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Abstract

The proliferation of papers on energy demand modeling has offered different dimensions both in terms of methodology and estimation. While this development has strengthened our understanding of the subject, it may render the identification of gaps in the literature arduous for future research. Thus, this study sets out to document some emerging issues that seem to have rendered new directions on energy demand modeling ranging from asymmetric price responses, time varying demand parameters, triangulation analyses to seasonal and climate change effects. It is hoped that access to this review complemented with the previous ones will facilitate the comprehension of the extant literature as well as areas of future research in energy demand modelling.

Key Words: Energy demand factors, Energy demand modelling, Asymmetric Price Responses, Triangulation analyses, Climate change

MODELING ENERGY DEMAND: SOME EMERGING ISSUES

1.0 Introduction

The growing literature on energy demand has offered different dimensions to the evaluation of its dynamics ranging from the choice of specifications to the methodological approaches as well as the underlying factors. While efforts in this regard are likely to be sustained given the increasing significance of energy to global growth; identifying gaps in the literature may become arduous with the proliferation of existing papers on energy modeling. Thus, this study sets out to document the various prominent articles published on energy demand modeling. [1-3] conduct a similar review; however, the focus was essentially on the different model structures and methodological approaches for forecasting energy demand. In the present review, we provide recent developments as well as emerging issues that seem to have rendered new directions on energy demand modeling. Essentially, we identified six areas namely: i) Asymmetric Price Responses and Technical Changes; ii) Time-varying and Fixed coefficients specifications; iii) Non-parametric modeling; iv) Triangulation Analyses; v) The role of Meteorological factors, and vi) Micro-econometric analyses in energy demand modeling. These issues have not been well situated in the previous reviews and it is hoped that with this review complemented with the previous ones, future research in the area of energy demand modeling will easily tease out the gaps in the literature and by implication advance the frontiers in energy demand modeling.

The remaining sections of the paper are arranged in line with the identified six areas. In essence, section 2 deals with the Asymmetric Price Responses and Technical Changes in energy demand modeling; section 3 captures Time-Varying Attributes and Time-Dependent Specifications; section 4 provides issues of non-parametric modeling; section 5 discusses Triangulation Analyses; section 6 is on the role of Meteorological factors while section 7 offers a broader perspective involving Micro-economic analyses in energy modeling. Section 8 however concludes the paper.

2.0 Asymmetric Price Responses and Technical Changes in Energy Demand

Traditionally, the modeling of energy demand, just like any other demand, is based on the assumption of symmetric price elasticities among others. Examples of studies in this regard are [4-12]. However, [13] criticized the assumption of symmetric price elasticities and consequently offered an alternative model that captures asymmetric price responses and energy-saving technical change in energy demand using OECD industrial energy as a case study. They utilized panel data of 15 OECD countries over the period 1962-2003. In this framework, asymmetry effects were considered as a proxy for energy-saving technical progress. The theoretical foundation proposed by [14-16] has continued to be the workhorse for the analysis of asymmetric price responses in energy demand modeling. This framework presupposes that energy demand response to price increase is not necessarily reversed completely by an equivalent price decrease, nor is the demand response to an increase in the maximum historical price necessarily the same as the response to a price recovery (sub-maximum increase). Thus, they decomposed the energy price variable into the asymmetric components that separately measure the impact of prices above the previous maximum (denoted as price-max), a price recovery below the previous maximum (denoted as price-rec.), and a price cut (denoted as price-cut) in order to capture any endogenous impact of technical progress. The idea being that increasing energy prices (particularly above any price-max) induces technical progress and more energy efficient processes, whereas when the energy price falls; these advances are not reversed – hence the expectation of a different response to price-max, price-rec. and price-cut. In addition, [14] and [15] suggested the inclusion of time dummies as a proxy for induced technical progress. They argue that this better represents the underlying demand trend than the asymmetries. [13] considered these two proxies using the non-linear least squares approach following a general-to-specific testing procedure suggested by [14]. Based on their results, they tentatively concluded that the preferred specification for OECD industrial energy demand incorporates asymmetric price responses but not exogenous energy-saving technical change. Nonetheless, their findings were confronted with some shortcomings. First, it was not possible for them to conclusively conclude that both asymmetric price responses and time dummies have a role to play; that is, they are 'complements' rather than 'substitutes'. Second, the coefficients were not consistent with the underlying economic theory. For instance, the coefficients on the price-max and price-rec. variables were either positive and/or insignificantly different from zero while the price-cut variable was the only significant price variable.

