



Modeling the Population of Child Laborers in the Philippines: A Time Series and Regression Analysis Approach

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ABSTRACT

Child labor refers to the employment of children in any work that deprives children of their childhood and their ability to attend classes which is totally dangerous for them. In the developing countries like in Philippines with high poverty and poor schooling opportunities, child labor is still present. To explore the problem, the study sought to examine further the Population of Child Laborers in the Philippines. The author determined its relationship to the socioeconomic determinants, specifically working children in Agricultural sector, Industrial sector, and Services sector.

Data from 2009 to 2020 were utilized through multiple linear regression to find out the relationship of the variables. Time series models were constructed to identify the best fit model in predicting the Population of Child Laborers in 2021. Based from the multiple regression analysis performed, the socioeconomic indicators have a significant linear relationship to the Population of Child Laborers. The best fit model for time series is the sextic polynomial model, it predicts that by 2024 the Population of Child Laborers will increase to 1,014,800

Keywords: child labor, hazardous work, inadequate social welfare, poverty, mathematical modeling

INTRODUCTION

Child labor is a global issue that continues to cast a dark shadow on the lives of millions of children across the world. This practice not only violates the fundamental rights and well-being of children but also hinders their chances of a better future. The International Labor Organization (ILO) defines Child Labor as work that deprives children of their childhood, interferes with their ability to attend regular schools, and is mentally, physically, socially, or morally harmful. (ILO,2014).In 2017, ILO reported that 152 million children aged 5 to 17 worldwide were involved in some form of labor, and that 73 million were engaged in hazardous child labor. Approximately 70.9% worked in agriculture, 17.2% in services, and 11.9% in industry. For children aged 5–14 involved in some form of labor, 32.0% did not attend school, and the other 68% divided their time between working and studying (International Labour Organization, 2017; Kwadzo & Annan, 2022).

Until the present, Child Labor remains one of the major concerns of the Philippine government where many children are exposed to poor living conditions, lack of education, and inadequate social welfare (Fernandez & Abocejo, 2018). Edmonds and Theoharides (2018) stated that despite strong economic progress in the Philippines over the last several decades, one in five Filipino families continues to remain below the poverty line, which results in the children in the family engaged in child labor. According to the International Labor Organization (2021), the COVID-19 problem has added to the poverty of these already vulnerable groups and may undermine years of progress in the battle against child labor. School closures have exacerbated the issue, and millions of children are working to contribute to their families' income. Agrarian, construction, and manufacturing are some of the main industries recruiting children. In these industries, adolescent can be exposed to noxious chemicals, expected to utilize and calibrate hazardous machinery, and expected to work long hours and risk maltreatment (Dalmacio et al., 2022). Additionally, Ibrahim et al. (2019) stated that children engaged in labor have poor health status, which could be precipitated or aggravated by labor. Malnutrition and poor growth were reported to be highly prevalent among working children. Moreover, child labor subjects children to abuse, whether verbally, physically or sexually which ultimately results in psychological disturbances and behavioral disorders. The effects of child labor on psychological health can be long lasting and devastating to the future of children involved.

Based from Edora et al. (2022), child labor can slow down economic growth through its effect on child development, wages, and technological advancement. Thus, child labor needs to be addressed the soonest possible time for it might result to future Filipino labor force that is deficient in skills and competencies. Solving the issue on child labor does not only benefit the children but also the business and industries. The socioeconomic growth of the Philippines lies on its competent and skilled work force (Fernandez & Abocejo, 2018).

To address this pressing issue, it is crucial to understand the scale and trajectory of child labor in the country. Forecasting the population of child laborers allows researchers and the government to anticipate future trends, identify risk factors, and develop targeted interventions to prevent and eliminate child labor. In this paper, the author examines the association of the working children in Agricultural sector, Industrial sector, and Services sector in the

prediction of the Population of Child Laborers in the Philippines. Through this research, policymakers, government agencies, and non-governmental organizations can proactively design and implements programs that effectively address the root causes of child labor and create a safer and more equitable society for all children.

Statement of the Problem

This study aimed to determine the Population of Child Laborers in the Philippines in relation to the socioeconomic factors such as working children in Agricultural sector, Industrial sector, and Services sector.

Specifically, this study aimed to:

1. Determine the trend of the Population of Child Laborers in the Philippines from 2009- 2020.
2. Find if the Population of Child Laborers in the Philippines has a significant linear relationship with the following variables:
 - a) Working in agricultural sector only
 - b) Working in industrial sector only
 - c) Working in services sector only
 - d) Working in agricultural sector, working in industrial sector, and working in services sector all together.
3. Construct time series model of the main variable using the following models to predict the population for year 2021.
 - e) Linear
 - f) Quadratic
 - g) Exponential
 - h) Polynomial (cubic, quartic, quintic, sextic)
 - i) Power
 - j) Moving Average
 - k) Exponential Smoothing
 - l) Autoregression
4. Determine the best fit models and predict the main variable for Year 2024.

METHODS

Participants

The Philippines was used primarily as the participant of the study. The yearly data of the dependent variable, the Population of Child Laborers, was gathered from 2009 to 2020. The predictors included in the study were working children in Agricultural sector (farming, fishing, hunting, and forestry), Industrial sector (mining, quarrying, manufacturing, and construction), and Services sector (Whole sale and retail trade, households employers, and other service activities).

Data Sources

The data for the Population of Child Laborers, working children in Agricultural sector, Industrial sector, and Services sector were from Philippine Statistics Authority Statistical Databases.

