residual versus original and fitted GALMP and GAUSG for cubic models

Table 2. Coefficients of each predictor variable for different modelling

Models	Response	Predictors	b_0	b_1	b_2	b_3
Quadratic	GALMP	BPD	11.94	0.069	0.0020	-
		HC	12.83	0.004	0.0002	-
		AC	7.42	0.087	0.0002	-
		FL	12.42	0.170	0.0020	-
Quadratic	GAUSG	BPD	14.22	0.003	0.0030	-
		HC	15.29	-0.016	0.0003	-
		AC	9.64	0.065	0.0006	-
		FL	13.65	0.120	0.0030	-
Cubic	GALMP	BPD	6.62	0.38	-0.0003	0.00003
		HC	9.15	0.06	-0.0007	0.00001
		AC	14.42	-0.03	0.0006	-0.00001
		FL	12.10	0.20	0.0020	0.00005
Cubic	GAUSG	BPD	21.21	-0.41	0.0100	-0.00004
		HC	24.12	-0.16	0.0001	-0.00001
		AC	20.63	-0.12	0.0001	-0.00001
		FL	18.36	-0.30	0.0010	-0.00008

3.1.3 Dynamical behaviour of logarithmic model

The regression equation for predicting GA based on the foetal parameters taken one at a time is shown as follows-

$$y = -\frac{\ln\left[\ln\left(\frac{b_1}{x}\right)\right]}{b_2} + b_3 \qquad (7)$$

where y is the response variable i.e. GA, and x is the predictor variable when each of the four foetal parameters considered once at a time. The choice of the parameters b_1, b_2 and b_3 are very crucial in order to get the correct estimates of the predicted value. We fix values of these coefficients based on the predictors by trial and error method as follows.

Table 3. Coefficients of logarithmic regression for each foetal parameter

Foetal Parameters→ **Coefficients↓**	**BPD**	**HC**	**AC**	**FL**
b_1	135.96	445.96	500.96	135.96
b_2	0.055	0.055	0.055	0.055
b_3	19.82	19.82	19.82	19.82

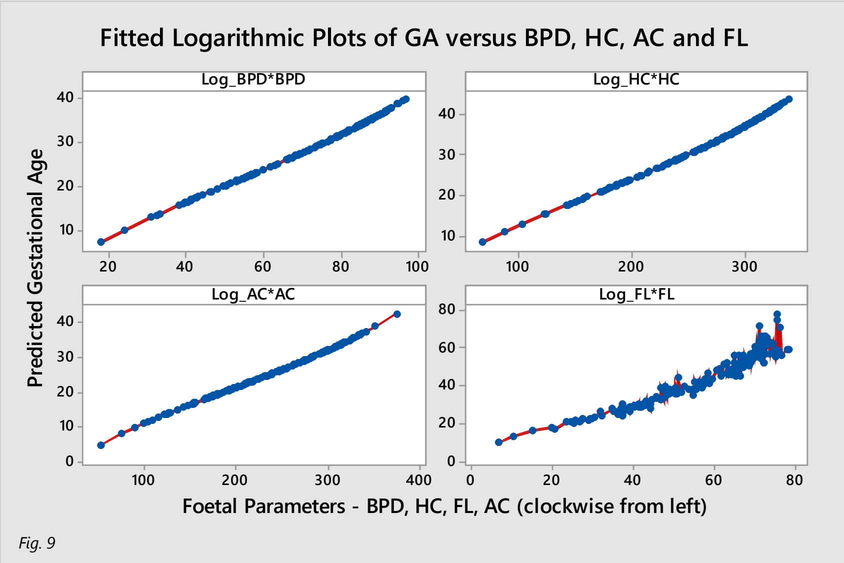


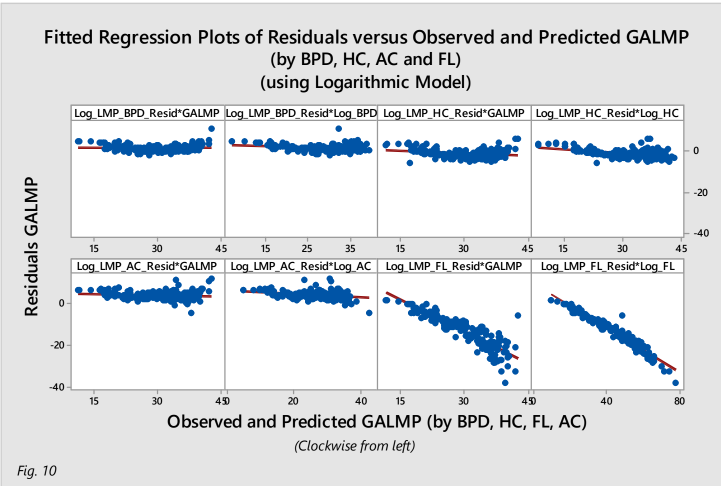
Fig. 8. Logarithmic modelling of GA for BPD, HC, AC and FL separately

