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Interactions Between Water Level, Crude Oil, and Hydroelectric Power Generation in Ghana; A Structured Vector Auto Regression Approach

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Abstract

Countries that suffer disturbances in their power generation are less likely to meet many of the sustainable development goals and general economic growth. This study used a three-variable SVAR model to examine the interactions of water level, crude oil and power generated from the Akosombo hydroelectric generation Dam in Ghana. Data used for this span from January 2010 to December 2019. From the results, none of the three important variables studied was found to be completely independent; dam level and crude oil are adjusted to absorb power generation shocks. All three variables drift away from their normal levels to contain shock before returning to their desired levels at varying time points. It has also been established that Dam water level shocks leads to a negative response in both power generation and crude oil in the short run. Overall, shocks to crude oil explains much of the variability in power generation than shocks to dam water level. These findings convey that there is exist very useful interactions among the three-variables studied in this paper. Policy makers should institute effective measures for early detection and intervention of the short-term power disturbance that characterizes the hydroelectric power generation to ensure a sustainable power and growth of the Ghanaian economy.

Keywords: SVAR, Hydroelectric, Ghana, long run shocks, impulse response

1. Introduction

If the world can achieve a high percentage of the targets set under the sustainable development goals, stable electricity supply will play a crucial role (Owusu & Asumadu-Sakodie, 2016; Owusu et al., 2016). About 10% of the population of the world still do are yet to be hooked onto electricity making it a matter of global concern (IEA, 2015). Among all the energy production mix, hydropower remains the largest renewable energy resource due to its cost-effectiveness and reliability (IEA, 2015). According to Benefoh and Ackom (2016), electricity supply that is both reliable and inexpensive is crucial to any country's development.

The Akosombo dam is a hydroelectric power generating station on the Volta River in the south-eastern of Ghana and it is managed by the Volta River Authority. It serves as the major source of electricity in Ghana. It has a powerplant which contains six turbine generator units, and it operates between 276ft maximum and 248ft minimum headwater level. Currently, the Akosombo dam produces 1000MW electricity at its maximum operating capacity (Miescher, 2021). According to Smokorowski (2021), the peak of the hydro is the only reliable flexible method of producing electricity besides fossil fuels. The Akosombo hydroelectric project was meant among others to open Ghana to industrialization and hence modern development. Fishing, farming, transportation, and tourism are some of the other good effects (Gyau-Boakye, 2001). The availability of water resources usually determines when and how much energy the hydroelectric plant will generate on a seasonal and annual time frame (Carpentier et al., 2017).

Long-run shocks in power generation are the unanticipated changes in power generations over long time. The shocks trigger the operation of the powerplants in production of electricity. Because the dam's primary source of water is rain, which is unpredictable and dependent on weather conditions (Mensah, 2013), there are a lot of factors that causes a disturbance either to increase or decrease the water level. During the dry season, the level of water in the reservoir and the surrounding area reduces, while during the rainy season, it swells. As a result, power generation becomes unstable which affect the growth and sustainability of a country. Ghana's industrial and economic growth has resulted in a rising demand for power that exceeds the capacity of the Akosombo dam power plant. Part of the reason for the limited producing capacity is a lack of fuel supply to existing thermal power plants (Kemausuor & Ackom, 2017).

Russ (2020) studied the effects of runoff shocks on general growth of the economy. His suggested that rainfall should not be considered a good determinant of water availability for power generation. According to Taghizadeh-hesary and Yoshino (2013), Oil-producing countries gain from shocks in oil price.

According to United State Agency for International development (2017), drought and reduced rainfall threaten access to reliable sources of power. Silver et al. (2012) showed that, apart from USA, an increasing Renewable Energy Source on Electricity share has economic cost on GDP per capita. Kumi (2017) indicated that despite the increased in electricity in Ghana and the doubling of installed generation capacity from 2006-2016, the country still suffers from inadequate electricity supply.

Ashong (2016) pointed out that poor rainfall and its resulting impact on hydropower generation are to blame for Ghana's lack of renewable energy. Boadi and Owusu (2019) found out that, changes in rainfall patterns accounts for 21% of year-on-year fluctuations in hydroelectric power generated from Akosombo. Kabo-Bah et al. (2016) indicated that temperature negatively correlate with hydropower generation while humidity and rainfall positively affect power generation. Eshun and Amoako-Tuffour (2016) pointed out that prolong drought usually is the root cause of unstable power supply.