Procedure

The author explored the internet on existing data to be used as variables in the regression analysis as it was a partial requirement in Mathematical Modelling course. After selecting and downloading the data to be used, it was organized first and run in the MS Excel for analysis and interpretation.

Data Analysis

Observation of data on a yearly basis within 2009 to 2020 was done. Scatter diagram was used to determine the trend of Population of Child Laborers from 2009 to 2020. Simple linear regression was utilized to illustrate if there is a significant linear relationship between dependent and independent variables. Multiple linear regression was utilized to predict Population of Child Laborers through the number of working children in Agricultural sector, Industrial sector, and Services sector at the same time. Construct a time series model of the Population of Child Laborers and determine the best fit model in predicting the Population of Child Laborers in the Philippines.

RESULTS AND DISCUSSIONS

Section 1: Trend of the Population of Child Laborers

The figure below, figure 1, illustrates the trend Population of Child Laborers in the Philippines from 2009 to 2020.

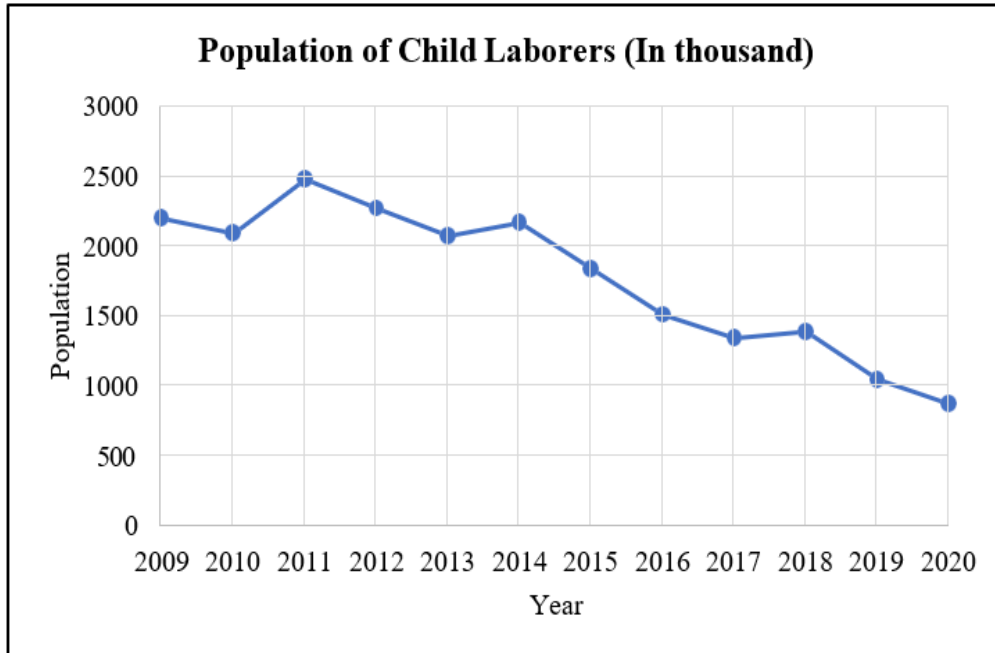


Figure 1. Trend of the Population of Child Laborers from 2009 to 2020.

The figure shown above denotes a decreasing Population of Child Laborers over the period. This suggests that Population of Child Laborers is dependent as it is affected by factors externally or internally.

Section 2: Significant Linear Relationship of Population of Child Laborers

2.1 Working Children in Agricultural Sector

The table shows the linear regression result for the Population of Child Laborers and working children in Agricultural sector from 2009-2020.

Table 1

Linear Regression Result of the Population of Child Laborers and working children in Agricultural sector.

	Coefficients	Standard Error	t Stat	P-value
Intercept	393.390	57.417	6.851	0.000
Agricultural sector	1.407	0.055	25.576	0.000

P-value = 0.000* R2 = 0.9849 **significant at 0.01 *significant at 0.05

Table 1 shows that working children in agricultural sector significantly influence the Population of Child Laborers, $p < 0.000^*$ as the result indicates that there exists a significant linear relationship between working children in agricultural sector and the Population of Child Laborers. The Population of Child Laborers can be predicted using the equation $y = 1.407x + 393.39$, where x is the number of working children in agricultural sector and y is the Population of Child Laborers. The model can explain 98.49 % of the variances.

2.2 Working Children in Industrial Sector

The table 2 shows the linear regression result for the Population of Child Laborers and working children in Industrial sector from 2009-2020.

Table 2

Linear Regression Result of the Population of Child Laborers and working children in Industrial sector.

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>
Intercept	-390.972	693.586	-0.564	0.585
Industrial sector	14.632	4.624	3.164	0.010

P-value = 0.010 R² = 0.5003 **significant at 0.01 *significant at 0.05

Table 2 linear regression result presents that the number of working children in industrial sector is a significant predictor of the Population of Child Laborers, $p < 0.010$ as the result indicates that there exists a significant linear relationship between the number of working children in industrial sector and the Population of Child Laborers. The Population of Child Laborers can be predicted using the equation $y = 14.632x - 390.97$ where x is the number of the working children in industrial sector and y is the Population of Child Laborers. The model can explain 50.03% of the variances.

2.3 Working Children in Services Sector

In table 3, the linear regression result between the Population of Child Laborers and working children in services sector from 2009-2020.

Table 3

Linear Regression Result of the Population of Child Laborers and working children in Services sector.