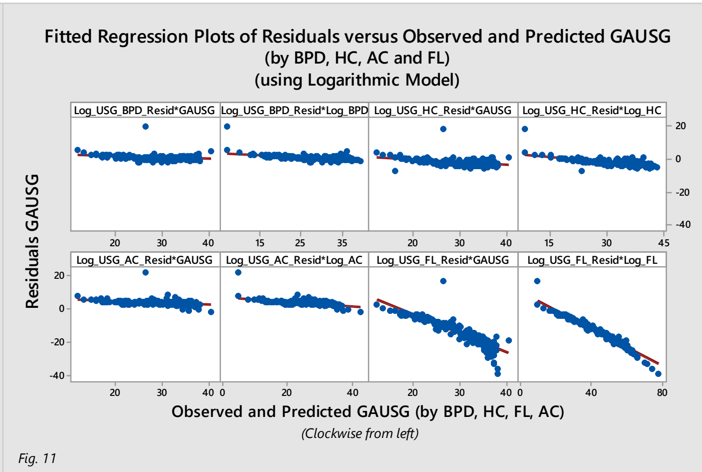
The correlation values for this modelling are in fact much higher than the above polynomial models.

Table 5. Correlation between GA and foetal parameters(GA obtained through logarithmic model)

GA versus Predictor	BPD	HC	AC	FL
Correlation	0.998	0.998	0.969	0.999

The plotted graphs of the residuals against the original and fitted values of the response help us to analyse the degree of accuracy of the predicted models. These are shown separately for GA by LMP and for that by USG.





a) Residual plot of original vs. fitted GALMP for logarithmic model

b) Residual plot original vs. fitted GAUGS for logarithmic model

Fig. 9. Plots of residual versus original and fitted GALMP and GAUSG for logarithmic models

3.2Analysis of regression models with more than one variable

3.2.1 Dynamical behaviour of ridge regression model

High correlations in the correlation matrix confirm the presence of multicollinearity. Since all the pairs show very high correlation, ridge regression may be a good choice for modelling of data.

Then ridge regression model is given as-

$$\frac{y-\bar{y}}{\sigma_y}=\beta_1\frac{x_1-\bar{x}_1}{\sigma_{x_1}}+\beta_2\frac{x_2-\bar{x}_2}{\sigma_{x_2}}+\beta_3\frac{x_3-\bar{x}_3}{\sigma_{x_3}}+\beta_4\frac{x_4-\bar{x}_4}{\sigma_{x_4}}$$

The ridge regression estimator is obtained by

$$\hat{\beta}=(\beta_1,\beta_2,\beta_3,\beta_4)^T=(X^TX+\lambda I)^{-1}X^TY$$

Here the choice of λ must be within 0.001-0.005, in order to get reliable estimates when the total number of observations is high. Let us choose λ=0.001.Also, $X=(\underline{x}_1,\underline{x}_2,\underline{x}_3,\underline{x}_4)$.Further, X^TX is nothing but the correlation matrix which is shown as follows separately for GALMP and GAUSG.

For GALMP, $X^TX=R=\begin{bmatrix}1 & & & & \\ 0.973 & 1 & & & \\ 0.962 & 0.987 & 1 & & \\ 0.969 & 0.974 & 0.975 & 1 & \\ 0.974 & 0.989 & 0.979 & 0.973 & 1\end{bmatrix}$.

Similarly, for GAUSG, $X^TX=R=\begin{bmatrix}1 & & & & \\ 0.973 & 1 & & & \\ 0.962 & 0.984 & 1 & & \\ 0.978 & 0.974 & 0.974 & 1 & \\ 0.975 & 0.988 & 0.979 & 0.973 & 1\end{bmatrix}$.

