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Systems Thinking and Systems Dynamics Approach to Demand Side Management

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Abstract- Context: Demand Side Management (DSM) provides utilities with tools to modify end users' consumption patterns, helping reduce peak demand, alleviate stress on the power grid, and even support with the integration of renewables. Nonetheless, DSM is an inherently complex and interdependent system stretching across numerous factors such as economic, behavioural, and technological with different feedback dynamics and competing incentives. To address this complexity a Systems Thinking and Systems Dynamics approach is applied. **Objective**: The aim of this paper is to develop a quantitative Systems Dynamics model in the Vensim simulation environment, capturing the dynamic transition between short run and long run price elasticities. **Method:** The model defines variables such as baseline demand, electricity price, and both short-run and long-run elasticities. A stock variable, Effective Price Elasticity, is used to dynamically represent the shift from short-run to long-run responses. Simulation parameters were gathered from literature. **Results:** Simulations demonstrate that the model confirms expected behaviour, showing an initial less elastic response to the price changes followed by a more notable gradual adjustment over time as the effective elasticity converges to its long-run value. **Conclusions:** This model can provide a framework for simulating the dynamic interplay between electricity price and demand. Its ability to simulate short-run and long-run elasticity effects offers valuable insights for energy planners and policy makers.

Keywords- Demand side management, Electricity demand, Price elasticity, System dynamics, Vensim software.

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1. Introduction

The global energy sector is characterised by increasing energy requirements, increased usage of renewable energy sources, and a global need for energy sustainability [1]. Demand Side Management (DSM) provides a set of measures for the optimisation of patterns of electricity consumption by end-users [2][3] Effective DSM is dependent on the responsiveness of electricity demand to stimuli, specifically price, which can for example be facilitated by real-time information technologies [4]. Further use of renewable sources of energy, while beneficial for sustainability, comes with some challenges such as the "duck curve" effect, and thus effective demand-side management and storage are required [5][6].

The demand for electricity has a dynamic, not a fixed, price elasticity that is determined by behavioural, economic, and technological factors. Industries and consumers do not react immediately in the short run to a price variation. They react in varying ways over time and have varying short-run and long-run elasticities. The short-run reaction involves instant and relatively less elastic or inelastic reactions (e.g., minor behaviour adjustment), while the long-run reaction involves increased elastic reactions, such as investment in energy-efficient appliances or infrastructural transformation [7]. The acceptability of time-varying electricity pricing for the public is also an important aspect of the success of such programs [8].

Conventional linear modelling techniques often struggle to capture the complex feedback processes, time delays, and emergent dynamics of systems of this kind [9]. An integrated approach must be used. Systems Thinking, and System Dynamics, offers a sound methodology for dealing with complex, dynamic systems in terms of interdependencies and feedback processes [10] [9].

The goal of this paper is to construct a quantitative system dynamics model of electricity price and demand responsiveness, to model formally and simulate dynamically short-run and long-run elasticities of price.

The remainder of this paper is organised as follows, Section 2 provides a background discussion on Demand Side Management as a complex system, electricity price elasticity of demand, and system dynamics in energy modelling. Section 3 compares the related literature and identifies the research gap addressed in this study. Section 4 outlines the methodology used. Section 5 presents the model structure and equations, while Section 6 explains the simulation design including scenario, sensitivity, and empirical validation setups. Section 7 then analyses the simulation results followed by a discussion in Section 8 on implications, limitations and Section 9 gives the conclusion and recommendations for future work.

2. Background

2.1. Demand Side Management as a Complex System

Demand Side Management is increasingly seen as a valuable tool in modern electricity systems, with the aim of changing consumer consumption patterns to align with grid constraints, pricing strategies, and sustainability goals [11] [2]. The effectiveness of DSM depends on a complex interplay of factors ranging from behavioural to technological, and economic. These interdependencies often lead to non-linear, hard to quantify effects and delayed system responses. Therefore, researchers have increasingly turned to methods like Systems Thinking and Systems dynamics to conceptualize and model complex systems such as DSM [9], with its interacting feedback loops and evolving behaviours [10].

2.2. Electricity Price Elasticity of Demand

An important component of DSM strategies is the price responsiveness of electricity demand usually represented as the concept of price elasticity. Price elasticity measures the percentage change in electricity demand from a corresponding percentage change in price. The responsiveness can vary depending on the sectors and timelines involved according to empirical studies [7]. Short-run price elasticities in the United States are typically inelastic, with the residential and commercial sectors showing values of around -0.1 and less. As opposed to short-run elasticities, long-run elasticities account for fundamental adjustments such as changing technology or usage behaviour and can reach around -1.0 in industrial sectors. Similar elasticity studies have been done in different geographic areas, such as a study that analysed EU residential and industrial data and found long-run elasticities between -0.5 and -1.0 [12], as well as a study implementing a time-varying parameter model in South Africa [13]. This shows us that DSM strategies relying on price signal may exhibit delayed effects, where consumers gradually adapt possibly over several years [7].

2.3. Systems Dynamics in Energy Demand Modelling

Static or Linear models are limited in capturing in feedback, adaption, and time delays, this necessitates the adoption of Systems Dynamics modelling in the energy domain. Systems Dynamics provide a powerful framework for modelling, feedback processes, complex interconnections, and non-linear effects [9][14]. In the context of DSM, Systems Dynamics allows for the integration of short-term behavioural responses with long term systemic changes, which offers a more comprehensive picture of how demand responds to pricing and policy over time.

3. Literature Review

3.1. Elasticity Studies

Econometric models have provided empirical estimates of the short and long run price elasticities across different regions and sectors [7][12]. They have an advantage in terms of statistical rigour and the ability to capture differences between sectors. However, these models remain static as they are retrospective analyses where the relationship between electricity price and demand is estimated at a single point in time or over short intervals using regression techniques, without the dynamic feedback of price and demand. Thus, they fail to capture the elasticity adaptation over time. [13] employs a time-varying parameter model using a Kalman Filter that allows elasticity coefficients to change over time, this offers an advantage over a fixed parameter model, but it lacks the underlying causal structures and a clear distinction between short-run and long-run elasticity.

Table 1. Summary of Literature Elasticity values

Study	Region	Method / Data	Sector(s)	Short-Run Elasticity	Long-Run Elasticity
[7]	USA	Econometric panel regression (ARDL / time-series panel)	Residential, Commercial, Industrial	-0.1	near -1
[12]	European Union	Panel econometrics with fixed effects	Industrial & Residential	-0.07 to -0.08 (residential), -0.08 to -0.1 (industrial)	-0.75 to –1.01 (industrial), -0.53 to –0.56 (residential)
[13]	South Africa	Time-varying parameter econometric model (state-space, Kalman filter)	Aggregate	Final single price elasticity of –0.288 estimated	
[15]	Global	Meta-analysis (across energy products)	Mixed sectors	-0.02 to –0.29	-0.19 to –0.77

3.2. Related Work

System Dynamics models offer a feedback driven approach to simulate the dynamic behaviour of a system over time.

[16] developed a quantitative DSM modelling framework that uses dynamic behavioural equations and fuzzy-logic decision structures to assess user responses to tariff-based load shifting strategies. Although it is inspired by system dynamics for its influence diagrams, the implementation is carried out in Modelica rather than a classical stock and flow system dynamics environment. The model's strength lies in its integration of behavioural factors such as energy culture and education, which accelerate customer response. However, it does not simulate long-term elasticity evolution.

A dynamic price-based demand response model for smart grids, using a game-theoretic framework was developed to represent real-time interactions between electricity prices and consumer load adjustments [17]. The model provides detailed short-term operational insights into peak shifting and utility-customer benefits. However, it does not include long-term behavioural change or the evolution of demand elasticity.

[18] developed a system dynamics model of the Iranian electricity sector to explore long-term interactions between electricity demand, generation capacity, fuel supply, emissions, and pricing/subsidy policies. While the model incorporates price and subsidy scenarios to assess their impact on the demand, the price elasticity of demand is represented through fixed econometric parameters and not as a dynamic or changing variable.

At the policy and planning level, [19] applied System Dynamics to electricity expansion and emission reduction in West Africa. While this shows the SD method's policy relevance even in developing regions, it does not model the price elasticity and its effect on demand in the short and long term.

3.3. Gap in literature

While the use of Systems dynamics is well established in energy modelling, there remains a gap in the explicit simulation of time-dependent price elasticity within DSM frameworks. Few models simulate the transition from short run to long run elasticity, despite its well established and empirical significance.