These inherent shortcomings were further revisited by [17] using 17 OECD countries over the period 1960-2006. The main objective was to examine whether asymmetric price responses and underlying energy demand trend were complements or substitutes. The study provided a testing procedure for the underlying energy demand trend (UEDT) and the asymmetric price responses (APR) models within both time series and panel frameworks. The authors owned up to methodological gap and subsequently suggested that conclusion from empirical studies were largely due to methodological differences between these two frameworks. For the time series; the static, dynamic and a partial adjustment models were adopted while a static, partial adjustment model and koyck models were considered for panel data structure. The tests generally indicated that the UEDT models are preferred to the APR models for the panel data structure but mixed for the time series. This finding partly reinforced the argument by [15] that the price decomposition used in the asymmetric case only acts as a proxy for energy-saving technical change and therefore the way to model energy in panel data models is via symmetric price models and time dummies which are analogous to UEDT.

Another dimension of dealing with technical-change-induced energy demand was proposed by [18]. They developed a simple and theoretically clear approach to the estimation of technological change in a multi-sector general equilibrium framework and they demonstrated the application of this approach with a typical example by examining the role of technological progress in Japanese energy demand during the oil crises period from 1970 to 1985. Specifically, they employed the Multiple Calibration Decomposition Analysis (MCDA) to evaluate technological change that is responsible for changes in energy use and carbon-dioxide emissions in the Japanese economy in the oil crises period. They argued that MCDA serves as an elementary way of separating structural change due to technological change from that due to price substitution effects, capturing the interdependence among economic sectors. The various advantages of using this approach were well documented by the authors and in particular, they noted that empirical result obtained provides a better understanding of the effects on the economy of technological change in that significant period.

[19] followed the [14] and [15] approaches to model asymmetric price response in energy demand using data covering 17 OECD countries for the period of 1960 to 2008. The parameter estimates for the different sample periods did vary somewhat for the asymmetric models; whereas the parameter estimates did not vary so much for the symmetric model without a decomposed price variable, thus suggesting that the symmetric model was likely to give support to the argument of [15] that asymmetric price response only serves as a proxy for energy-saving technical change. Therefore, it may be more appropriate to model energy demand with symmetric price response and time dummies rather than asymmetric price response. In addition, the decomposition of energy price into asymmetric components does matter for the stability of the price elasticity estimates.

Recently however, [20] expanded the modeling structure adopted in [13] and [17] in order to better demonstrate the way technical progress and improvements in energy efficiency are captured when modeling OECD industrial energy demand. Specifically, they formulated a generalized model that accounts for the role of both endogenous and exogenous technical progress in energy demand. They covered the period 1962 -2010 for 15 OECD countries. Using the Structural Time Series Model framework, the general specifications allow for both asymmetric price responses (for technical progress to impact endogenously) and an underlying energy demand trend (for technical progress and other factors to impact exogenously, but in a non-linear way). The results show that almost all of the preferred models for OECD industrial energy demand incorporate both a stochastic underlying energy demand trend and asymmetric price responses. Furthermore, their analysis suggests that when modeling industrial energy demand, there is a place for ‘endogenous’ technical progress and an ‘exogenous’ underlying energy demand trend. In addition, they propose that any modeling strategy for energy demand should start by including both endogenous and exogenous technical progress.

On the whole, one of the promising areas for future research would be to verify the plausibility of asymmetric price responses under different energy products in order to ascertain whether the results are sensitive to the nature of energy product(s) being studied or not.

3.0 Time Varying Coefficients vs Fixed Coefficients in Energy Demand Modeling

3.1 Time Varying Coefficients

The consideration of time varying coefficients is increasingly gaining prominence over the fixed coefficients in energy modeling owing to the growing evidence of parameter instability (see recent papers such as [21-27]. For example, [24] tested and estimated time-varying elasticities of Swiss gasoline demand. The author adapted the approach employed by [28] for the US gasoline demand. This approach was preferred over the introduction of structural breaks often employed in empirical literature such as [29-30]. The investigation was accomplished with the use of quarterly time series data for the period 1973-2010.The analytical procedure included an iterative procedure around time-varying cointegrated model for long-run situation while a two-step [31] was employed for the short-run dynamics. The results obtained show that time-invariant assumption does not hold for long-run price and income elasticities. Also, the estimates indicated that gasoline demand in Switzerland had passed through two phases with demand considered sensitive to price barely till mid 1990s but responded insignificantly there-forth. In addition, the environment pre-occupations were found to change the behaviour of energy demand-price nexus. More so, [28] used smooth time-varying cointegration approach to estimate the US gasoline demand for the period 1976-2008. The results showed that both price and income elasticities share quite a similar pattern of variation; except during the 1990s.