Many previous studies, most of them focused on factors affecting renewable energy sources (Ashong, 2016; Kabo-Bah et al., 2016; Salub et al., 2020). This may be due to the environmental and climate factors in which power production from both renewable and non-renewable sources depend on. As such, any change in those factors also affect the production process. Others looked at shocks from either water level or oil price in relation to the growth of an economy (Russ, 2020; Taghizadeh-hesary & Yoshino, 2013; Lorde et al., 2009).

There exist a growing body of literature on the two key components of hydroelectric power generation; water level, and Crude oil used to power the turbines (Miescher, 2021; Dehghani et al., 2019; Mekonnen & Hoekstra, 2012; Harrison & Whittington, 2002). That notwithstanding, the question that needs to be addressed is, if we hold environmental, geographical and climate conditions constant, how does power generation respond to shocks in dam level and crude oil? This study therefore attempts to address some three critical issues. First, it seeks to empirically examine the joint dependence of water level of dam, crude oil used, and amount of power generated and to establish whether these variables help explain one another. Second, the study examines whether any of the variables has a higher (or lower) influence on other variables. Third, how is a shock in one of the variables absorbed by the other variables.

To achieve the study objectives, we model water level, crude oil use and power generated in a three-variable structured vector autoregression (SVAR) framework. SVAR is a very useful method developed by Sims (1989) and remains the preferred method of many researchers investigating interactions between structured variable (Mertens & Olea, 2018; Mumtaz & Theodoridis, 2020). Flexibility in allowing variables to be determined endogenously, and ability to reveal a theoretical model closely related to empirical reality are some advantages SVAR has over other methods. To the best of our knowledge, no previous study exists in Ghana that examines joint dependence of dam level shocks, crude oil shocks and power generation. This study may therefore contribute to knowledge in this regard and form a good basis for policy formulation and decision making.

2. Materials and Methods

This study used a monthly secondary data on dam from January 2010 to December 2019. The data consist of three variables namely, power generation, dam level and crude oil for the sample period. In this study, we analyze the relationship between power generation, dam level and crude oil in the context of Ghana in Structural Vector Autoregression (SVAR) framework. The model building involves four steps to obtain an appropriate model that will help develop the relationship among the variables. The Eviews version 11 (Eviews11) statistical software would be used to analyze the data to achieve the aim of the study.

2.1 Series Transformation

The SVAR model provides an avenue to transform all the series into their natural logarithm form. This will minimize fluctuations in the data set (Tiwari, 2011). Detailed overview of the SVAR model is available in (Sims, 1989) and (Christiano, 2012).

2.1.1 Test for Stationarity

To identify the order of integration, the Augmented Dickey-Fuller (ADF) test of unit root will be used to access the stationarity of the series. The ADF test is a regression test that analyze a series stationarity under the null hypothesis; there is a unit root in the series. The regression equation of the model is given by:

$$\Delta y_t = \alpha + \beta t + \gamma y_{(t-1)} + \delta_1 \Delta y_{t-1} + \cdots + \delta_p \Delta y_{t-p} + \varepsilon_t$$

Where,

y_t is the observed time series

α is constant

β is the coefficient of the time trend

p is the order of AR process.

If $\gamma = 0$, the series is random walk and if -1 < 1+ γ < 1, the series is stationary.

2.2 Model Estimation Using SVAR

Before estimating the model, model order p to be used in the study must be determined using the Akaike Information Criteria (AIC). The AIC has been proved to perform better especially when the sample size is small (Liew, 2004).

2.3 Structural Vector Autoregressive (SVAR) Model

The structural VAR model helps to impose long-run restrictions on the variables. This study make use of three variables namely, power generation, dam level and crude oil. By following the Kandil and Trabelsi (2012) estimation procedure, the representation of the variables in SVAR framework are as follows: Using the log transform of the variables, let $\Delta x_t = [\Delta P_t,\ \Delta D_t,\ \Delta O_t]$' and $\varepsilon_t = [\varepsilon_{pt}, \varepsilon_{dt}, \varepsilon_{ot}]$ where Δ represent the first order differenced operator $\varepsilon_{pt}, \varepsilon_{dt}, \varepsilon_{ot}$ represent power, dam level and crude oil shocks. The structural VAR model can be written as:

$$\Delta x_t = B_0\varepsilon_t + B_1\varepsilon_{t-1} + B_2\varepsilon_{t-2} + \cdots = B(L)\varepsilon_t$$

$$\text{where } B(L) = \begin{pmatrix} B_{11}(L) & B_{12}(L) & B_{13}(L) \\ B_{21}(L) & B_{22}(L) & B_{23}(L) \\ B_{31}(L) & B_{32}(L) & B_{33}(L) \end{pmatrix}$$