This Study addresses the gap in existing Demand Side Management modelling by explicitly simulating the dynamic transition from short-run elasticity to long-run elasticity in response to price changes. This seeks to build upon previous works which have recognized the distinction between short-run and long-run elasticities, but few have captured this transition within a formal Systems Dynamic simulation framework.

The core aspects of this study are:

- Introduce a quantitative Systems Dynamics Model of the Electricity Price-Demand Loop which considers the time-varying elasticity behaviour based on empirically derived values.
- Formulate the concept of Effective Price Elasticity as a stock variable that changes over time, thus the gradual shift from short term behaviour to long term adjustments can be seen explicitly.
- Demonstrate how this changing elasticity effects the electricity demand across multiple simulation scenarios.

Therefore, the model simulates the Price-Demand Loop with a specific focus on how Effective Price Elasticity changes over time, instead of the fixed constant elasticity.

4. Materials and methodologies

This study applies a combined Systems thinking and Systems Dynamics approach to model the relationship between electricity price and demand with respect to Demand Side Management. This is designed to reflect the interdependencies and feedbacks common to DSM systems.

The Systems Thinking/Dynamics process follows the phases outlined in Figure 1, that transitions from a qualitative conceptualisation of the Electricity Price-Demand system to a quantitative simulation model that can be tested by various scenarios. This process is grounded and established in Systems Dynamics practices, as articulated by [20], and aligns with prior research in the energy sector [10] [9].

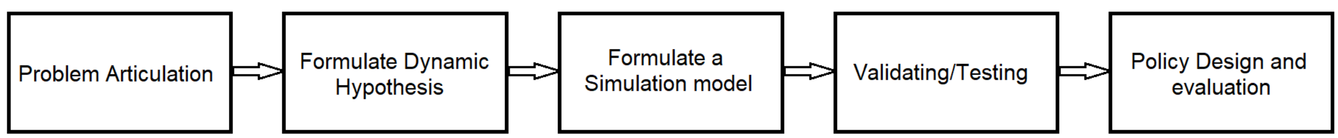


Figure 1. Methodological framework combining Systems Thinking and System Dynamics modelling adapted from [10].

The phases are:

Problem Articulation:

- Demand Side Management is a complex, interdependent and non-linear system that spans behavioural, economic, technological and more dimensions, included with time delays. The interaction of these different factors makes it difficult to model using static or linear models. This phase defines the system boundary or core challenge.

Formulating a Dynamic Hypothesis:

- A qualitative understanding of the system is developed using Systems thinking tools namely Causal Loop Diagrams (CLDs). Among the different DSM related feedback structures, the Price-Demand Loop is focused on for this study. This loop represents how electricity prices affect consumption, which then affects load profiles.

Formulating a Simulation model:

- This conceptual understanding is then formalised into a stock and flow model in the Vensim simulation environment. The core of the model includes variables such as Baseline Electricity Demand, Average and Reference prices, Short and Long Run Elasticities, and a stock variable called Effective Price Elasticity that dynamically evolves over time. This concept explicitly captures the delay between price signals and consumer consumption pattern changes.

Validation and Testing:

- Multiple scenarios are simulated over a multi-year period with a time step of 1 year. Scenarios to be tested are baseline (no DSM), price increases or decreases (%), and direct DSM interventions (load reduction).

Outputs such as the Actual Electricity Demand, Effective Price Elasticity, and Price effect on Demand are observed and compared against expected behaviour. The model should demonstrate short-run inelasticity followed by a gradual approach to its long-run elasticity, after this sensitivity testing and running the model with real world data are implemented.

Policy Design and Evaluation:

- Not fully explored in this paper, but the model can be developed to extend to DSM strategies and policy interventions.

4.1. Selection of Numerical Values

The empirical Short Run Price Elasticity and Long Run Price Elasticity metrics are crucial to the model's accuracy and are derived from empirical studies. Specifically, we have considered [7], which offers a comprehensive three-dimensional analysis of United States electricity demand elasticity by sector and time interval.

Short Run Price Elasticity: Fixed at approximately -0.1. Based on results of [7], short-run estimates of -0.1 and below have been found to hold for all American sectors, including domestic consumption. Similar studies around the world hold values in a similar range such that the assumed -0.1 is kept [12]. It is short-run inelastic consumption behaviour with little room for changing their consumption levels in extremely short run.

Long Run Price Elasticity: Approximately -1.0. That is also in line with [7] estimates for aggregate US electricity sales perhaps an ideal case, this is not too dissimilar to EU studies [12] and most notably the industrial sector, where it is implied that a 1% price increase leads to approximately a 1% decrease in long-run demand. The long-run estimate is substantially more elastic since consumers and industries have more time to adjust through means of investment in energy-efficient technology, relocation, or changing underlying patterns of energy consumption. [15] reports a lower long-run elasticity estimate of -0.77 and -0.61 for electricity demand specifically.

Adjustment Rate: Set to approximately 0.2 year $^{-1}$ which determines how quickly the effective elasticity transitions from its short-run to long-run value, adaptation periods lie between 3 to 10 years. Thus 0.2 produces a medium speed transition.

5. Modelling

5.1. Causal Loop Diagram: Price-Demand Feedback Structure

The high-level qualitative structure of the system is captured in Figure 2, which represents the Price-Demand Feedback Loop. A rise in electricity price reduces demand through short-run behavioural adjustments, sustained high prices lead to the long-run elasticity which indicates behavioural and technological adaptations through a delay. That reinforces demand responsiveness. As demand decreases the pressure for further increased prices falls.

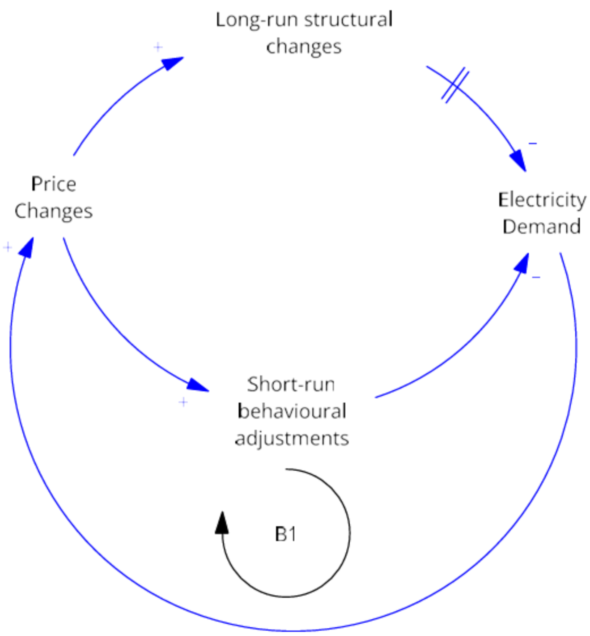


Figure 2. Causal Loop Diagram of a High-level Price-Demand elasticity system.

This reflects the time dependent nature of electricity-price demand elasticity, where the short-run reactions are inelastic while long-run adjustments are more pronounced.

5.2. Model Structure and Variables

The model is now constructed using Vensim, variables used to construct this model can be categorised into stocks and auxiliaries, a flow variable is not explicitly utilised (Table 2). The stock and flow representation in Figure 3, formalises the relationships identified in the CLD. The model is built around the Effective Price Elasticity (stock) that evolves according to the difference between short and long run elasticities. The adjustment rate determines the speed of transition. Electricity demand is then recalculated dynamically based on this changing elasticity and the average to reference price.

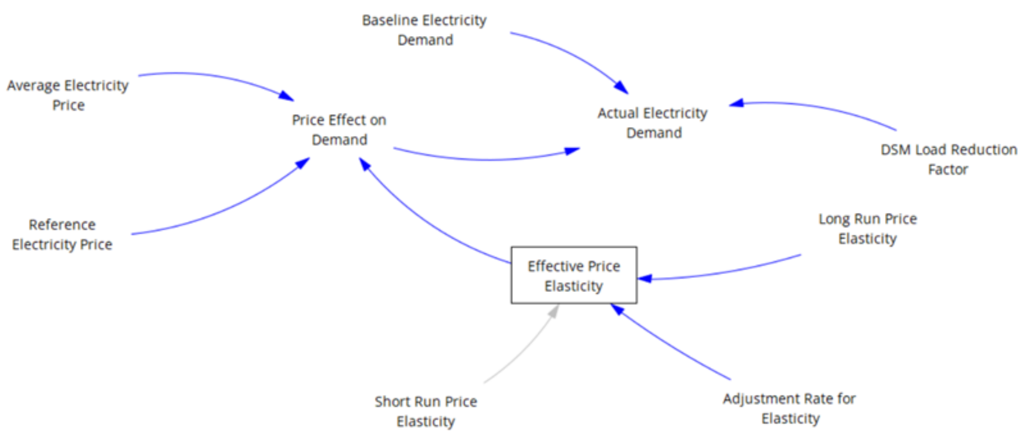


Figure 3. Electricity Price-Demand System Dynamic Model in Vensim.