Additional evidence was also offered by [32] supporting the time-varying attributes of energy demand elasticities. Based on the rolling regression technique, the author showed that the demand elasticities vary over time, on average. More recently, [27] modeled long-run sectoral electricity demand using a time-varying cointegrating vector for Korean data over 1995:01-2012:12 for the residential sector and 1985:01-2012:12 for the commercial and industrial sectors. They justified the choice of time varying specification on the premise that Korea had witnessed rapid development over the estimation period that may allow the coefficient on income/output to vary over time. Nonetheless, they demonstrated both analytically and empirically, that fixed coefficient (FC) models overestimate income/output elasticities, which translates into underestimation of scale economies in electricity in the commercial and industrial sectors. They further argued that the bias persists even if the FC models are estimated over rolling windows to allow for structural change.

3.2 Fixed Coefficients Specifications

Notwithstanding the increasing evidence of time varying coefficients, there is still evidence of fixed coefficient regression in energy modeling. These techniques range from Engle-Granger Cointegration, Johansen Cointegration, Error Correction Models (ECMs) to Autoregressive Distributed Lag (ARDL) and Bound testing approach to long run relationship. For example, [33] encapsulated modeling energy demand in Germany under a cointegration approach and error correction modeling technique where he employed annual data set over the period 1960-1993 for the estimations of both short-run and long-run energy demand elasticities. The results obtained showed that energy demand was presumably inelastic with respect to price changes while the coefficients for technological progress; both in disaggregated and aggregated form, were mixed with considerable variations. Generally, however, the ADL re-parameterised ECM estimates suggested slow and gradual adjustment to disequilibrium and substantial smoothing of activity and energy prices in obtaining the energy demand.

Also, [34] examined the dynamic conditions surrounding South Korean energy demand upon entering the new millennium. The model specification was based on Autoregressive Distributed Lags (ARDL) model for robustness checks. [35] examined the demand elasticity of oil in Barbados for the period 1998 to 2009 on a monthly data structure. The paper estimated the elasticities of demand for oil by employing the [36] Unrestricted Error Correction model (UEM) of long-run cointegration which was also used to capture the short-run dynamics; when re-parameterized. [37] employed the autoregressive distributed lags (ARDL) technique to model aggregate domestic electricity demand in Ghana. [38] employed the same methodology to obtain dynamic elasticities of natural gas demand in Colorado. The study of [39] conducted a meta-review of modeling transport (energy) demand and policies. The paper documented comprehensive theoretical cum technical and modeling as well as econometric approaches around the energy-transport service demand nexus as evident in various empirical studies [see 40-41] with an array of static and dynamic model structures identified in empirical estimations. The attraction found in the latter model, unlike the former which is only for short-run and long-run income elasticities, was that it considered both price and income elasticities under short- and long-run situations. The authors posited that the static models employed in previous researches included the simple static model, stock model and the stock characteristic model while the dynamic modeling structures identified in previous empirical investigations included the distributed lag model, lagged endogenous model, VAR and the re-parameterised error correction model (ECM). Similarly, [2] did a comparative study of energy demand models for policy formulation. The authors conducted a critical review of existing energy demand forecasting methodologies by highlighting the methodological diversities and developments over the past four decades in order to investigate whether the existing energy demand models are appropriate for capturing the specific features of developing countries. All existing modeling structures on energy demand were synchronized into two basic approaches of econometric and end-use accounting models. Though marred with paucity of data, the latter model was considered more realistic than the former as the former models were seen to suffer from key social issues.