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>
Intercept	-525.205	175.815	-2.987	0.014
Services sector	3.565	0.267	13.373	0.000

P-value = 0.000* R² = 0.9470 **significant at 0.01 *significant at 0.05

The linear regression result in table 3 shows that the number of working children in services sector is a significant predictor of the Population of Child Laborers. In addition, the result indicates that the data for the number of working children in services sector has a significant linear association to the Population of Child Laborers, $p < 0.000^*$. The Population of Child Laborers can be predicted using the equation $y = 3.565x - 525.21$, where x is the number of working children in services sector and y is the Population of Child Laborers. The model can explain 94.70% of the variances.

2.4 Working Children in Agricultural sector, Industrial sector, and Services sector.

Table 4 demonstrates the multiple linear regression result of the number of working children in agricultural sector, industrial sector, and services sector for 2009-2020.

Table 4

Linear Regression Result of the Three Variables

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>
Intercept	-2.2488	1.6385	-1.3725	0.207
Agricultural sector X_1	0.9970	0.0021	474.3479	0.000
Industrial sector X_2	0.9917	0.0166	59.6183	0.000
Services sector X_3	1.0099	0.0066	152.2837	0.000

P-value = 0.000* R² = 0.9999 **significant at 0.01 *significant at 0.05

When combined, the multiple linear regression result shows that the number of working children in agricultural sector, industrial sector, and services sector have significant linear relationship to the Population of Child Laborers. The predictors indicate a significant effect to the Population of Child Laborers, $p < 0.000^*$. All the three variables, number of working children in agricultural sector, industrial sector, and services sector suggest greatest influence to the Population of Child Laborers. Every one unit increase in the number of working children in Agricultural sector, industrial sector, and services sector the population of child laborers increase to 997, 991, and 1010 respectively. The model that can be used in the prediction of Population of Child Laborers is

$y = 0.9970X_1 + 0.9917X_2 + 1.0099X_3 - 7.8195$, where X_1 is the number of working children in Agricultural sector, X_2 is in Industrial sector, X_3 is in Services sector and y is the Population of Child Laborers. The model can explain 99.99% of the variances.

Section 3: Time Series Model

a. Linear

Figure 2 shows the linear time series model of the Population of Child Laborers (in thousand) from 2009 to 2020.

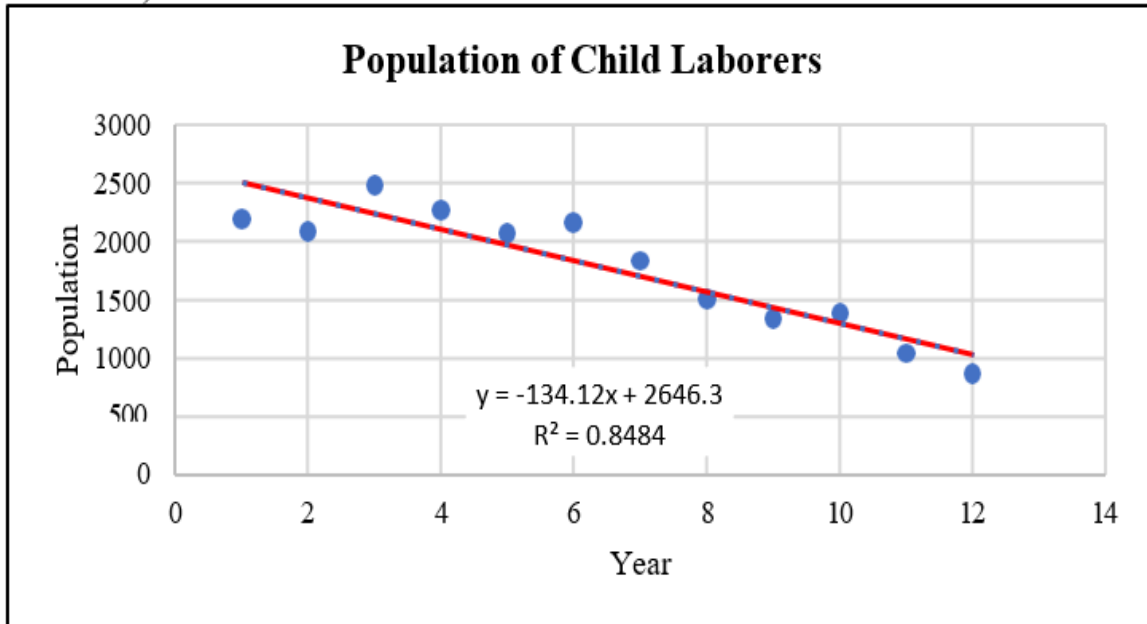


Figure 2. Linear time series model of the Population of Child Laborers from 2009-2020

As indicated in figure 2, the model for linear time series to predict Population of Child Laborers is $y = -134.12x + 2646.3$. The coefficient of determination (R^2) is 0.8484 indicating that a unit change in time leads to 84.84% change in the Population of Child Laborers.

b. Quadratic

Figure 3 shows the quadratic time series model of the Population of Child Laborers (in thousand) from 2009 to 2020.