Price Effect on Demand:

$$P_d = e^{\varepsilon_{eff} \cdot \ln\left(\frac{P_{avg}}{P_{ref}}\right)} \tag{1}$$

Eq. (1) expresses the relative change in electricity demand resulting from deviations of the Average electricity price (P_{avg}) from a reference price (P_{ref}), scaled by the current values of Effective Price Elasticity (ε_{eff}).

Actual Electricity Demand:

$$D_{act} = D_{base} \cdot P_d \cdot (1 - L_{DSM}) \tag{2}$$

Eq. (2) shows the Demand at any given time, where D_{base} is the baseline electricity demand and L_{DSM} represents the DSM load reduction factor.

Effective Price Elasticity:

$$\frac{d\varepsilon_{eff}}{dt} = \alpha\left(\varepsilon_{LR} - \varepsilon_{eff}\right) \tag{3}$$

Eq. (3) is a state variable that dynamically transitions from short-run (ε_{SR}) and long-run (ε_{LR}) elasticity values.
Where α = adjustment rate for elasticity, representing the speed of the shift from short-run to long-run, t = time (years) and initially $\varepsilon_{eff} = \varepsilon_{SR}$.

Table 2. describes the variables used in the System Dynamics model with units (e.g. Dmnl indicates a dimensionless variable) and gives the equations in the vensim environment format of Eq. (1), Eq. (2), and Eq. (3) with the constants of the other variables.

Table 2. Vensim variables with equations included.

Variable Name	Type	Equation / Definition	Units
Average Electricity Price	Constant	= 200 (Varied)	$/MWh
Reference Electricity Price	Constant	= 200	$/MWh
Price Effect on Demand	Auxiliary	= EXP (Effective Price Elasticity × LN (Average Electricity Price / Reference Electricity Price))	Dmnl
Effective Price Elasticity	Stock	= Adjustment Rate × (Long-Run Elasticity – Effective Elasticity); Initial = Short-Run Elasticity	Dmnl
Long Run Price Elasticity	Constant	= -1.0	Dmnl
Adjustment Rate for Elasticity	Constant	= 0.2	1/Year
Short-Run Price Elasticity	Constant	= -0.1	Dmnl
Baseline Electricity Demand	Constant	= 5000	MWh/Year
DSM Load Reduction Factor	Constant	= 0.1	Dmnl
Actual Electricity Demand	Auxiliary	= Baseline Demand × Price Effect on Demand × (1 – DSM Load Reduction Factor)	MWh/Year

6. Simulation Design

This section outlines the simulation setup, tools, and configurations to evaluate the behaviour of the model and confirm its validity, different test cases or scenarios are developed to test the system's dynamic response under the different DSM related interventions. Scenario testing like this in Systems Dynamics modelling is standard practice used to verify behavioural consistency, test model sensitivity, and explore policy outcomes under varying test conditions [20]. Three categories of simulation experiments were conducted to test the model: (1) Behavioural Scenario Tests, (2) Parameter Sensitivity Analysis, (3) Validation using Real-World data.

6.1. Model Behaviour Scenario Tests

The focus of these scenarios is geared towards observing the price elasticity dynamics specifically how electricity demand responds to price increases, price decreases, and non-price related DSM measures over time. The scenarios are simulated over a 15-year period, this allows the model to capture the short term and long-term effects.

All scenario simulations use the following common reference values:

- Baseline Electricity Demand (D_{base}): 5000 MWh/year
- Reference Electricity Price (P_{ref}): 200 $/MWh
- Short-Run Elasticity (ε_{SR}): –0.1
- Long-Run Elasticity (ε_{LR}): –1.0
- Adjustment Rate (α): 0.2 (representing a 20% shift per year from short to long run elasticity)

The key levers that are varied to test the different model responses:

- Average Electricity Price (As an external signal to consumers)
- DSM Load Reduction Factor (As a proxy for behavioural, incentive based, or technical interventions)

Table 3. States the Scenario tests to be simulated using the model to assess its behaviour under differing price changes (increase or decrease). The Price and DSM Load reduction factor values for each scenario are shown.

Table 3. Test Scenario parameters.

Scenario	Price ($/MWh)	DSM Load Reduction Factor	Description
S1: Baseline (No DSM)	200	0	Control scenario to confirm model stability under neutral conditions
S2: Price Increase (10%)	220	0	Models consumer response to higher tariffs; used to test negative elasticity over time
S3: Price Decrease (10%)	180	0	Models consumer response to lower tariffs; tests upward elasticity and potential rebound
S4: DSM Load Reduction (10%)	200	0.1	Models impact of non-price interventions such as peak clipping, appliance control, etc.

6.3. Sensitivity Analysis Setup

To determine model sensitivity to changes in variable values and identify the parameters with the highest influence on system behaviour, sensitivity analysis was performed using the SENSITIVITY2ALL function. The target variable selected for testing was Effective Price Elasticity.

The parameters varied within ±10% of their base values were:

- Short-Run Price Elasticity
- Long-Run Price Elasticity
- Adjustment Rate

Each run compared deviations in model behaviour from the base scenario using multiple sensitivity measures:

- Mean Absolute Deviation (MAD)
- Payoff Percentage (Integrated and Final Time)

6.4. Empirical Validation Setup

To extend the model's relevance and test its empirical validity, a simulation was performed using real-world electricity demand and price data from the U.S. Energy Information Administration (EIA) [21]. Specifically, Tables 2.5 and 2.7 from the Electrical Power Annual were used covering the period from 2014 – 2024.

Data Description:

- Electricity Consumption (Demand): EIA's "Sales of Electricity to Ultimate Customers" (All Sectors) Table 2.5, measure in thousand MWh, used as a proxy for actual electricity consumption (demand).
- Electricity Price: Average price of Electricity to Ultimate Customers (All Sectors) Table 2.7, measured in cents/kWh and converted to $/MWh for model consistency.

Model Integration:

Eq. (4) describes a lookup table variable, Yearly Price Data which was introduced to represent the empirical EIA average electricity price over time. This lookup function then connects to the Average Electricity Price input of the model via

$$Average\ Electricity\ \text{Price} = Yearly\ \ \text{Price}\ Data\left(\frac{Time}{Const\ year}\right) \tag{4}$$

Where Const year (unit: Year) ensures unit consistency across time.

The following empirical parameters were applied:

- Reference Electricity Price: $104.4/MWh (2014 price baseline)
- Baseline Electricity Demand: 3.7647×10^9 MWh/year (2014 total demand baseline)
- Simulation Period: 2014 - 2024
- Time Step: 1 year

The model then simulated Actual Electricity Demand dynamically as prices changed according to real data. This demand produced a time series of estimated demand trajectories that were later compared to observed EIA trends to assess whether the simulated system behaviour reflects real-world elasticity responses.

7. Results

This section presents and interprets the outcomes of the simulation experiments described in the 6. Simulation Design. The analysis focuses on the model's behavioural validity, sensitivity to elasticity parameters and correspondence with real-world electricity price-demand data.

7.1. Model Behaviour Scenario Analysis

The baseline and DSM-related scenarios were simulated over a 15-year horizon to test the internal behaviour of the model.

7.1.1. Actual Electricity Demand

Figure 4 illustrates the Actual Electricity Demand under different scenarios. The baseline (grey line) remains constant at 5000 MWh/Year, as expected, confirming the model's behaviour with no stimuli.

The results of the various test cases/scenarios using the values in Table 4. As inputs are as follows:

Scenario 1:

- Baseline: In this case, the DSM Load Reduction Factor is zero and the Average Electricity Price is maintained at the Reference Electricity Price. As anticipated, Actual Electricity Demand stays at 5000 MWh/Year, exactly the same as Baseline Electricity Demand. This confirms how the model behaves in a steady-state scenario, in which demand is not changed by outside stimuli.