The matrix B is a 3×3 matrix that provides the impulse responses of endogenous variables to structural shocks and L is the lag operator. It is assumed that the shocks $\varepsilon_t = [\varepsilon_{pt}, \varepsilon_{dt}, \varepsilon_{ot}]$ are serially uncorrelated and have a covariance matrix normalized to the identity matrix. This implies that power generation is subjects to three structural shocks.

To compute the above model, restrictions must be imposed on the parameter matrices. The restrictions can either be of contemporaneous type or long-run type. This study applies the long-run restrictions method proposed in (Herwartz, 2019). Similar to Kim and Chow (2003), the following restrictions are imposed:

- Dam level shocks and crude oil shocks will have no effect on power generation in the long-run. This is equivalent to $B_{12}(L)$= $B_{13}(L)$=0. Thus, the cumulative effects of dam level shock and crude oil shock on power generation will be zero (0).
- Crude oil shocks have no long-run effects on dam level. This amount to $B_{23}(L) = 0$.

The long-run restrictions amount to $B_{12}(L) = B_{13}(L) = B_{23}(L) = 0$ which are enough to identify matrix B_i.

2.4 Impulse Response Function

After estimation of the model, we then obtain the impulse response functions of the variables. The impulse response functions assess the dynamic effect of a structural shock of one standard deviation on the variable over a given period [35]. Using Kandil and Trabelsi (2012) SVAR methodology, let us consider a reduced VAR model

$$w_t = \mu + \textstyle\prod_1 w_{t-1} + \prod_2 w_{t-2} + \cdots + \prod_j w_{t-j} + \varepsilon_t$$

Where w_t represent the endogenous variables (power-generation, damlevel and crude oil) $\prod_j$ for j = 1… represent coefficient matric and μ represent the error term

To interpret the coefficients (μ, $\prod_1, \ldots, \prod_j$), we then employ the impulse response analysis. We make a shock to ε_t and look at the dynamic propagation based on the MA representation:

$$w_t = \varepsilon_t + C_1\varepsilon_{t-1} + C_2\varepsilon_{t-2} + \cdots + C_j\varepsilon_{t-j} + C_0$$

where, $\frac{\partial(w_t)}{\partial\varepsilon_t'} = I_p, \frac{\partial(w_{t+1})}{\partial\varepsilon_t'} = C_1,\ \frac{\partial(w_{t+2})}{\partial\varepsilon_t'} = C_2$ ...

constants C_1 ... C_{t-j} are matrices. These derivatives are represented in a graph called impulse response function.

2.5 Variance Decomposition

It is very useful that we determine variations among the variables in terms of percentages. Variance decomposition will help determine the amount of variation in the dependent variable that is explained by the independent variables. This study placed more emphasis on power generation in response to one standard deviation shocks in dam level and crude oil.

3. Results

3.1 Graphs of the Series

To better understand the series, we obtained the graph of the series and found out that, series exhibit changes in mean over time which suggest a nonstationary nature of the series. This movements in the series indicates a presence of shocks over a given time. It can be observed that, all the time series show possible change in mean which suggest that the series is possibly non-stationary. This can further be approved using ADF statistical test.