[42] employed an international panel smooth transition error-correction model to estimate the non-linear relationship among energy consumption, real income and real energy prices for 24 OECD countries. The study departed from existing literature on two grounds. First, they considered the non-linear cointegration of the energy-income-price nexus as against the linear functional form assumed in previous studies [see 43-46 among others]. Secondly and unlike other existing studies where the non-linear cointegration methodology was conducted on time series [see 47-48], the authors investigated on cross-sectional time series data structure. The conclusions obtained from the study showed long-run equilibrium condition among energy consumption, real income and real energy prices and that direct linear relationship existed between energy consumption and real prices while energy and consumption were indirectly related. Also, evidence for non-linear relationship existed for energy-income-price nexus when energy intensity and the ratio of gross capital formation to GDP were taken as threshold variables and that these threshold variables impacted on different energy-growth nexus among countries.

[49] considered the short- and long-run elasticities of electricity demand in the Korean service sector; using annual data covering the period 1970-2011. The analytical procedure employed revolved around conducting tests of analyses such as the unit-root and contegration while the technique of analysis was the conventional Error Correction Model (ECM) with the Cobb-Douglas demand function as the framework for econometric model. The findings in the long-run analysis differ from that of the short-run situation as electricity demand in the service sector was elastic for both price and income for the former but inelastic for the latter. Also, [50] did a comparative study between the US and China rapid urbanization stage on energy demand in China. The paper applied the panel data model and the cointegration model and examined the determinants of energy demand in China, and then forecasts China's energy demand based on scenario analyses. The authors adopted a logarithmic transformation of energy demand model of [9] which was derived from the consumption function for the investigation of long-run situation which later incorporated an adjustment mechanism for short-run analyses.

In essence, the modelling of energy demand can follow either the time varying approach or fixed coefficients approach. Nonetheless, it may be necessary to evaluate the underlying statistical behaviour of the demand parameters before any meaningful inference can be drawn. Essentially, there are standard diagnostics evident in the econometric literature than can be used to determine the stability of estimated coefficients in regression models. Therefore, future research involved in the modelling of energy demand may consider these diagnostics to validate the choice of estimation technique(s).

4.0 Non-Parametric Vs. Parametric Modeling of Energy Demand

The use of non-parametric approach in energy modeling is gradually gaining recognition. [51], for example, examined the functional form and aggregate energy demand elasticities for 17 OECD countries over the period 1960 – 2006 using the non-parametric approaches. While empirical literature is replete with numerical properties of functional specifications (such as the static and dynamic models) – [see 52-55] as well as [56] – [51] filled the void of statistical properties in energy modeling by considering the data generating process of the underling parametric functional specifications. Although, these authors identified two studies that have tested for the appropriateness of the functional parametric models such [57] – who used a non-parametric specification test developed by [58] and [59]; and [60] – who adopted a Bayesian model selection criterion proposed by [61]; but they found that these two studies have inherent defects such as assuming apriori long run equilibrium in the energy demand. These defects appear to have been addressed by [51]. The authors tested for the linear specification of the parametric model using non-parametric model specification test proposed by [58] and [59] as extended by [62].

The studies of [63] and [64] rather developed different models to model energy demand. The former study modeled energy demand of the residential sector in the United States using regression model and artificial neural networks. The authors developed a set of indicators so as to fathom the evolution of household energy use and predict future energy needs. To achieve this objective, two sets of models were developed. The primary model was the Artificial Neural Network (ANN) technique which results were compared to those predicted by the more traditional multiple linear regressions modeling technique. By studying the possible scenarios for growth of the parameters, the future residential energy demand in United States was then forecasted based on the models. The forecast was based on the historical data from 1970 using a regression method. The extrapolation was linear for GDP per capita, resident population, median household income and household size while the trends of the cost of residential electricity follow a quadratic trend during the forecast period. Although, the results from regression models showed a decrease with different slopes corresponding to different models for energy demand in the near future, the results from the ANN models express a significant change in demand in the same time frame. The ANN predicted a more realistic approximately uniform result with slower growth while the regression models only saw the overall long-term trend as they are not sensitive to the recent fluctuations.

For [64]; linear and non-linear models based on evolutionary algorithms to forecast energy demand in Iranian metal industry were used. The study used two linear and three non-linear functions to forecast and analyzed energy where Particle Swarm Optimization (PSO) and the novel approach of Real Coded Genetic Algorithm (RCGA) had been developed based on real numbers. The authors contributed to existing literature in two ways. The genetic algorithm method to properly capture the convergence process was proposed and the use of adequate model and variables inclusion to accurately investigate the Iranian metal industry. The findings suggested that the RCGA produced better, valid and more reliable results than the PSO algorithm and that generally, the accuracy and precision of the models using evolutionary algorithms relied on three factors such as the applied algorithm, forecasting and fitness function.