Thus, the predicted response is given by

$$y_{pred}=\sigma_y\left[\widehat{\beta_1}\frac{x_1-\bar{x}_1}{\sigma_{x_1}}+\widehat{\beta_2}\frac{x_2-\bar{x}_2}{\sigma_{x_2}}+\widehat{\beta_3}\frac{x_3-\bar{x}_3}{\sigma_{x_3}}+\widehat{\beta_4}\frac{x_4-\bar{x}_4}{\sigma_{x_4}}\right]+\bar{y}$$

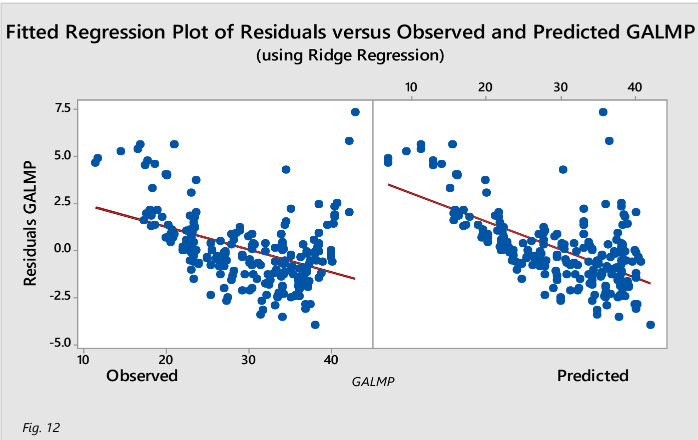
We obtain the following estimates of $\hat{\beta}$, which are tabulated as follows.

Table 6. Parameter estimates for GALMP and GAUSG

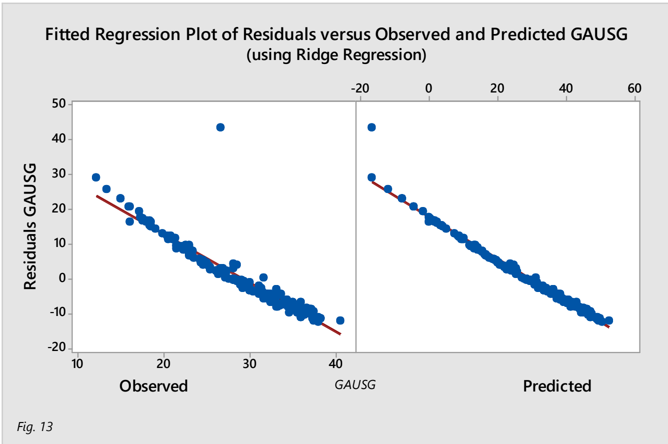
Parameter estimates	$\widehat{\beta_1}$	$\widehat{\beta_2}$	$\widehat{\beta_3}$	$\widehat{\beta_4}$
GALMP	0.0334	0.2541	0.6152	0.2537
GAUSG	0.2640	0.4168	1.2035	0.5871

The correlation between GALMP and GALMPpred is 0.976 and also correlation between GAUSG and GAUSGpred is 0.982.As the correlations are very high, the model must be a reliable one.

The graphs of residuals versus original and fitted values of GALMP as well as that of GAUSG are shown below.



a) Residuals plot of original vs. fitted GALMP for ridge regression model



b) Residuals plot of original vs. fitted GAUSG for ridge regression model

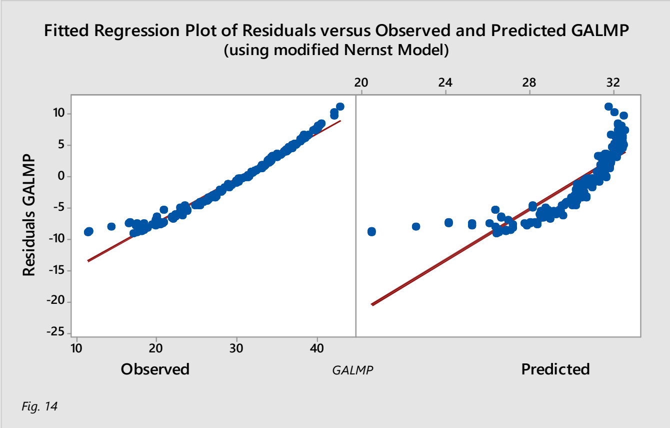
Fig. 10. Plots of residual versus original and fitted GALMP and GAUSG for logarithmic models