Scenario 2:

- 10% Price Increase: At the start of the simulation, the green line indicates an abrupt, slight decrease in Actual Electricity Demand (from 5000 to 4952.57 MWh/Year at Time=0). The Short Run Price Elasticity (-0.1) is reflected in this initial decrease. The demand continues to decline over time as the Effective Price Elasticity progressively moves in the direction of the more elastic long-run value (-1.0), exhibiting a greater overall demand drop that falls to 4811.63 MWh/Year by Year 2. This graphic illustrates how consumers react slowly to price increases, with the full effects taking years to manifest. This plot's design, which shows a steep drop at the beginning and a more gradual decline later, effectively depicts both the immediate short-term impact and the long-term adaptation that follows.

Scenario 3:

- Price Decrease (10%): Conversely, the red line shows an immediate rise in demand at Time=0 (from 5000 to 5052.96 MWh/Year), mild at first. Over time, as Effective Price Elasticity becomes more elastic, a stronger, gradual increase in demand is observed, increasing to around 5216.83 MWh/Year by Year 2. This reflects the long-run adaptation to lower prices. The plot's mirroring of the price increase scenario, but in the opposite direction, confirms the symmetrical (though delayed) response of demand to price changes.

Scenario 4:

- With DSM (10% Reduction): The blue line shows a direct 10% reduction in Actual Electricity Demand from the baseline (from 5000 to 4500 MWh/Year), as this scenario models a direct load cut factor independent of price effects. This represents a clear policy-only impact, such as Direct Load Control. This plot is drawn as a flat line below the baseline, indicating a constant, non-price related reduction.

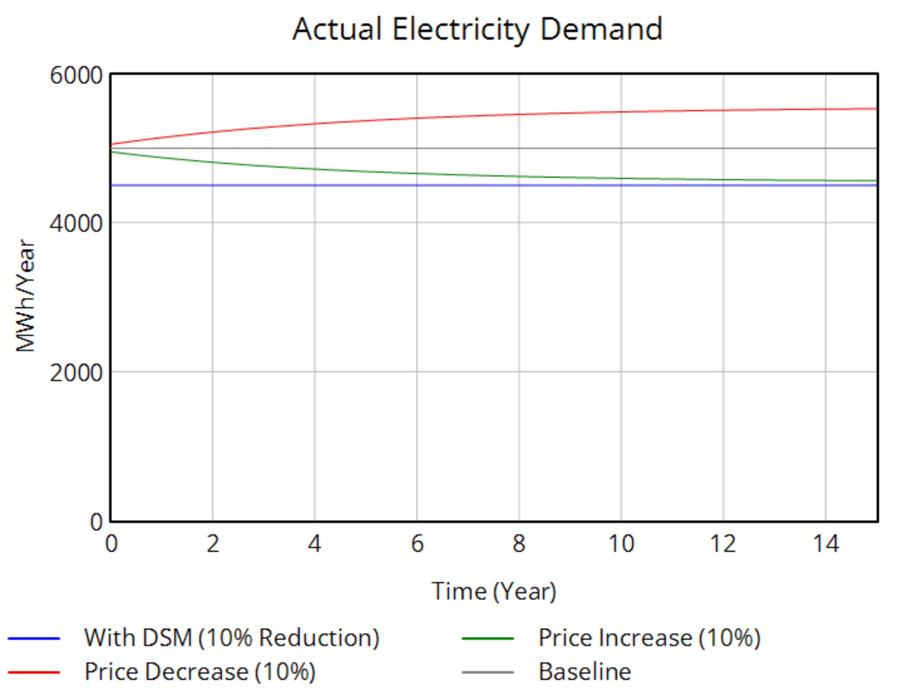


Figure 4. Output Graph of the Actual Electricity Demand.

7.1.2. Effective Price Elasticity

Figure 5 clearly depicts how Effective Price Elasticity evolves over time, revealing the dynamic responsiveness of demand.

The results of the Effective Price Elasticity are as follows:

- The curve starts at the Short Run Price Elasticity value (-0.1) at Time = 0.
- Over the simulation period, it gradually approaches the Long Run Price Elasticity value (-1.0), forming a characteristic exponential decay like curve as it transitions. This behaviour is a direct result of the Rate of Elasticity Adjustment flow, which continuously narrows the gap between the current effective elasticity and the long-run elasticity. The rate of adjustment is determined by the Adjustment Rate for Elasticity (set at 0.2 for this simulation), which implies that about 20% of the remaining gap between the current and long-run elasticity is closed each year. The plot's smooth, asymptotic curve towards the long-run value is a direct visual confirmation of the INTEG (Stock) function's behaviour in System Dynamics, representing a gradual adjustment process.
- The fact that all scenario lines overlap indicates that the Effective Price Elasticity is an intrinsic dynamic of the model's structure, driven by the fixed Short Run Price Elasticity, Long Run Price Elasticity, and Adjustment Rate for Elasticity, rather than being directly altered by the specific price scenarios themselves. The price scenarios merely provide the stimulus against which this evolving elasticity acts.

Figure 5. Output Graph of the Effective Price Elasticity.

7.1.3. Price Effect on Demand

Figure 6 shows how the price multiplier directly impacts demand: values greater than 1 lead to an increase in demand, while values less than 1 lead to a decrease.

The results of the Price Effect on Demand are as follows:

- The Price Effect on Demand responds instantly to the initial price change, but its magnitude continues to change over time as the underlying Effective Price Elasticity evolves. For a price increase, the multiplier decreases more significantly over time (e.g., from an initial 0.95 to 0.85), while for a price decrease, it increases further (e.g., from 1.05 to 1.15), reflecting the increasing impact of long-run adaptation. The way these curves are drawn, with their initial step and subsequent gradual change, directly reflects the instantaneous application of the Price Effect on Demand formula, whose value is then modulated by the dynamically changing Effective Price Elasticity.

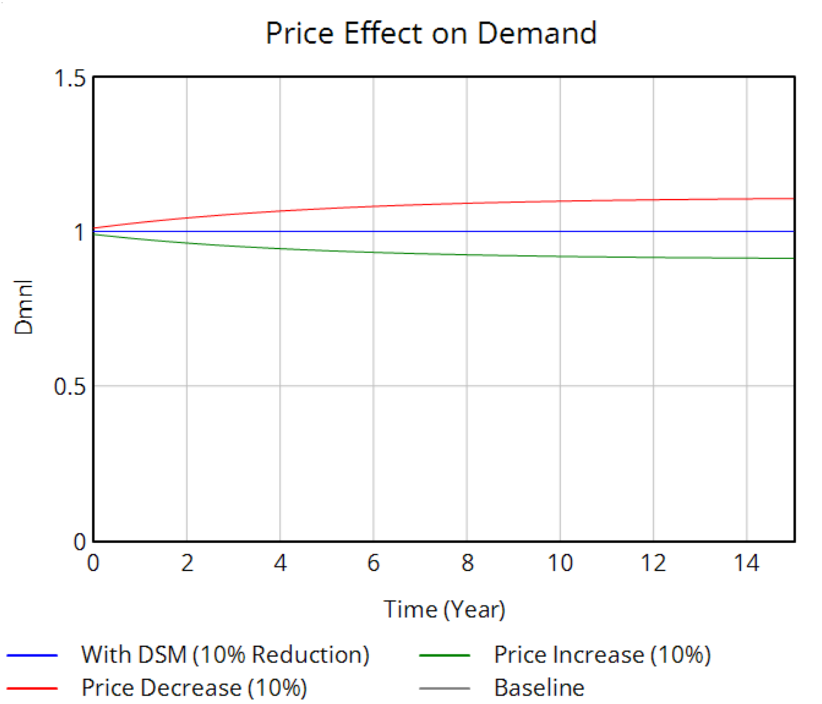
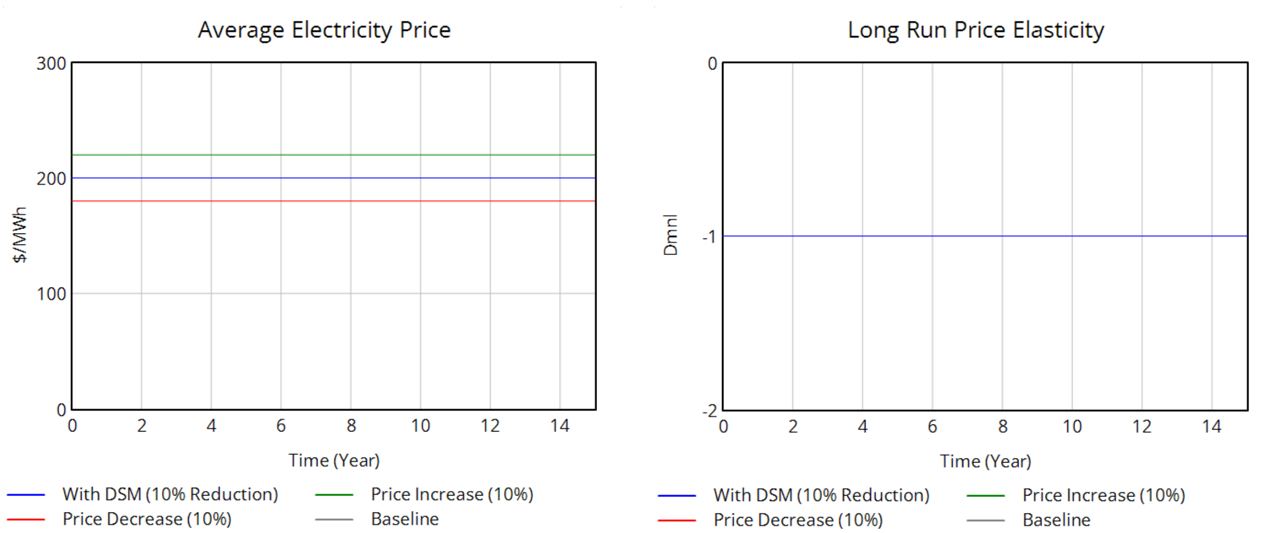