More recently, [65] worked on a full demand response model in co-optimized energy and reserve market. A new duplex demand response model; which allows one demand to bid in both energy market and spinning reserve market, was developed. Numerical simulation results on the reliability test system showed the effectiveness of the model and, compared to conventional demand shifting bids, the proposed full demand response model could further reduce the need to commit capacity from generators, on/off cycling of generators and fluctuations in system reliability. In particular, simulation results showed that the proposed full demand response model outperformed conventional demand shifting bids in operating efficiency.

Notwithstanding the growth in the application of the non-parametric approach in energy demand modelling, the computational simplicity of the parametric approach has actually increased the attraction of working in the area.

5.0 Triangulation Analyses of Energy Demand

The increasing evidence of mixed results with respect to energy demand has necessitated the need for the consideration of a battery of techniques and tests to ascertain the robustness of results. For instance, [66] estimated energy demand elasticities for OECD countries through the dynamic panel data approach over the period 1978 to 1999. The study employed the one-way General Method of Moment (GMM) and compared its results with the Ordinary Least Square (OLS) and the Within-Estimates with partial adjustment model of Autoregressive Distributed Lag (ADL) to investigate the short-run, intermediate and long-run elasticities with respect to the relevant variables. Compared with the OLS and the Within Estimator, the one-step GMM estimator was found to produce more intuitive results in terms of sign and magnitude.

Also, [67] employed time-series analysis to forecast electricity demand in Sri Lanka for the period 1970-2003 with six (6) different econometric techniques such as the Static Engle & Granger (Static EG) model, dynamic Engle & Granger (Dynamic EG) method, Fully-Modified OLS (FM-OLS) method, Pesaran, Shin & Smith (PSS) method, Johansen method and the Structured Time Series Method (STSM) for stochastic underlying energy demand trend (UEDT) log-linear model. The study showed that there was variation in the estimated results both for the preferred specifications and resultant coefficients. The estimated effect of the underlying energy demand trend varied between the different techniques; ranging from being positive to zero to predominantly negative. The authors advocated triangulation analysis of models especially where no statistical rationale exists. Despite these differences, the forecasts from the six techniques up to 2025 converged.

By the same token, [68] estimated the cointegration and investigated the demand for gasoline and perform a triangulation analysis of five (5) alternative time series techniques with data from Fiji for the period 1970-2005. These alternative techniques include the Dynamic Engle-Granger (DEG), Fully-Modified Ordinary Least Square (FMOLS), Bound Tests (BT), Johansen Maximum Likelihood (JML) and the General-to-Specific (GETS) approaches. The results showed that estimates of the long-run parameters were close to the estimates of the systems JML method. The paper found that the GETS dynamics was more plausible than the JML estimates as consumers were found to generally respond in the short-run to price changes than changes in income. The study was limited with the result from the Bound test (BT) where the null hypothesis of no cointegration could not be rejected. Following this was [69] who provided new insights on gasoline demand in Europe with a panel data set from 14 countries over the period 1990-2004 using nine (9) common dynamic model specifications. The paper only addressed the omitted variable of the number of gasoline-powered cars as against total passenger cars as indicator of gasoline consumption together with the flow adjustment model introduced by [70]. Uniquely, the study introduced gasoline consumption per gasoline-powered passenger cars as the explained variable and the number of gasoline-powered passenger cars per driver as a regressor variable. Both pooled and a collection of instrumental variables (IV) dynamic models such as the first-differenced GMM (FD-GMM), FD-2SLS, and system-GMM were used. The results obtained aligned with those of previous studies [see 71-73] where positive income elasticity and negative price elasticity coupled with negative car ownership-gasoline consumption were obtained. The results indicated that the standard pooled estimators were more efficient than the instrument variables estimators and that neglecting the share of diesel cars overestimated short-run income, price and car ownership elasticities.

Realistically, the use of the triangulation analyses provides robust results and in fact strengthens the estimations process. However, where the researcher is incapacitated to conduct such, it may be necessary to perform relevant diagnostics in order to authenticate the appropriateness of the chosen methodology.