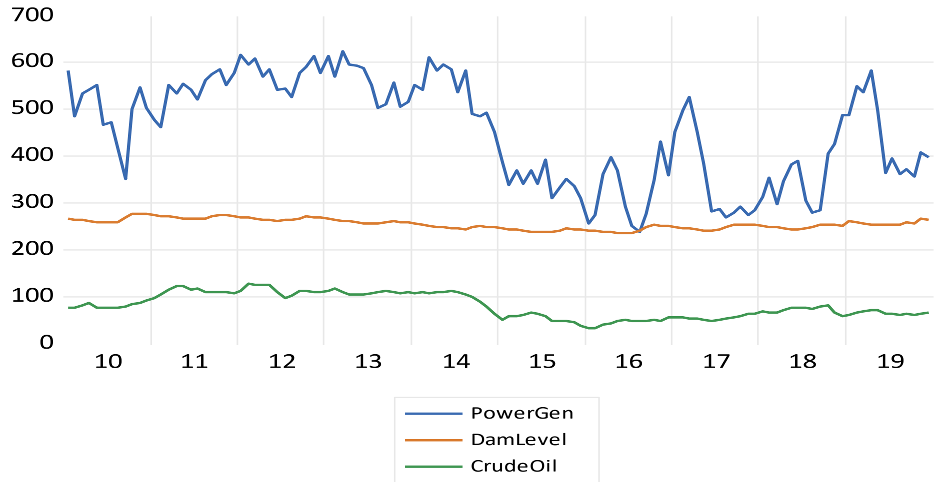

Figure 1. Graph of the series

The ADF statistical test was used to test stationarity of the series. All series were nonstationary at their levels since the p-values for power generation dam level and crude oil were greater than 5% level of significance. The series then became stationary after first differencing which satisfy the stationarity requirement of the underlying model. Table 1 shows the results of the ADF test at 5% level of significance.

Table 1. ADF test results

At their levels	**ADF-Stat**	**P-value**
Powergen	-2.077335	0.2542
Damlevel	-1.013997	0.7565
Crudeoil	-1.561538	0.4990
At first difference		
Powergen	-8.010330	0.0000
Damlevel	-6.524328	0.0000
Crudeoil	-8.111935	0.0000

It can be observed that the log transform of all the variables were non-stationary at levels and became stationary after first difference. This is because all the p-values are less than 5% level of significance after first difference.

3.3 Model Estimation

Now that all the variables followed a unit root but are stationary at first difference, we proceed to estimate the model. Before that, we need to determine the optimum lag order for the model. Table 2 below displays the results of the optimum lag selection.

Table 2. Optimum lag selection

Lag	LogL	AIC	SC	HQ
0	561.0366	-10.05471	-9.981483	-10.02501
1	589.4967	-10.40535*	-10.11242*	-10.28652*
2	595.4129	-10.34978	-9.837168	-10.14183
3	601.1303	-10.29064	-9.558331	-9.993562
4	607.3263	-10.24011	-9.288117	-9.853917
5	615.5950	-10.22694	-9.055249	-9.751618
6	625.8826	-10.25014	-8.858757	-9.685695
7	637.4988	-10.29727	-8.686203	-9.643711
8	646.4955	-10.29722	-8.466452	-9.554529

SVAR model demands that we obtain an appropriate lag for the model. This prevents the model from giving a spurious result. We obtained the lag using the AIC and the results suggested lag 1 for the model. This was the lag order used throughout the model estimation.

3.4 Variance Decomposition

From the above table, all the information criteria returned lag 1 as the optimum lag for the model to be estimated. To estimate the structural vector autoregressive model, we impose long-run restrictions. This will help know the effect of shocks on the variables in the long-run. The table below summarizes the parameter estimates of the SVAR model. The results of fitted model tell us that, a cumulative shocks of dam level and crude oil are zero. Thus, they have no long-run effects on power generation.

Table 3. SVAR model estimates

Structural VAR is just-identified

Model: e = Phi*Fu where E[uu]=1				
F =				
C(1)	0	0		
C(2)	C(4)	0		
C(3)	C(5)	C(6)		
	Coefficient	Std. Error	z-Statistics	Prob.
C(1)	0.112565	0.007327	15.36229	0.0000
C(2)	0.002955	0.001444	2.046518	0.0407
C(3)	0.039659	0.008791	4.511396	0.0000
C(4)	0.015548	0.001012	15.36229	0.0000
C(5)	-0.018361	0.008318	-2.207454	0.0273
C(6)	0.089417	0.005821	15.36229	0.0000
Log likelihood	617.1500			
Estimated S matrix:				
0.094532	-0.042454	-0.038000		
0.004263	0.008280	0.001760		
0.030850	-0.020085	0.064167		
Estimated F matrix:				
0.112565	0.000000	0.000000		
0.002955	0.015546	0.000000		
0.039659	-0.018361	0.089417		

3.5 Impulse-Response Function

In the SVAR model, the impulse response functions trace the effects of a shock on endogenous variables. Figure 2 displays the impulse-response function of the variables. Shock 1 represent the shocks in power generation, shock 2 represent shocks in dam level and shock 3 represent the shocks in crude oil. It can be observed that the effect of a shock in dam level and crude oil vanishes over a short period. Also, the effect of a power generation shock on both dam level and crude oil is immediate. Thus, sudden and permanent increase can be seen.