Figure 6. Output Graph of the Price Effect on Demand.

7.1.4. Important constants

Figure 7 displays the consistent inputs for (a) Average Electricity Price, (b) Reference Electricity Price, (c) Long Run Price Elasticity, and (d) Short Run Price Elasticity across the simulation horizon, confirming their static nature as constants or fixed scenario inputs within this model component.



(a) (b)

(c) (d)

Figure 7. Output Graphs of Important Constants.

7.2. Sensitivity Analysis Results

Sensitivity testing using Vensim's SENSITIVITY2ALL assessed how variations in elasticity parameters affected model behaviour. The target variable was Effective Price Elasticity, and deviations were measured using mean absolute deviation (MAD) and payoff metrics, with the +10% being represented by the blue line/bar and the –10% run represented by the red line/graph.

Figure 8 illustrates a tornado plot of the mean absolute deviation (MAD), which is the absolute difference between the base run and ±10% runs. Long run elasticity is the most influential parameter governing model behaviour the (MAD = ~0.069), the adjustment rate has a secondary influence (MAD = ~0.026), primarily in the speed of transition, with short run elasticity producing only a minimal effect (MAD = ~0.003).

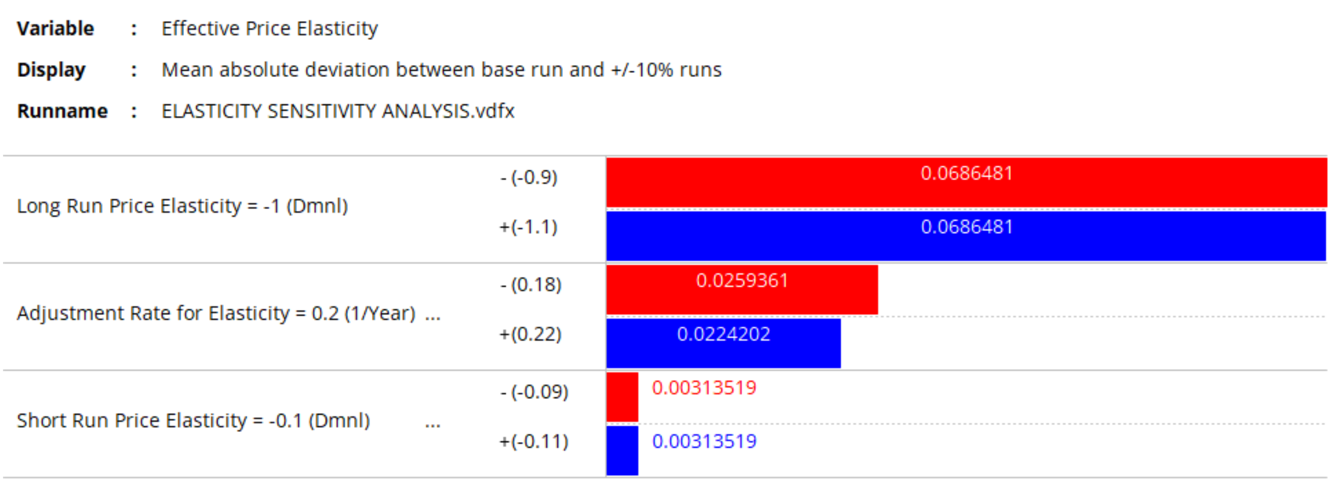


Figure 8. Mean Absolute Deviation of elasticity parameters tornado plot.

Figure 9 illustrates a tornado plot of the final time payoff percentage, which is the deviation at the final time step between the base run and ±10% runs. Equilibrium elasticity is almost entirely determined by the long-run parameter (± 9.95% variation), with negligible sensitivity to short-run conditions.

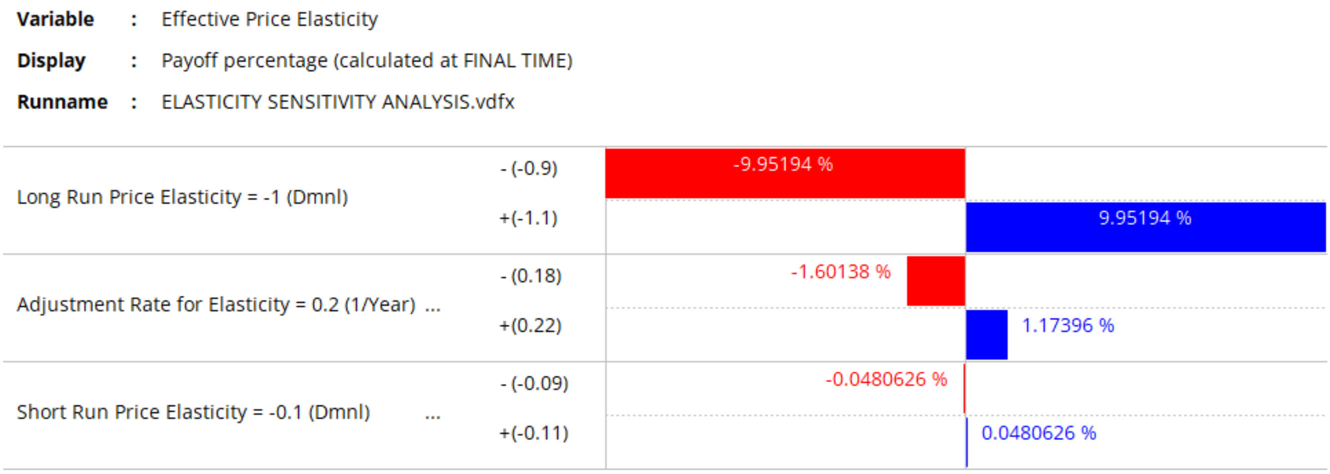


Figure 9. Payoff percentage (Final time) of elasticity parameters tornado plot.

Figure 10 shows the plots of Effective Price Elasticity for the different varied parameters, with the long-run elasticity having the largest impact when varied, followed by the Adjustment rate and finally the short-run elasticity with the lowest impact when varied.

7.3. Empirical Validation Using U.S. Data (2014 - 2024)

The model was tested against real U.S. electricity price data from the EIA Electric Power Annual (2024) (from Tables 2.5 and 2.7 of the Electric Power Annual) [21]. Historical prices (2014 - 2024) (Average Price of Electricity to Ultimate Customers - Table 2.7) were input as an exogenous driver through the lookup variable Yearly Price Data, while the historical demand (Sales of Electricity to Ultimate Customers - Table 2.5) for the same period were used for comparison.

Figure 11 shows the plot of Average Electricity Price from the EIA Power Annual from Table 2.7. this data shows relatively stable electricity prices until 2020 where it rises significantly.