6.0 Dealing with Meteorological and Seasonal Factors

The role of meteorological and seasonal factors in energy demand has also been captured in the literature. The significance of these factors may be valid for energy demand involving heat which is expected to be significantly influenced by temperature, wind speed, global radiation and humidity. Similarly, the power and heat energy demand is most likely to be higher on working days than at the weekend, holidays and vacation and thus, the demand for some energy types can be seasonal in nature. In addition, the power and heat demand can also be affected by the daily cycle with low temperature during the night hours and with relatively different magnitudes of high temperatures at different hours of the day. Therefore, modeling the demand of such energy types may necessarily require including both meteorological and seasonal factors as the case may be. For instance, [74] established that the demand for electricity is influenced by temperature increases in summer and spring through a double effect. On one hand, the demand for electricity in summertime in hot countries increases, most likely because of the use of cooling devices [74]. On the other hand, the demand for electricity in spring in cold countries diminishes because of the warmer temperatures and the consequent lower heating needs [74]. They also envisaged similar temperature effects for gas and coal between hot and cold countries, although of slightly different magnitude. Overall, they concluded that hot countries are more influenced by the cooling effect, whereas cold countries are more affected by the heating effect.

In the same way, [75] investigated the link between electricity demand and temperature for 24 OECD countries from the period 1978–2004. Their empirical results demonstrated that there is a strongly non-linear link among electricity consumption and temperature. The empirical finding also supported a U-shaped relationship between electricity consumption and temperature; thus, suggesting that the significance of temperature in modeling electricity demand. Similar findings were obtained from related earlier papers such as [76-82]. Interestingly, these papers used different reference temperatures and they arrived at the same conclusion about the link between temperature and energy demand.

In a related study by [83], household response to weekday differentials in peak and off-peak electricity prices was examined. Data were drawn from Auckland, New Zealand, which is assumed to experience peak residential electricity consumption during winter for heating. Their findings revealed that, there was no response except in winter. They found that participating households reduced electricity consumption by at least 10% during winter in order to take advantage of lower off-peak prices but they did not respond to the peak price differentials. In addition, they reported that response varied with house and household size, time spent away from home, and whether water was heated with electricity.

In another study by [84], the number of cooling degree days – indicating the weather effect – was found as one of the most influential factors of electricity demand both in the long run and short run. Even, [85] compared the periodic autoregressive and dynamic factor models in intraday energy demand forecasting. This was a novel approach which used semi-parametric regression smoothing to account for calendar and weather components. The study showed that employing meteorological variables could enhance the accuracy of demand forecasts greatly over a one-week horizon. The results obtained further conveyed the expected relationship between the current air temperatures and both heating and electricity demand which confirmed the findings of previous studies [see 77, 86]. They also found that the relationship varied by both the day and the season since any heating and cooling degree day measures constructed also varied by day and season.

6.1 Climate Change, Global Warming and Energy Demand

There have been increasing empirical studies suggesting that the incessant monumental rise in global average surface temperature and atmospheric carbon dioxide will have implications on energy demand ranging from energy demands for cooling and heating to costs of electricity consumption. In fact, the growth of research in this regard in recent times is phenomenal and that reiterates the significance of climate change and global warming to energy discourse and policy [see 87 for a review of earlier studies]. In a recent paper by [88] funded by the European Commission, they projected that over the next 100 years, climate change could cause up to a 20 per cent decrease in demand for electricity for heating in Northern Europe and up to a 20 per cent increase in demand for electricity for cooling in Southern Europe. This finding was also buttressed by [89] who also assessed the impact of climate change on the European energy system and found that demand side impacts (heating and cooling in the residential and services sector) are larger than supply side impacts; power generation from fossil-fuel and nuclear sources decreases and renewable energy increases; and that impacts are larger in Southern Europe than in Northern Europe.

At the country level, the findings are not different. For example, [90] predicted changes in energy demands for heating and cooling in Slovenia due to climate change. Their results indicated that energy use for heating would decrease from 16 percent to 25 percent (depending on the intensity of warming) in subalpine region, while in Mediterranean region the rate of change would not be significant. During summer time, they predicted that the country would need up to six times more energy for cooling in subalpine region and approximately two times more in Mediterranean region. They concluded that low-energy building proved to be very economical in wintertime while on average higher energy consumption for cooling is expected in those buildings in summertime. This finding was also authenticated by [91, 92] who also found that future energy demand by current buildings in the U.S. will decline for heating, and will increase for cooling.

By the same token, [93] indicated that, in Norway, climate change will reduce the heating demand and increase the cooling demand, among others. Also, they showed that the reduction of heating demand will be significantly higher than the increase of cooling demand.