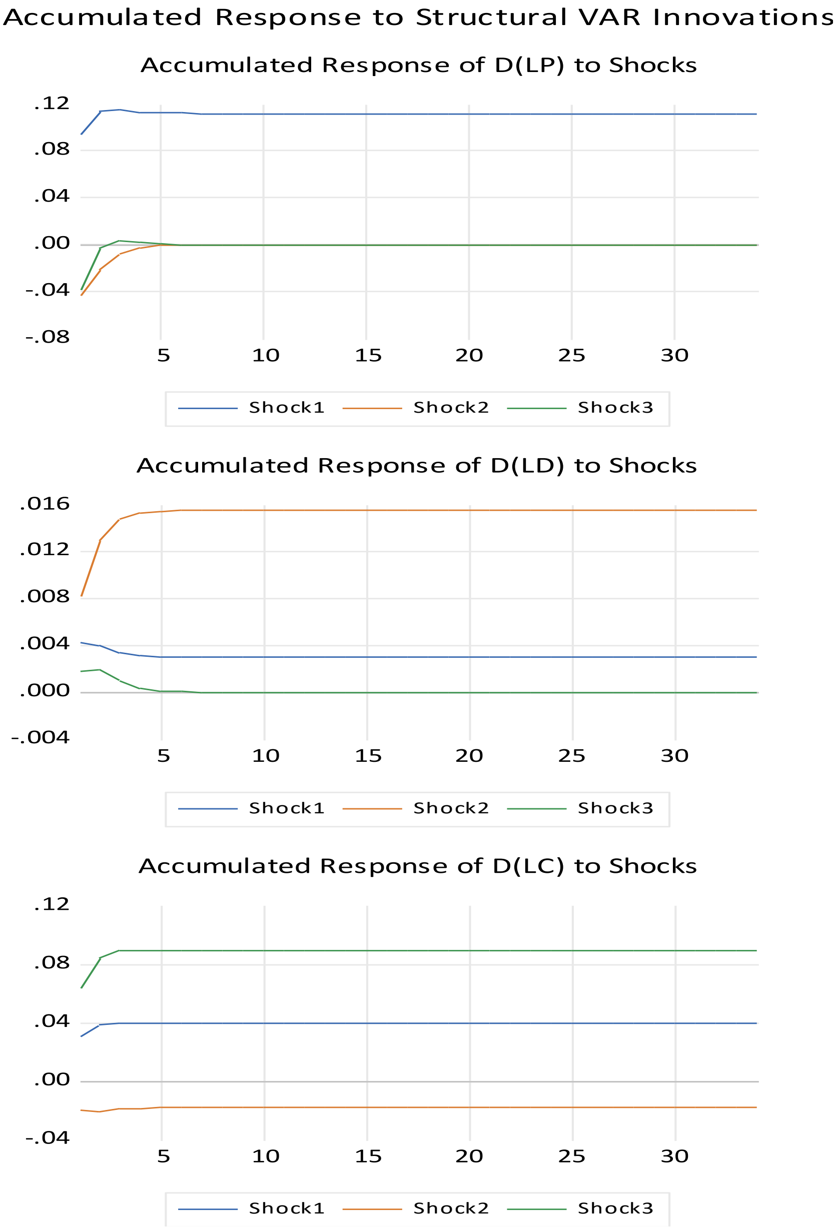

Figure 1. Accumulated impulse response functions (D(LP) = Power Generated, D(LD) = Dam level, D(LC) = Crude oil)

To better understand the response behavior to shock, Figure 3 (the orthogonal inpulse response function (OIRF)) is constructed. OIRF assumes that, the hydroelectric production system is in a steady state prior to any shock and that shocks apply to one variable only at any given time. Each row of the OIRF plot explains how the hydroelectric production system absorbes a one-standard-deviation of orthogonal shock and the length of time it takes for these variable to return to a steady state.