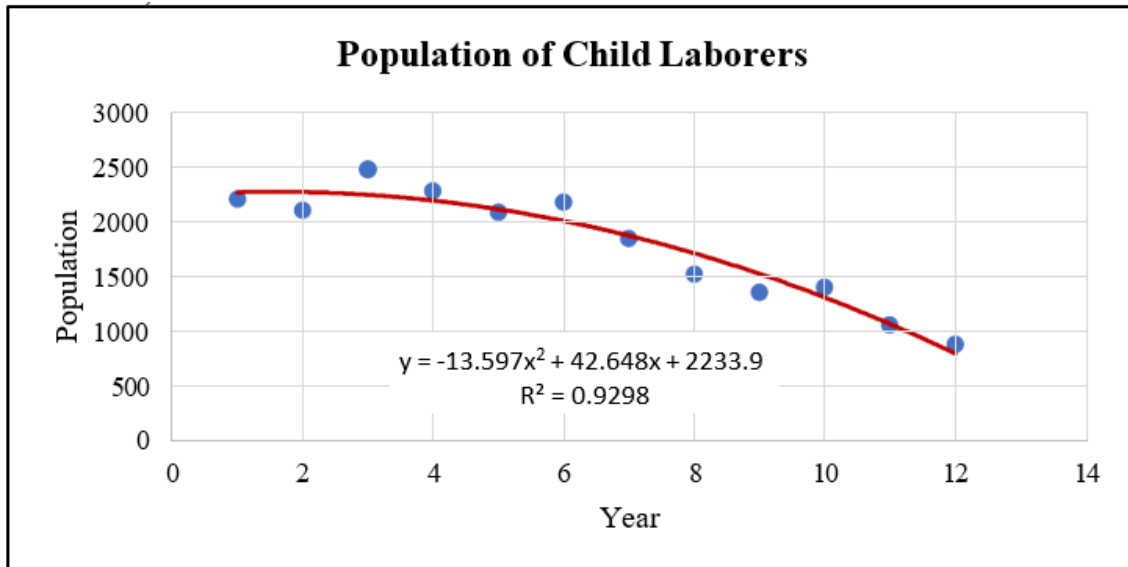


Figure 3. Quadratic time series model of the Population of Child Laborers from 2009-2020

Figure 3 shows that the quadratic model for time series of Percentage of Child Laborers is $y = -13.597x^2 + 42.648x + 2233.9$. The model has a coefficient of determination (R^2) equal to 0.9298 which means that 92.98 % of the variation can be explained by the quadratic model.

c. Exponential

In figure 4, the exponential time series model of the Population of Child Laborers (in thousand) from 2009 to 2020.

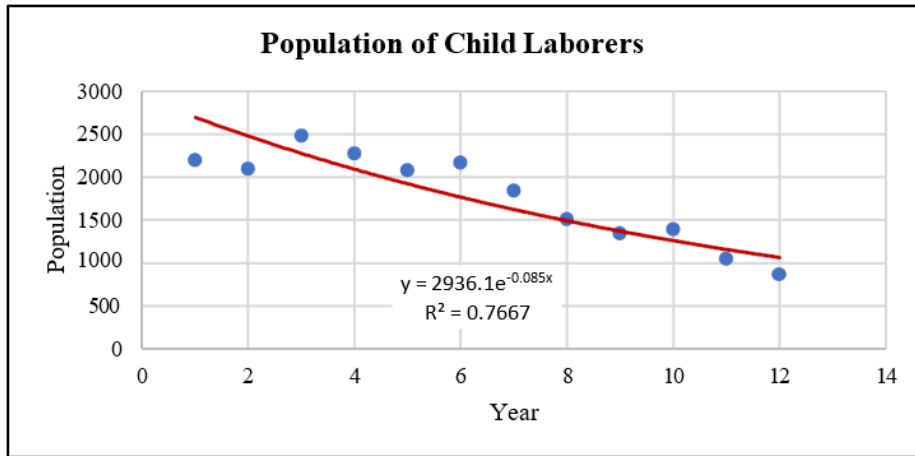


Figure 4. Exponential time series model of the Population of Child Laborers from 2009-2020

The figure 4 has $y = 2936.1e^{-0.085x}$ as the model for exponential time series with the coefficient of determination (R^2) equals 0.7667. This means that 76.67% is being explained by the model.

d. Polynomial (cubic, quartic, quintic, sextic)

d.1 Cubic

Figure 5 below shows the Population of Child Laborers (in thousand) from 2009 to 2020 in a cubic polynomial time series model.

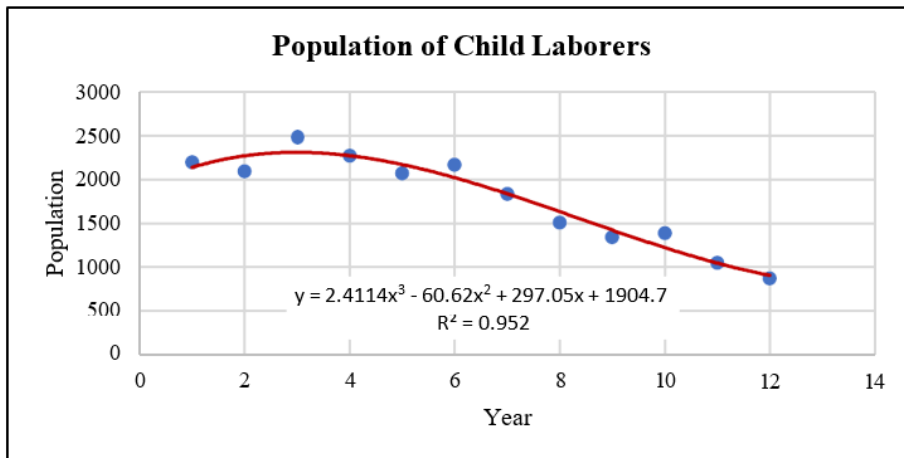


Figure 5. Cubic polynomial time series model of the Population of Child Laborers from 2009-2020

The model in figure 5, $y = 2.4114x^3 - 60.62x^2 + 297.05x + 1904.7$, describes the cubic polynomial time series of Population of Child Laborers. Given the coefficient of determination (R^2) equals 0.952, the model can explain 95.2% of the variation.

d.2 Quartic

Shown in figure 6 is the quartic polynomial time series model of Population of Child Laborers (in thousand) from 2009 to 2020.