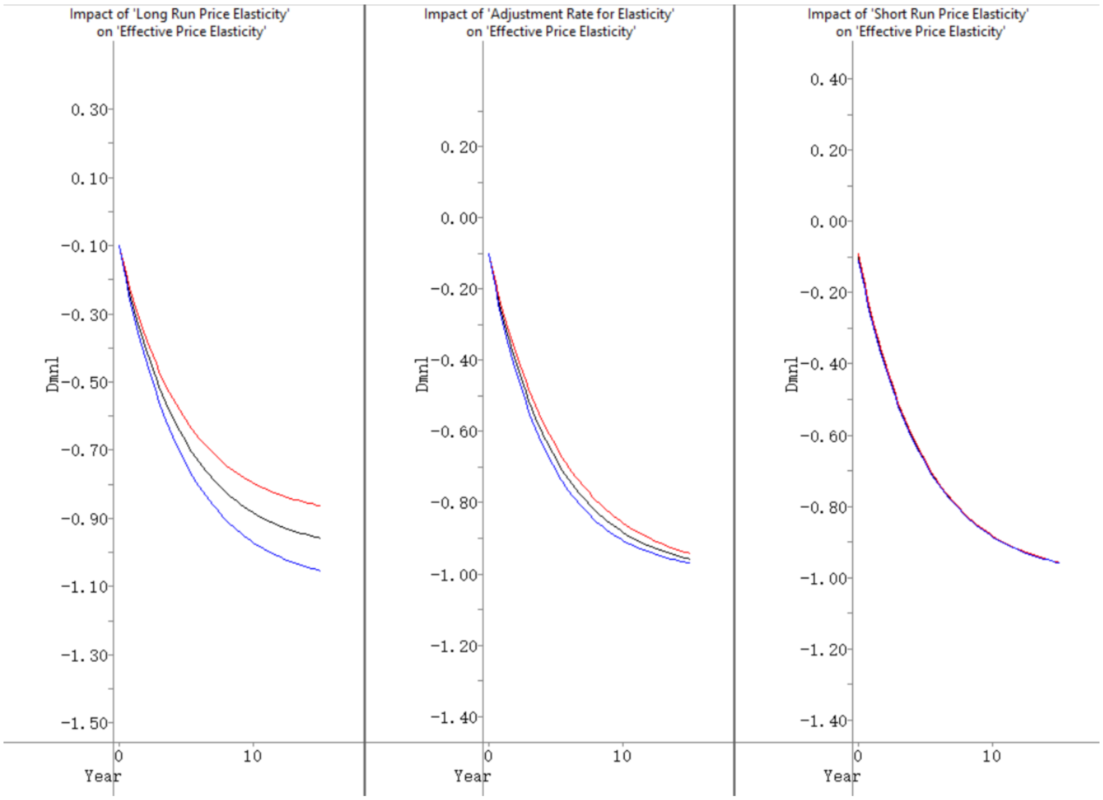


Figure 10. Plots of Effective Price Elasticity of varied ±10% elasticity parameters (Long Run Elasticity, Adjustment Rate and Short Run Elasticity respectively).

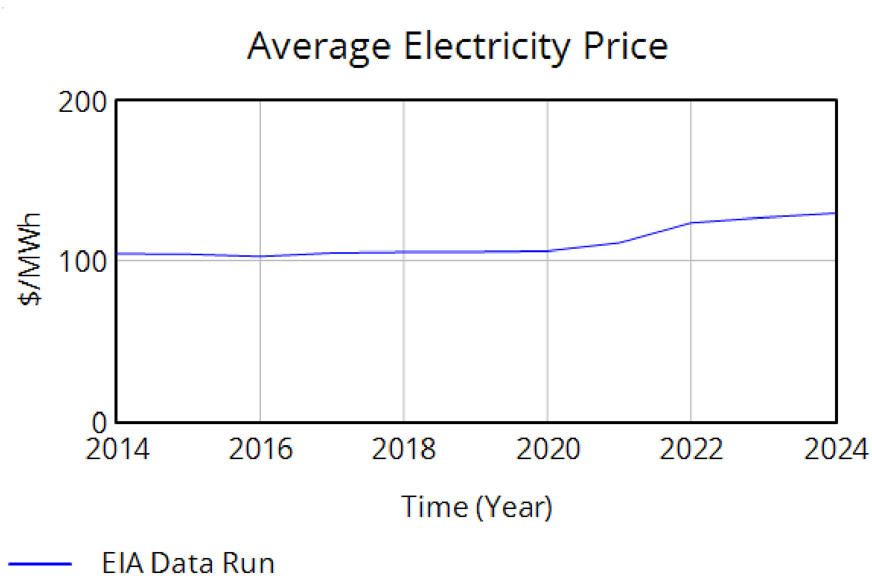


Figure 11. Output graph of price data from EIA Power Annual.

Figure 12 shows the plot of Electricity Consumption (EIA, Sales to Ultimate Customers) which represents the Real-world (U.S.) demand data, which shows a relatively stable demand with a trend upwards after 2020.

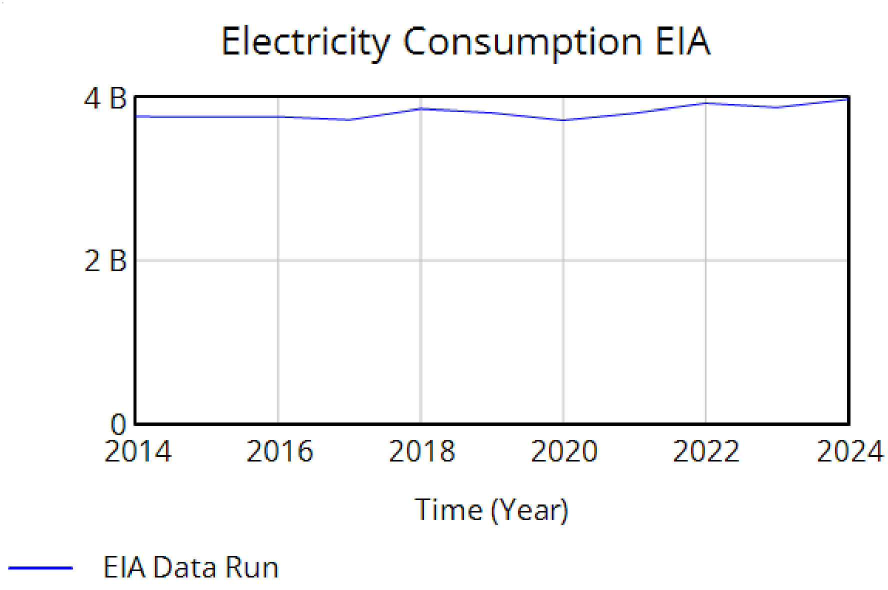


Figure 12. Output graph of consumption/demand data from EIA Power Annual.

Figure 13 shows the plot of the simulated electricity demand during the period 2014 - 2024, deviating by less than 10% for the first 6 years (see Figure 15). The period 2014 to 2020 shows that the demand is relatively stable, which in the model demonstrates the early inelastic behaviour and relatively small price changes. As prices rose sharply after 2021 the model predicted a proportional decline (3.101×10^9 MWh by 2024) whereas the actual Electricity Consumption (EIA) data increased. This divergence can be seen on Figure 14.

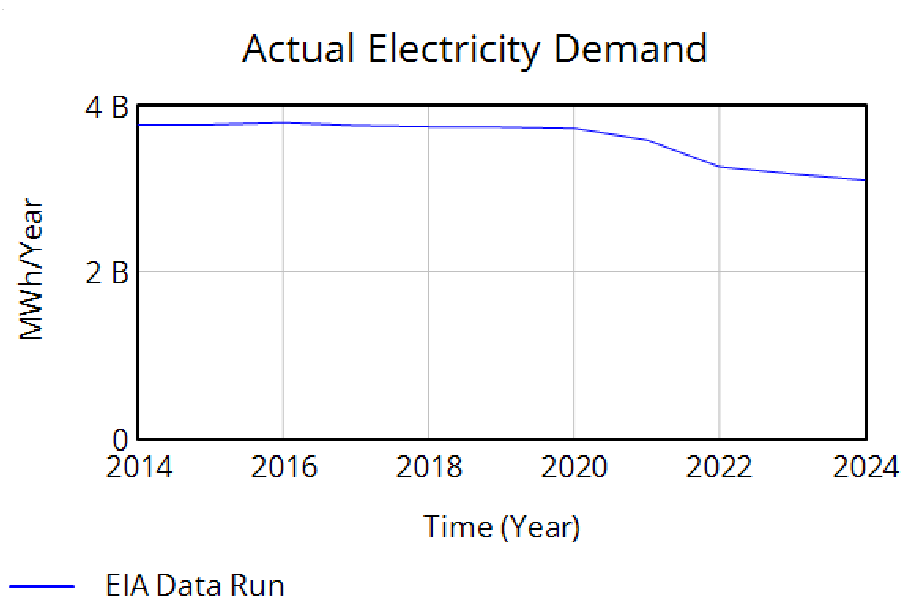


Figure 13. Output graph of the simulated Demand from the model.