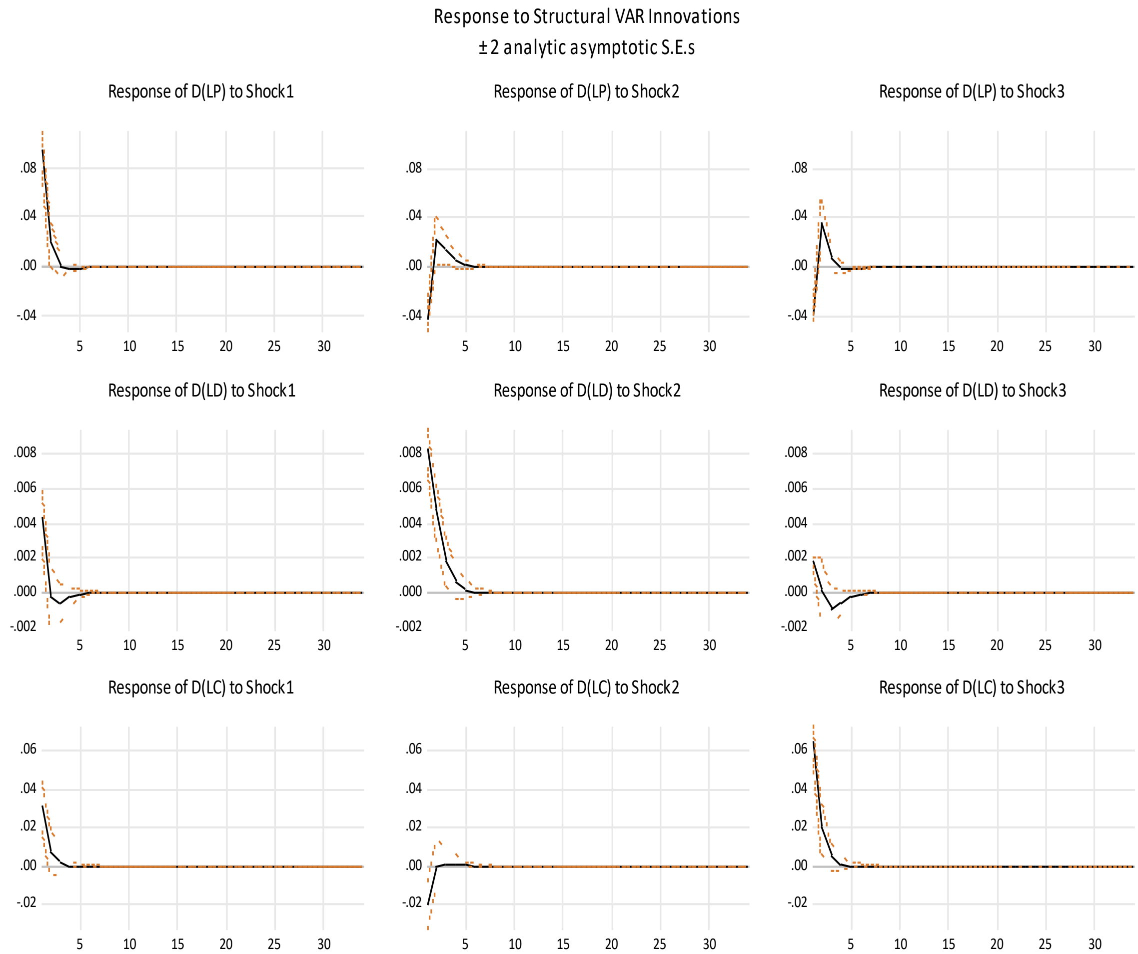

Figure 2. orthogonalized impulse response function. * broken lines denotes a 95% confidence interval; *x-axis = forecast in months; y-axis = magnitude of response; * D(LP) = Power Generated = shock 1, D(LD) = Dam level = shock 2, D(LC) = Crude oil = shock 3; * Graph D(LP) to Shock A = response of variable Power to a shock in variable A; * Graph A:A shows how the shock is absorbed)

The impulse response function as shown in Figure 3 dipicts a one-standard deviation of shock to the dam level, crude oil and power generated. First row of shows that, dam level and crude oil are adjusted to absorbe power generation shocks. As revealed by Graph (D(LP) to shock 2), a positive shock in power generation is followed by a positive response in dam water level which remains statistically significant for close to 8 months. Also, crude oil response positively to power generation siginificantly for almost 8 months. It is clear from the second row that Dam water level shocks leads to a negative response in both power generation and crude oil while crude oil shocks leads to responses in dam level and power generation. It can be observed from figure 3 also that, as dam level and crude oil increases, power generation increases in the short run but returns to a steady state in the long-run. An increase in dam level will decrease crude oil in the short run. Also, an increase in power generation will increase crude oil in the short run, but it will remain steady in the long-run.