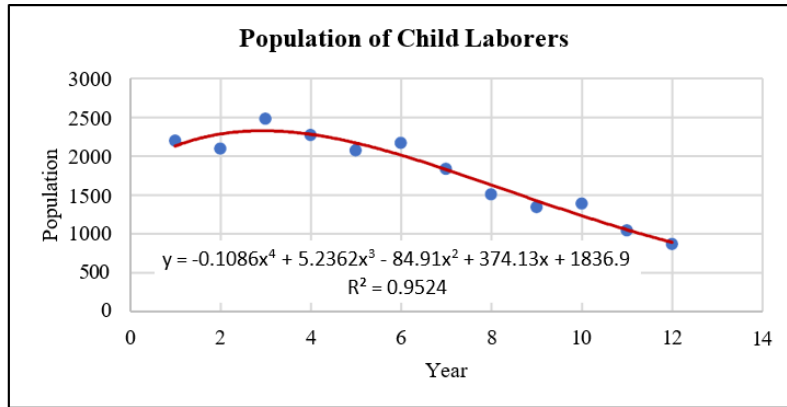


Figure 6. Quartic polynomial time series model of the Population of Child Laborers from 2009-2020

Figure 6 above tells that the equation for quartic polynomial time series model of the Population of Child Laborers $y = -0.1086x^4 + 5.2362x^3 - 84.91x^2 + 374.13x + 1836.9$ with coefficient of determination equivalent to 0.9524 indicating that 95.24% of the variation is being explained by the model.

d.3 Quintic

The quintic polynomial time series model of the Population of Child Laborers (in thousand) from 2009-2020 is shown in the figure 7 below.

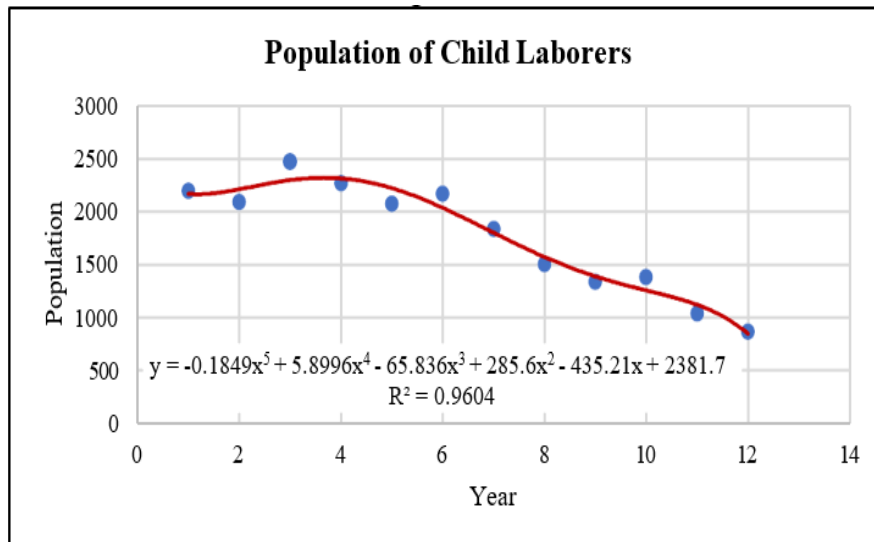


Figure 7. Quintic polynomial time series model of the Population of Child Laborers from 2009-2020

The figure 7 shows that the equation for quintic polynomial time series model of the Population of Child Laborers is $y = -0.1849x^5 + 5.8996x^4 - 65.836x^3 + 285.6x^2 - 435.21x + 2381.7$.

The coefficient of determination is equivalent to 0.9604 indicating that 96.04% of the variation is being explained by the model.

d.4 Sextic

The figure 8 below shows the sextic series model of the Population of Child Laborers (in thousand) from 2009 to 2020.

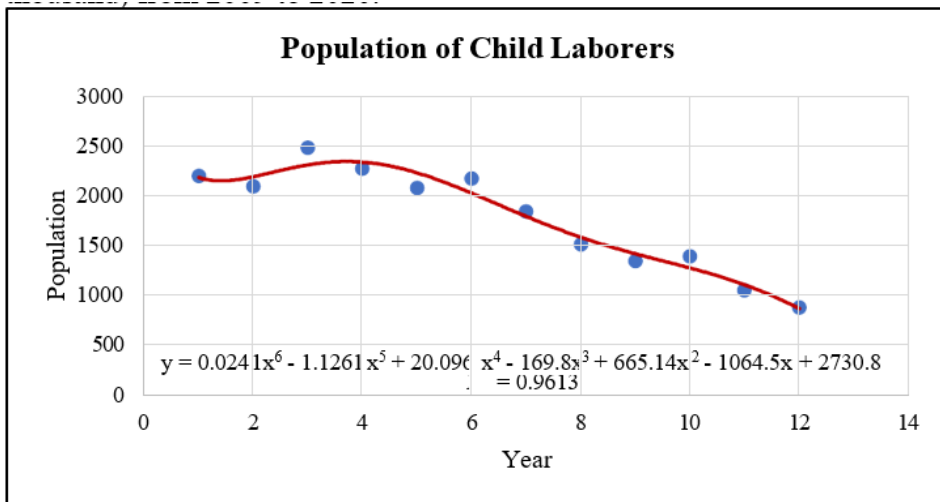


Figure 8. Sextic polynomial time series model of the Population of Child Laborers from 2009-2020

As indicated in figure 8, the model for sextic polynomial time series to predict the Population of Child Laborers is $y = 0.0241x^6 - 1.1261x^5 + 20.096x^4 - 169.8x^3 + 665.14x^2 - 1064.5x + 2730.8$.