3.2.2 Dynamical behaviour of modified Nernst regression model

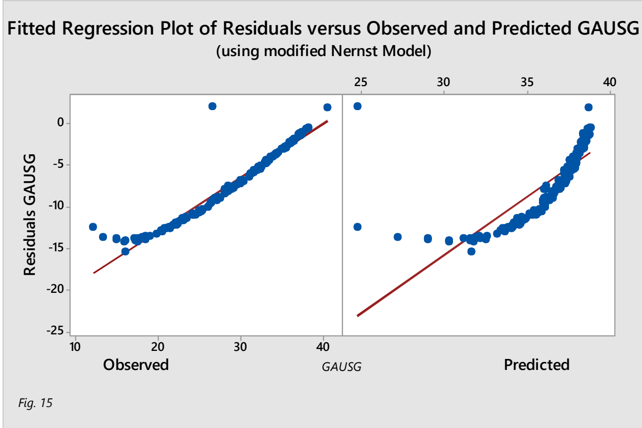
The Nernst model is a combination of logarithmic models of individual variables and is only applicable for multivariate situations with at least more than two predictor variables [14].The model is slightly modified to incorporate the fluctuating parameters and all the explanatory variables. The modified regression equation may be represented as follows-

$$y = \ln(x_1) + \beta_1\beta_2 \ln(x_1 + \beta_1) + \ln(x_2^2) + \beta_2\beta_3 \ln(x_2 + \beta_2) + \ln(x_3) + \beta_3\beta_4 \ln(x_3 + \beta_3) + \ln(x_4^2) + \beta_4\beta_1 \ln(x_4 + \beta_4).$$

Also we have corr (GALMP, GALMPpred) = 0.928 and corr (GAUSG, GAUSGpred) = 0.926.The graphs of residuals versus fitted and original values of GALMP and GAUSG are plotted below-



a) Plot of residuals versus original and fitted GALMP for Nernst model



b) Plot of residuals versus original and fitted GAUSG for Nernst model

Fig. 11. Residual plots of original vs. fitted GALMP and GAUSG for Nernst models

4. Discussion

Now that we have seen the different forms of regression models for the prediction of gestational ages, let us try to discuss of the determinants which combination among the four foetal parameters serve as the best predictors. For this, we compute partial correlation coefficients of the response and the predictor variables. The various foetal parameters are strongly connected, such as if HC increases, then FL also increases, and likewise, which is represented similar results [26,27,28].

For univariate modelling, we observed that the choice of predictor variables varies for different polynomial modelling. Also, there is variation in the response variable for different multivariate modelling techniques used. Although the variations are very minor, yet the predictor for the former and the response for the latter are serving to be a good choice for the analysis and to determine the precision of modelling used to predict GA. Like some other researches, USG was noticed to be more precise than the observed LMP as a basis for estimating GA[26,27].We drop the case of choosing only one predictor variable, as we have already seen the best predictor when a single parameter is considered (while discussing Quadratic and Cubic Models). We have computed the partial correlation coefficients by considering two, three and four response variables and tabulated the choice of predictors for univariate as well as multivariate modelling as shown in tables 7 and 8.

Table 7.Choice of predictors for univariate modelling

Models	GALMP	GAUSG
Quadratic	BPD	BPD
Cubic	BPD	FL
Logarithmic		FL

Table 8. Choice of response for multivariate modelling

Models	Ridge regression	Nernst model
Response	GALMP	Both GALMP & GAUSG

Also, we find that the partial correlation coefficients are equally high for any combination of foetal parameters where we observe that for GALMP the coefficient value is highest for the combination (HC, AC, FL), i.e. 0.984 and for GAUSG it is highest for the combination (BPD, HC, AC), i.e., 0.985[28]. Hence outputs are best predicted when these combinations are used for predicting GA by the respective methods[12,16,20]. The Cubic model offers better prediction performance in comparison with the quadratic models[28].

The next highest value is $r_{1.2345}$ = 0.979 for the combination (BPD, HC, AC, FL) for GA by both methods. So if all the four parameters are available for patients, then the modelling can be done in a much better way as compared to the previous case where some of the parameters are missing. However, we observed that for all the other combinations the values of partial correlation coefficients are significantly high. Hence even if any one of the four foetal parameters under consideration is available, then the modelling is no doubt effectively good.