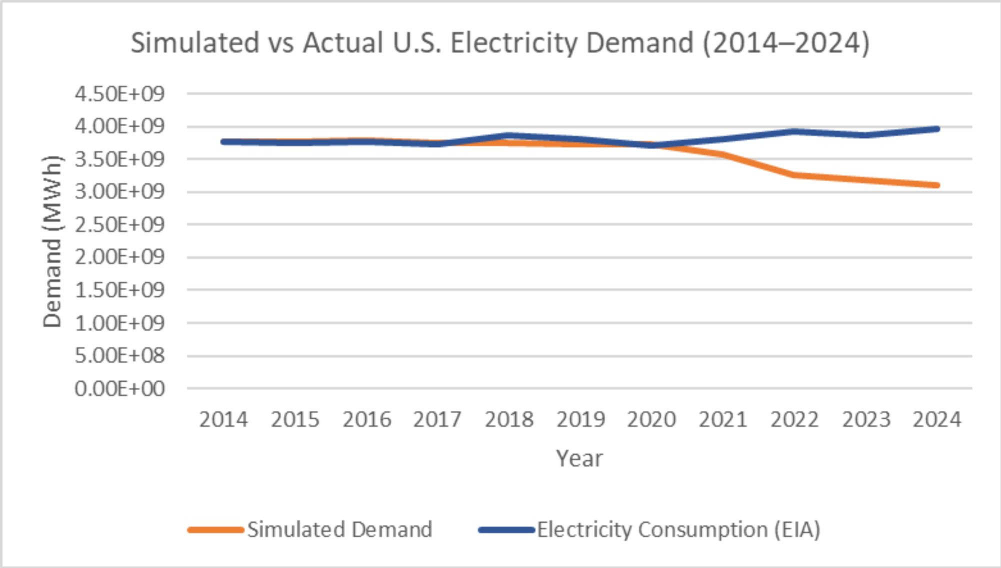


Figure 14. Plot of Simulated vs. Actual Electricity Demand.

The error metrics, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) were calculated using the Simulated and EIA data, the results can be seen in Table 4.

Table 4. Error Metric Table.

Metric	Value	Interpretation
MAE	247991727.30 MWh	Average Absolute Deviation
RMSE	400997847.10 MWh	Larger penalty for latter year deviation
MAPE	6.35%	Prediction accuracy ≈ 93.65%

The model demonstrates a strong short-term fidelity as can be seen from Figure 15 with percentage errors below 10% before 2021 with a MAPE of 6.35% overall. While MAE (~2.5×10^8 MWh) and RMSE (~4.01×10^8 MWh), with RMSE >> MAE this can be due to the increasing gap between the model simulated demand and the actual EIA data during the latter post 2020 years.

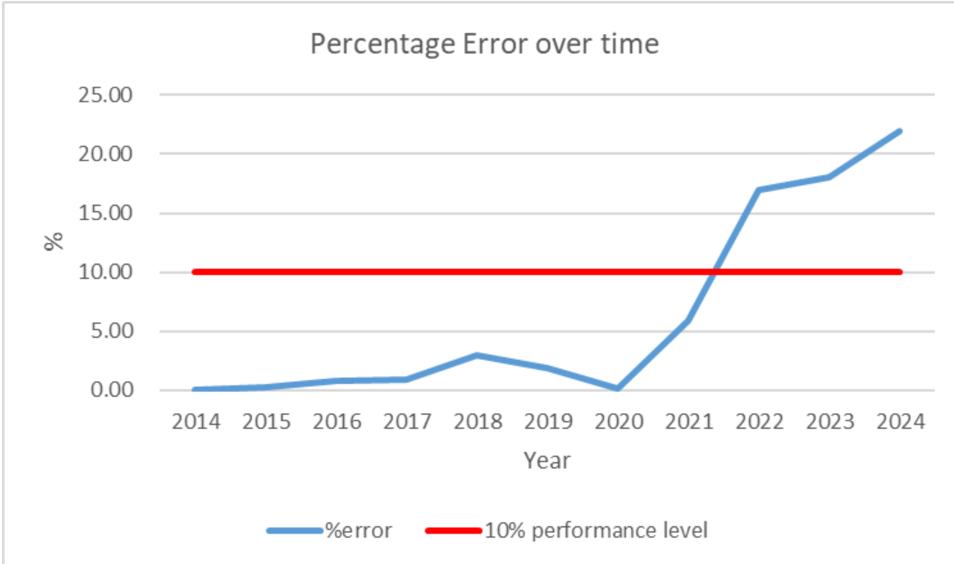


Figure 15. Plot of the year-by-year error percentage.

The divergence between simulated and actual EIA Electricity Consumption data can be explained by exogenous drivers that the current model does not take into account, namely GDP growth, population increase, renewable integration and more. The study isolates the price-demand elasticity loop to investigate its dynamic behaviour independently.

8. Discussion

The simulation results provide clear validation of the model's ability to represent the dynamic relationship between electricity price and demand, particularly the critical distinction between short-run and long-run price elasticities. The consistent behaviour of Effective Price Elasticity gradually converging from its short-run to its long-run value, and the corresponding time-lagged response in Actual Electricity Demand, are entirely consistent with established economic theory and empirical findings, notably those by [7][12]. This provides strong evidence that the model is well-grounded and rigorous in its representation of this fundamental economic dynamic.

Systems Thinking and System Dynamics application as the modelling methodology is justified by its ability to capture complexity, feedback mechanisms, and delays. This aligns with the arguments of [9] and [10], who advocate and demonstrate for systems methodologies in addressing energy demand reduction and sustainability challenges.

While the studies [7], [12], [13] and [15] provided the empirical elasticity estimates, this study extends their findings by integrating those values into a dynamic simulation.

The broader context of Demand Side Management as a strategic tool for managing electricity systems is well-supported by literature (e.g., [2] [3] [22][11]). The model contributes to understanding a fundamental aspect of price-based DSM strategies, particularly the "Price-Demand Loop" which captures the interaction between electricity pricing schemes (e.g., Time-of-Use) and consumption behaviour [4][8].

The primary strength of these results lies in their accurate depiction of Effective Price Elasticity gradually transitioning from the Short Run Price Elasticity to the Long Run Price Elasticity. The exponential decay like curve is the expected behaviour which helps confirm the model's internal consistency and theoretical soundness for the modelling process.

The corresponding lagged response in Actual Electricity Demand to price changes (initial small dip/rise, then a larger, gradual change) is an important insight. This behaviour gives us an insight on how consumers adapt over time, from immediate, limited adjustments to more significant long-term changes. The model helps to confirm the transition of dynamic elasticity into realistic demand outcomes.

The empirical validation using EIA (2014 - 2024) data, demonstrated the model's realism in simulating the demand trajectory that followed the observed electricity consumption (demand) closely over the period 2014 to 2020, after 2020 the there was a significant deviation between the simulated and real values that can be attributed to the model's focus on price elasticity effects alone and without other structural drivers of demand.

From a DSM policy perspective, these simulations reveal these insights:

Short-run responses are limited: confirming that immediate behavioural changes to price fluctuations are small and temporary.

Long-run elasticity dominates consumption behaviour: meaning that DSM effectiveness relies on enabling long-term consumer adaptation such as through efficient technology adoption.

Tariff Elasticity as a Policy Lever: Elasticity itself can be treated as a policy-sensitive variable. The model's effective elasticity transition illustrates that the rate of elasticity adjustment (represented by the adjustment rate parameter) reflects how quickly consumers can respond to policy stimuli. [15] found that informational and awareness-based measures can enhance consumers' responsiveness to price changes. A higher adjustment rate thus corresponds to environments where consumers have access to efficient technologies, financing mechanisms, or strong information campaigns, all of which enable faster adaptation. This suggests that DSM programs should not only adjust prices but also target elasticity acceleration, for example through:

- Subsidies for energy-efficient appliances.
- Public awareness campaigns improving price sensitivity.

By shaping the elasticity trajectory, policymakers can enhance the speed and effectiveness of DSM programs.

These results provide a good starting point for proving the fundamental dynamic of price elasticity in electricity demand using a systems dynamic framework. They visually and quantitatively support the theoretical distinction between short-run and long-run responses.

8.1. Model Limitations

While the model Adequately simulates the dynamics of price elasticity, its focus is solely on the Price-Demand Loop and does not take into account the other DSM feedback structures involving incentives, technological adoption, or renewable integration.