The coefficient of determination (R2) is 0.9613 indicating that a unit change in time leads to 96.13% change in the Population of Child Laborers.

e. Logarithmic

Figure 9 shows the logarithmic time series model of the Population of Child Laborers (in thousand) from 2009-2020.

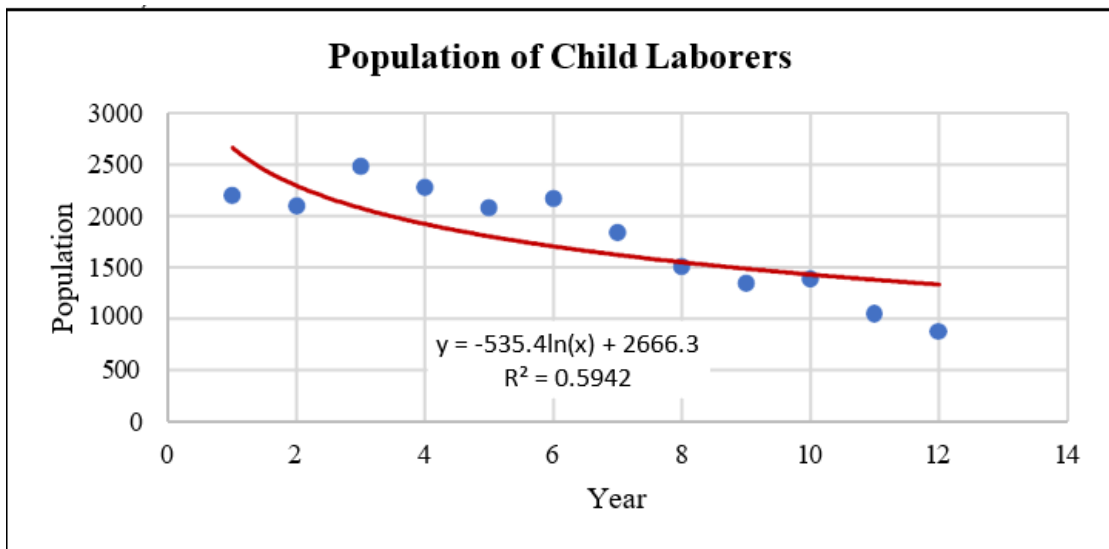


Figure 9. Logarithmic polynomial time series model of the Population of Child Laborers from 2009-2020

The model in figure 9 $y = -535.4\ln(x) + 2666.3$, describes the logarithmic time series of the Population of Child Laborers. Given the coefficient of determination (R2) equal 0.5942, the model can explain 59.42% of the variation.

f. Power

The power time series model of the Population of Child Laborers (in thousand) from 2009 to 2020 is shown in the figure 10 below.

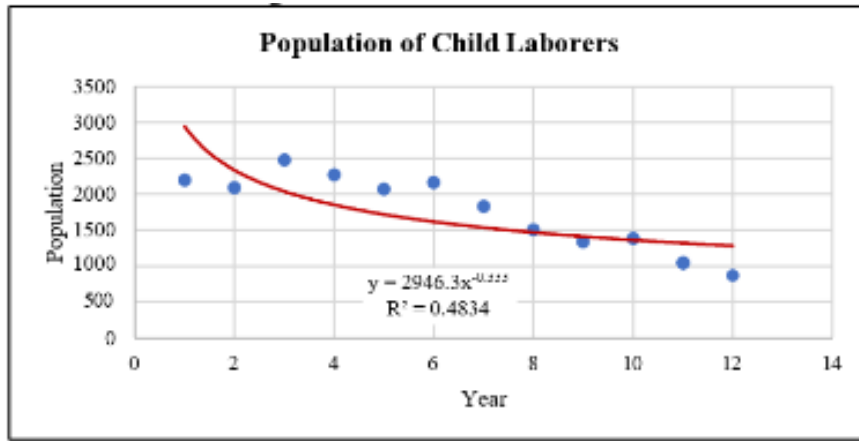


Figure 10. Power polynomial time series model of the Population of Child Laborers from 2009-2020

As indicated in figure 10, the model for power time series to predict the Population of Child Laborers is $y = 2946.3x^{-0.333}$. The coefficient of determination (R^2) is 0.4834 indicating that a unit change in time leads to 48.34% change in the Population of Child Laborers.

g. Moving Average

Figure 11 shows the moving average of the Population of Child Laborers (in thousand) from 2009 to 2020.