Again, as we have already seen the correlated variables are creating the problem of multicollinearity in the present analysis. Further, as the covariates are related to each other, it seems pointless to include several correlated independent variables in our considered model as according to the principle of parsimony, fewer covariates must be included in any model for better accuracy. Hence choosing one predictor variable at a time, we have already seen that the logarithmic model has given the best service as per our proposed purpose in this analysis[15]. Ridge regression analysed multiple regressions for the dataset as it suffers from multicollinearity[24]. It was found in 3.2 that, there was a very significant association between GALMP and GALMPpred, i.e. 0.976 and also a very high association between GAUSG and GAUSGpred, i.e. 0.982.The Nernst model gave more or less satisfactory results for the determination of GA by both LMP as well as by USG. As for Nernst model, we can say that both GALMP and GAUS are good technique to identify GA under the predictors which were found in Nernst models also[2,26]. The results are to identify GA by LMP and USG show almost same significance which was found from different regression analysis[26,27].

GA regression test approaches have been employed which are more reliable than commonly used tests in regular clinical practices in this study [29]. Biparietal diameter, head circumference, abdominal circumference and femur length were implemented by ultrasonography between the 10th and 42nd weeks of gestation and the last menstrual cycle to predict gestational period. GAALMP estimates are more prone to random error than GAUSG[30,31,32].

5. Conclusions

The different techniques of prediction of gestational ages by last menstrual period (LMP) and by ultrasonography (USG) have been done through necessary regression models. The different foetal parameters are highly associated amongst each other, such as if HC increases, then FL are also increasing or vice-versa which is quite expected. Even though, determination of GA by LMP is not a good choice in the 21st century but the results do not differ too much from the GA as predicted through medical sonography. The slight mismatches in the predicted gestational ages are acceptable as no method can be devised which is completely free from errors. So one should obviously go for the model which produces a response with minimum error. The ridge model also gives good results only for GALMP, whereas for GAUSG, it gives highly inaccurate results. The Nernst model is giving more or less satisfactory results for determination of GA by both LMP as well as by USG. The best form of model that can be used to predict the gestational ages is perhaps the logarithmic model which we have considered in this study. And as the strength of association between the observed and predicted values is indeed very high so the best predictor happens to be BPD. However, prediction of gestational ages in the first trimester of pregnancy is sometimes inaccurate by using logarithmic models as for large values; the range gets fixed within a small interval. In such cases, polynomial modelling is the only choice in reality.

A simple but uniform approach to the evaluation of gestational age may be performed in all foetuses. The ultrasound assessment of foetal age is based on the earliest ultrasound study as the measurement is technically adequate. Accurate assessment of gestational age either clinically or by ultrasound evaluation helps in correct foetal growth analysis. Foetal growth retardation or macrosomia may occur on account of missed or inaccurate gestational age assignment. Foetal heart rate reactivity and foetal breathing are found to develop with advancing gestational age as the absence of these biophysical parameters may be interpreted as abnormal for foetuses to which the gestational age has been overestimated. Proper decisions regarding presumed preterm labour or postdate pregnancies are accurately possible with correct estimations of gestational ages[16,17].

Given a realistic number (usually between 6 and 7) of repeated measurements of the foetal parameters, at least two weeks apart, with corresponding dates derived from routine Ante-Natal Check-ups, the multiple measures model has the potential to predict gestational age to a higher level of accuracy than previously published methods. It can be applied to the present population using any mathematical models. Entry of a series of measurements of the foetal parameters and the corresponding dates from the model will generate a prediction of the date of birth with corresponding accuracy.

Assessment of gestational age is fundamental to obstetric care and must be a carefully thought-out process which depends on history and physical examination as well as ultrasound evaluation.Use of the multiple parameters method of assessing gestational age is valid when the gestational age estimates to the various ultrasound parameters which are similar. If the gestational age estimates of one or several parameters which is greater than 2 weeks different than the estimates of the other parameters then either the abnormal ultrasound parameters will be excluded or a different method is to be used for estimation of gestational age. When the various ultrasound parameters predict different gestational ages then the foetus should be further evaluated to explain these differences. For example, an abnormally or small FL measurement may suggest short-limb defects and a large BPD may be secondary to hydrocephalus. Another abnormality which is quite common is the small or large AC measurement which suggests asymmetric intrauterine growth retardation or macrosomia respectively. It has also been mentioned earlier that the different ultrasound ratios (CI, HC/AC, and FL/BPD) are sometimes used to identify the abnormally small or large parameters. For case of an abnormal cephalic index, the HC must be used to estimate gestational age rather than the BPD measurement[18].These mathematical models could also be applied to other populations after excising to the same data which were used to obtain SFH, i.e. symphysial fundal height of the foetus growth curves and then a new model could be derived for predictive purposes [19,20]. The application of the model for different populations, particularly those with a different ethnicity may be done of in future time.

Conflict of Interest: The authors have declared that no conflict of interest exists.

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