3.6 Variance Decomposition

The variance decomposition identifies which shock is more important in accounting for variability in power generation after presenting the contribution of each shock to the movement in power generation. From table 4 below, it can be observed that power generation explains much of the variations by itself (about 64%) while dam level explains about 17% and crude oil explains about 19% of the variations in power generation in the long-run. This shows that crude oil contributes more in explaining the variability in power generation.

Table 4. Variance decomposition results

Variance Decomposition of D(LP)				
Period	S.E.	Shock1	Shock2	Shock3
1	0.110374	73.35282	14.79435	11.85282
2	0.119646	65.17989	15.78681	19.03330
3	0.120583	64.17588	16.80794	19.01619
4	0.120716	64.04831	16.96176	18.98992
5	0.120740	64.02735	16.97390	18.99875
6	0.120744	64.02443	16.97429	19.00127
7	0.120744	64.02412	16.97426	19.00162
8	0.120744	64.02409	16.97425	19.00165
9	0.120744	64.02409	16.97425	19.00166
10	0.120744	64.02409	16.97425	19.00166
11	0.120744	64.02409	16.97425	19.00166
12	0.120744	64.02409	16.97425	19.00166

4. Discussion

This study aimed at analyzing the response of power generation to shocks in dam level and crude oil. The variables included in the study were monthly data for power generation, dam level and crude oil. The structural vector autoregressive methodology was used in the study to obtain an appropriate model that analyzed the relationship among the variables in terms of shocks. The variance decomposition analysis reveals shocks to dam level and crude oil only account for about 36% of total variability in power generation from the Akosombo dam in the short run but in the long run, these variations will become steady. This finding is supported by (Miescher, 2021; Eshun & Amoako-Tuffour, 2016; Dehghani et al., 2019). One interesting finding of this study is the revelation that shocks to crude oil explains much of the variability in power generation than the water level of the Akosombo dam. This finding is supported by (Russ, 2020; Taghizadeh-hesary & Yoshino, 2013; Lorde et al., 2009). Again, both dam level and crude oil cumulative shocks to power generation vanishes in a relatively short period and returns to desired levels in the long run. The short-run decrease in power generation in Ghana usually results in power rationing which affect the economy (Ashong, 2016; Owusu & Owusu, 2019; Kabo-Bah et al., 2016; Eshun & Amoako-Tuffour, 2016; Sulub et al., 2020).

Ghana experience longer periods of rainy season than dry season (USAID, 2017). During rainy seasons, dam level increases which provide much water to regulate the operation of the hydropower plants, thereby increasing power generation. Reduction in water levels negatively affect hydropower generation as supported by (USAID, 2017). Availability of crude oil also improve the operations of the powerplants thereby increasing power generation (Russ, 2020; Taghizadeh-hesary & Yoshino, 2013; Lorde et al., 2009).

The variance decomposition result has assured that, dam level and crude oil donate approximately 17% and 19% in total variation in power generation respectively. This may be because of climate variability and fuel supply challenges as indicated by (Kumi, 2017; Boadi & Owusu, 2019).

5. Conclusions

This study used a three-variable SVAR model to examine the interactions of water level, crude oil and power generated. From the results, none of these three important variables are completely independent; dam level and crude oil are adjusted to absorb power generation shocks. It has also been established that Dam water level shocks leads to a negative response in both power generation and crude oil while crude oil shocks lead to responses in dam level and power generation. With the aid of the orthogonal impulse response function this study can confirm that all three variables deviate from their desired levels to absorb shock before returning to their desired levels at varying time points.

The impulse response identifies a decrease in power generation in the short run. This means that increase in dam level and crude oil negatively affects power generation in the short run. In the long-run, shocks to dam level and crude oil will have no effect on power generation. Therefore, policy makers should institute effective measures that will detect and avert the short-term power disturbance to ensure power sustainability and growth of the economy. The energy sector should also explore in alternative ways of obtaining fuel, such as, regasification, to reduce fuel supply challenges. This paper draws conclusions based on a single model without controlling for other possible factors that influence hydroelectric power generation and hence recommend that further research considers that.

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