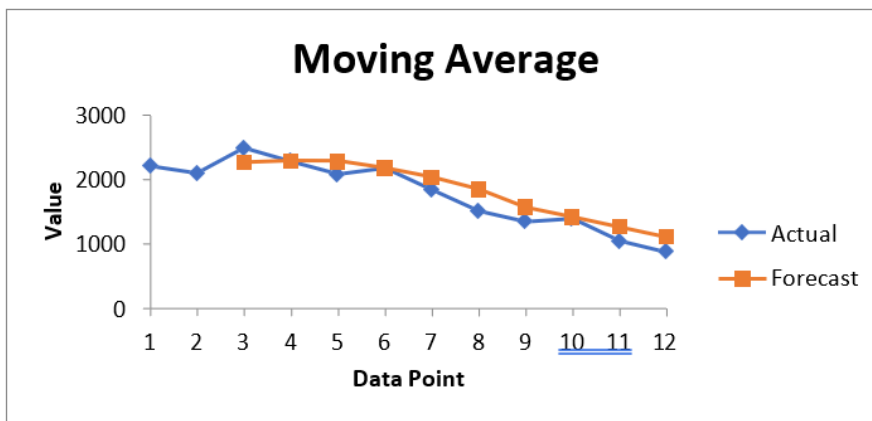


Figure 11. The moving average model of the Population of Child Laborers from 2009-2020

Figure 11 above shows the actual data gathered and its forecast. The model for moving average is $MA(3)_{2021} = Y_{2018} + Y_{2019} + Y_{2020}$.

h. Exponential Smoothing

Figure 12 below shows the exponential smoothing of the Population of Child Laborers (in thousand) from 2009 to 2020.

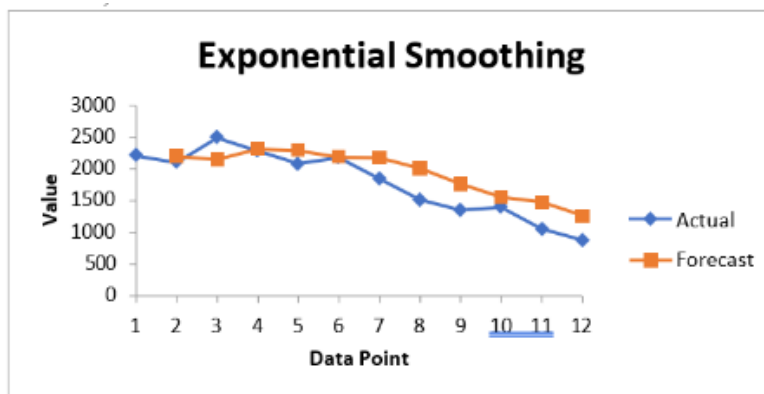


Figure 12. The exponential smoothing model of the Population of Child Laborers from 2009-2020

The figure 12 above illustrates the actual data of the Population of Child Laborers over the year 2009 to 2020. The equation is $E_{2021} = 0.5Y_{2019} + (1-0.5) Y_{2020}$

Autoregression

i.1. First Auto regression

The table 5 below shows the first autoregression result of the Population of Child Laborers from 2009 to 2018.

Table 5

First Autoregression Result for the Population of Child Laborers

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>
Intercept	-209.4789	301.7596	-0.6942	0.5051
X Variable 1	1.0479	0.1581	6.6268	0.0001

P-value = 0.0001 *R²= 0.8299

The first autoregression model that can be used in predicting the Population of Child Laborers is

$y = -209.48 + 1.0479Y_{(n-1)}$. This can be explained 82.99% of variances.

i.1 Second Auto regression

The table 6 below demonstrate the second autoregression result of the Population of working children.

Table 6

Second Autoregression Result for the Population of Child Laborers

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>
Intercept	-378.4053	427.9128	-0.8843	0.4059
X Variable 1	0.8421	0.3675	2.2916	0.0557
X Variable 2	0.2807	0.4373	0.6418	0.5414

P-value= 0.002 R²= 0.8309

The second autoregression model that can be used to predict the Population of Child Laborers is

$y = -378.4053 + 0.8421Y_{(n-1)} + 0.2807Y_{(n-2)}$. This can explain 83.09% of the variances.

Summary Table

Model	Equation
a. Linear	$y = -134.12x + 2646.3$
b. Quadratic	$y = -13.597x^2 + 42.648x + 2233.9$
c. Exponential	$y = 2936.1e^{-0.085x}$
d. Polynomial	
d.1. Cubic	$y = 2.4114x^3 - 60.62x^2 + 297.05x + 1904.7$
d.2. Quartic	$y = -0.1086x^4 + 5.2362x^3 - 84.91x^2 + 374.13x + 1836.9$
d.3. Quintic	$y = -0.1849x^5 + 5.8996x^4 - 65.836x^3 + 285.6x^2 - 435.21x + 2381.7$
d.4. Sextic	$y = 0.0241x^6 - 1.1261x^5 + 20.096x^4 - 169.8x^3 + 665.14x^2 - 1064.5x + 2730.8$
e. Power	$y = 9.0794x^{-0.229}$
f. Logarithmic	$y = -535.4\ln(x) + 2666.3$
g. Moving Average	$MA(3)_{2021} = Y_{2018} + Y_{2019} + Y_{2020}$
h. Exponential Smoothing	$E_{2021} = 0.5Y_{2019} + (1-0.5)Y_{2020}$

i. Auto-regression	
i.1. First auto regression	$y = -209.4789 + 1.0479Y_{(n-1)}$
i.2. Second auto regression	$y = -378.4053 + 0.8421Y_{(n-1)} + 0.2807Y_{(n-2)}$