[94] evaluated how climate change has affected the design of energy efficient residential building envelopes. Using a building thermal model for the mild temperate climate of Adelaide, Australia, which requires both heating and cooling, but is dominated by heating, climate change was found to increase and shift this demand to cooling dominated. They argued that with climate change, heating becomes significantly less important in better insulated buildings and that measures which reduce cooling load are more critical. They also emphasized hat in this climate zone, climate change design approaches need to dramatically change to focus on cooling, contrary to present strategies.

The impacts of climate change on the costs of electricity consumption have also been investigated in the literature. In a related study by [95], the impacts of climate change on energy demand were evaluated with a focus on energy demand in commercial and residential sectors (mainly for heating and cooling). Among other things, they found that Climate change damages, as measured by increases in total system cost, increased with the demand for electricity, overtime, but were still relatively small. In addition, they demonstrated that allowing the electricity supply system to adjust capacity "optimally" to climate change did not always reduce total system costs, which was the opposite of what was expected.

Similarly, [96] analyzed the potential impacts of changes in temperature due to climate change on the U.S. power sector. They projected that, without mitigation actions, total annual electricity production costs in 2050 will increase by 14% ($51billion) due greater cooling demand as compared to a control scenario without future temperature changes. With global emissions mitigation, including a reduction in U.S. power sector emissions in 2050, they predicted that increase in total annual electricity production costs is approximately the same as the increase in system costs to satisfy the increased demand associated with unmitigated rising temperatures.

One of the limitations of some of these empirical studies on the link between climate change and energy demand is that the outcome is sensitive to the choice of climate scenarios. This was empirically validated by [97]. They established that the reduction in heating demand depends on the climate scenario and the differences can be up to 30 kWh/m2 (around 30% in the 20-year mean values). Similarly for the cooling demand, there are huge differences between the climate scenarios, even more than 500%.

7.0 Micro-economic Analyses of Energy Demand

There is a growing body of literature involving the use of micro-data for the analysis of energy demand. For example, [98] documented the various advantages of using micro data for fuel energy demand modelling. They argue that micro-data allow us to capture the heterogeneity of households' fuel consumption decisions and the impact of key variables (including habits, place of residence, the socioeconomic status and household size) on such decisions. They based their micro-economic analysis on the Almost Ideal Demand System (AIDS) model proposed by [99, 100] which has remained prominent in the analysis of demand for any good or service by households. Uniquely, [98] evaluated the implications for public policies of the price and income elasticities of demand for passenger transport fuels in Spain over the period 1998:1 to 2001:4. The data were obtained from the Continuous Family Budget Survey database (ECPF, in its Spanish initials), which provides quarterly data on automotive fuel consumption by families (various years). Essentially, the ECPF provides household socioeconomic information, such as expenditure on the consumption of goods and services, place of residence, employment status, size of the family and economic status of the principal breadwinner. Generally, their results are within the ranges of the studies found in the literature, although income elasticities are closer to the upper bound and price elasticities are lower than those ranges.

Also, [101] utilized micro data from the Ugandan National Household Energy Survey 2009–10 covering all 80 districts and 6775 households in Uganda to examine household energy mix in the country. These findings are consistent with the energy ladder theory which assumes that as income increases, households consume more modern fuels and less traditional and transitional fuels. As evident in the findings, as household income increased, solid and transitional fuel use evolved in an inverse U manner, while electricity consumption showed a direct relationship with income. While education had been considered as a significant factor in determining movement along the energy ladder, persistent reliance upon charcoal as household income increases which suggested inaccessibility to alternative modern cooking fuels was noticed.

Following from this therefore, the analysis of energy demand should not be constrained by the nature of data as the results are not likely to differ substantially irrespective of the data type used.

8.0 Conclusion

This paper provides a review of recent developments in energy demand modeling particularly areas that have not received much attention in the previous reviews. This review is motivated by the proliferation of papers on energy demand modeling offering different dimensions both in terms of methodology and estimation. While this development has strengthened our understanding of the subject, it may render the identification of gaps in the literature arduous for future research. Thus, this study documents recent developments as well as emerging issues that seem to have rendered new directions on energy demand modeling; and it is hoped that access to this review complemented with previous reviews will facilitate the comprehension of the strength of the extant literature as well as areas of future research in energy demand modelling.

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