Section 4 Best fit model and Prediction

Model	Equation	R2	SE	Prediction [2024, (000)]
a. Linear	$y = -134.12x + 2646.3$	0.8484	0.2144	500.38
b. Quadratic	$y = -13.597x^2 + 42.648x + 2233.9$	0.9298	0.1459	-564.6
c. Exponential	$y = 2936.1e^{-0.085x}$	0.7667	0.2781	753.6
d. Polynomial				
d.1. Cubic	$y = 2.4114x^3 - 60.62x^2 + 297.05x + 1904.7$	0.9520	0.1206	1015.9
d.2. Quartic	$y = -0.1086x^4 + 5.2362x^3 - 84.91x^2 + 374.13x + 1836.9$	0.9524	0.1201	416.3
d.3. Quintic	$y = -0.1849x^5 + 5.8996x^4 - 65.836x^3 + 285.6x^2 - 435.21x + 2381.7$	0.9604	0.1097	-8377.8
d.4. Sextic	$y = 0.0241x^6 - 1.1261x^5 + 20.096x^4 - 169.8x^3 + 665.14x^2 - 1064.5x + 2730.8$	0.9613	0.1121	1014.8
e. Power	$y = 9.0794x^{-0.229}$	0.4834	0.4188	1170.3
f. Logarithmic	$y = -535.4\ln(x) + 2666.3$	0.5942	0.3508	1181.9
g. Moving Average	$MA(3)2021 = Y2018 + Y2019 + Y2020$	N/A	0.1512	N/A
h. Exponential Smoothing	$E2021 = 0.5Y2019 + (1-0.5)Y2020$	N/A	0.2308	N/A
i. Auto-regression				
i.1. First auto regression	$y = -209.4789 + 1.0479Y_{(n-1)}$	0.8299	0.2315	887.7
i.2. Second auto regression	$y = -378.405 + 0.8421Y_{(n-1)} + 0.2807Y_{(n-2)}$	0.8309	0.2551	893.2

SUMMARY, CONCLUSION AND RECOMMENDATIONS

Summary

Forecasting is a valuable tool that enable researchers to anticipate and prepare for future trends and developments. By analyzing historical data, identifying key variables, and employing statistical models, researchers can make informed predictions about various phenomena, including population dynamics, economic trends, and social issues. In the context of child labor, forecasting the population of child laborers allows the government to understand potential trajectory of this problem, identify risk factors, and develop targeted interventions to prevent and eliminate child labor in the country.

Summary of Findings

1. The trend of the Population of Child Laborers from 2009 to 2020 is decreasing over time.
2. There is a significant linear relationship between the Population of Child Laborers and the three independent variables included. When the variables were combined together, still, there exist a significant linear relationship. All the three variables, number of working children in agricultural sector, industrial sector, and services sector suggest greatest influence to the Population of Child Laborers.
3. The time series models using the data in 2009 to 2020 are:
 - $y = -134.12x + 2646.3$ for linear;
 - $y = -13.597x^2 + 42.648x + 2233.9$ for quadratic;
 - $y = 2936.1e^{-0.085x}$ for exponential;
 - $y = 2.4114x^3 - 60.62x^2 + 297.05x + 1904.7$ for cubic polynomial;
 - $y = -0.1086x^4 + 5.2362x^3 - 84.91x^2 + 374.13x + 836.9$ for quartic polynomial;
 - $y = -0.1849x^5 + 5.8996x^4 - 65.836x^3 + 285.6x^2 - 435.21x + 2381.7$ for quantic polynomial;
 - $y = 0.0241x^6 - 1.1261x^5 + 20.096x^4 - 169.8x^3 + 665.14x^2 - 1064.5x + 2730.8$ for sextic polynomial;
 - $y = 2946.3x^{-0.333}$ for power;
 - $y = -535.4\ln(x) + 2666.3$ for logarithmic;
 - $MA(3)2021 = Y2018 + Y2019 + Y2020$ for moving average;
 - $E2021 = 0.5Y2019 + (1-0.5)Y2020$ for exponential smoothing;
 - $y = -209.4789 + 1.0479Y_{(n-1)}$ for 1st auto-regression; and
 - $y = -378.405 + 0.8421Y_{(n-1)} + 0.2807Y_{(n-2)}$ for 2nd auto-regression.
4. The best fit model is the sextic polynomial model. Using this model, the Population of Child Laborers for 2024 will increase to 1,014,800.

Conclusion

The findings of the study established that the number of working children in agricultural sector, industrial sector, and services sector have an effect to the Population of Child Laborers in the Philippines. This implies that the number of working children in agricultural sector, industrial sector, and services sector might indicate a change in the Population of Child Laborers. The decrease of the population of child laborers is a good augury in the socioeconomic growth of the country. However, if the population of child laborers will increase, it will not only threaten the quality of labor force, but also encourages a vicious cycle of using children as insurance against future crises.

Nevertheless, this result should not be taken as conclusive since the data from 2009 to 2020 and the indicators chosen are too limited, hence, suggesting a further study. Studies on these subjects will make the government better assess the issue and appropriately respond to sensitive issues on poverty and child labor in the Philippines.

Recommendations

As manifested in the findings and conclusions of the study, the following are hereby recommended:

1. Strengthen and enforce existing labor laws and regulations. This includes ensuring that employers who exploit child labor are held accountable and face penalties, and that children are protected from hazardous work conditions.
2. Expand and improve access to quality education for all children in the Philippines. This can be achieved by increasing government spending on education, improving school infrastructure in rural and marginalized areas, providing scholarships and financial aid to vulnerable children, and implementing inclusive education policies.
3. Develop vocational and skills training programs for older children who are already engaged in labor. These programs should offer alternative pathways for education and skills development, enabling children to acquire marketable skills that will lead to decent employment opportunities in the future.
4. Strengthen social protection programs for families living in poverty, as poverty is one of the main underlying causes of child labor. This can include cash transfer programs, livelihood support, and access to basic services such as healthcare and housing.

5. Implement awareness campaigns to educate communities, parents, and employers about the negative consequences of child labor and the importance of education. These campaigns should promote a shift in cultural attitudes and social norms regarding child labor, emphasizing the rights and well-being of children.

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