Another limitation is the use of sector - aggregated elasticity values. Although grounded in empirical research, a sector specific modelling scheme with each having their own empirically derived elasticity values can give a more realistic and accurate insight into an Electricity Price-Demand model.

Finally, the current model assumes exogenous price changes. Making use of endogenously determined prices based on factors such as supply-demand equilibrium or dynamic tariffs would be able to enhance realism and policy relevance.

9. Conclusions and Future Work

A system dynamics model for electricity demand and price elasticity is effectively developed in this paper. The dynamic shift from short-term to long-term price responsiveness, is adequately demonstrated and simulated by the model. Through a series of simulation scenarios, the model showed expected and consistent behavioural patterns, which being limited immediate response to prices changes followed by a gradual increase in elasticity, which gives stronger shifts in electricity demand. These results align with the empirical elasticity literature.

This work's primary contribution is its dynamic, quantitative depiction of how electricity demand changes over time in response to price signals due to short-run and long-run elasticities. This highlights that the full advantages of price-based DSM strategies come gradually as consumers make long-term adjustments, these are in line with Demand Side Management principles and rationale. The model serves as a first building block for future, more comprehensive system dynamics simulations of Demand Side Management.

Building upon this validated model for electricity demand and price elasticity several areas for further investigation and model expansion are recommended:

- Integration with Other Loops: The current model focuses on the Price-Demand Loop. Future work should integrate the other important Feedback structures to create a holistic DSM simulation model.
- Sectoral Disaggregation: While the current model uses general elasticity values, a more advanced model could incorporate sector-specific elasticities (residential, commercial, industrial) and their unique constraints and drivers [22].
- Policy Design and Evaluation: Although not fully explored in this standalone paper, the ultimate intention is to use such models to test policy interventions and understand their long-term impacts and potential unforeseen consequences. This approach can also be extended to analyse complex decision-making processes in the energy sector, including green financing [23] and multi-criteria decision analysis for energy systems [24].

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Appendix A: Model Equations and Variable Definitions

A.1 Overview

This appendix presents the full set of stock-flow equations and variable definitions used in the system dynamics simulation of electricity price-demand elasticity. All equations were implemented in Vensim PLE.

Variables are categorised as Stocks, Auxiliaries, or Constants with corresponding units for dimensional consistency.

A.2 Model Variables and Explanations

Table 5. Variables used in simulation model.

Variable Name	Type	Units	Explanation
Baseline Electricity Demand	Constant	MWh/Year	The projected electricity demand without any changes in price or DSM interventions; acts as the reference point for actual demand.
Average Electricity Price	Constant	$/MWh	The current market price of electricity, which can vary in different test scenarios and influence demand.
Reference Electricity Price	Constant	$/MWh	A fixed value representing the typical or starting electricity price, used as a baseline to assess price deviations.
Short Run Price Elasticity	Constant	Dmnl	The initial responsiveness of electricity demand to price changes over a short period (usually <1 year); typically, low (inelastic).
Long Run Price Elasticity	Constant	Dmnl	The eventual responsiveness of demand to price changes after behavioural and technological adaptation; significantly more elastic.
Adjustment Rate for Elasticity	Constant	1/Year	The rate at which consumers shift from short-run to long-run responsiveness; controls the speed of elasticity adjustment over time.
Effective Price Elasticity	Level (Stock)	Dmnl	A dynamic variable that transitions from short-run to long-run elasticity over time, simulating gradual consumer adaptation.
Price Effect on Demand	Auxiliary	Dmnl	A multiplier that adjusts baseline demand based on price changes and elasticity, calculated using an exponential-logarithmic function.
DSM Load Reduction Factor	Constant	Dmnl	Represents the fractional reduction in demand due to DSM programs (e.g., 0.1 = 10% load reduction); independent of price effects. This factor was included in the model for potential effects of other DSM activities.
Actual Electricity Demand	Auxiliary	MWh/Year	The final demand output after accounting for both price-induced effects and DSM interventions. This is the key outcome variable.

A.3 Core Model Equations

1. Effective Price Elasticity (stock)

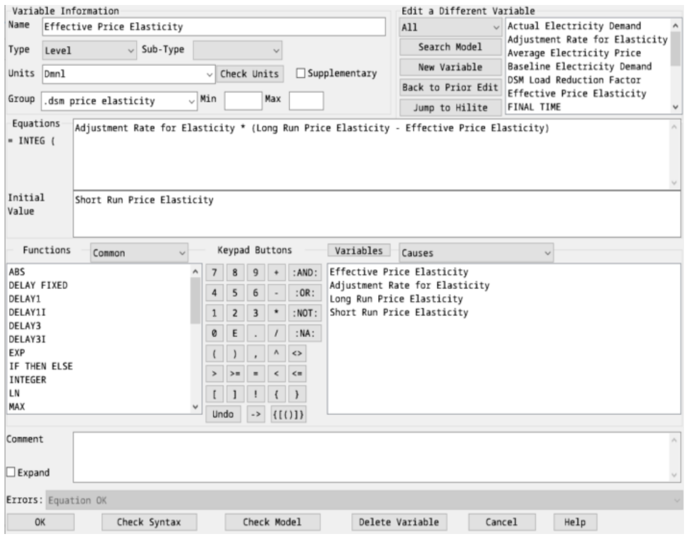

Figure 16. Effective Price Elasticity equation implementation via the Vensim equation editor tool

2. Price Effect on Demand (Auxiliary)

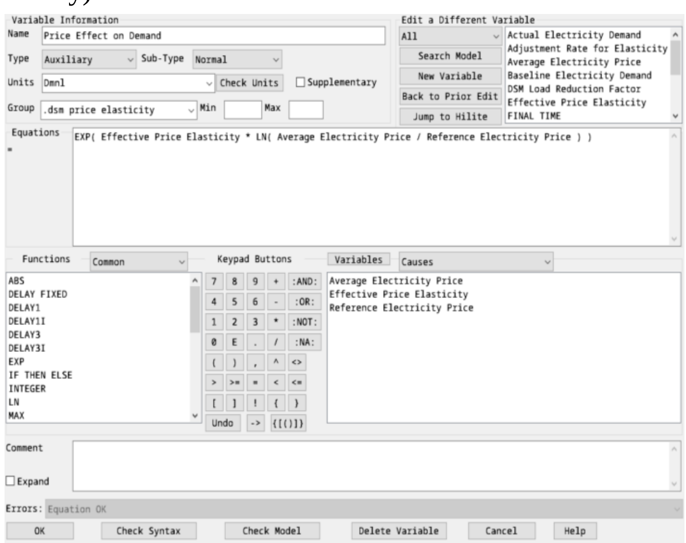

Figure 17. Price Effect on Demand equation implementation via the Vensim equation editor tool

3. Actual Electricity Demand (Auxiliary)

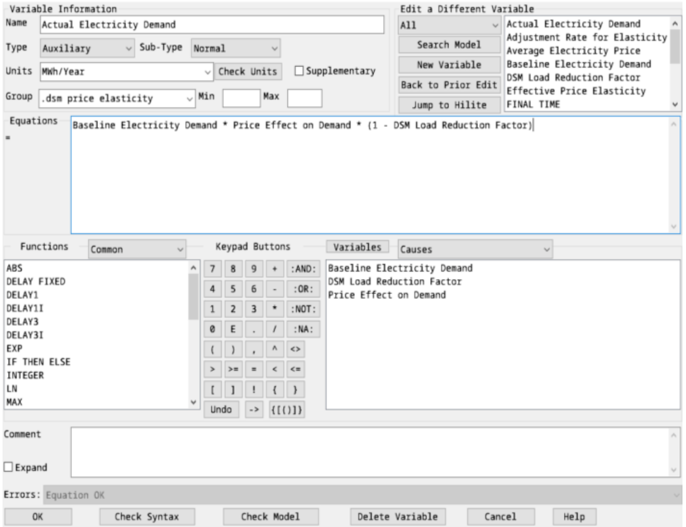

Figure 18. Actual Electricity Demand equation implementation via the Vensim equation editor tool

A.4 Dimensional Consistency

All equations were checked in Vensim for dimensional consistency.

- Dimensional (Dmnl) quantities include elasticity and price ratios.
- Demand related quantities are expressed in MWh/year.
- Prices are expressed in $/MWh.
- The Adjustment Rate is expressed in 1/year (change in elasticity per year).

A.5 Time bounds and Integration technique

Table 6. Model Settings

Parameter	Description	Value
Simulation Time	Time horizon	15 years
Time Step (DT)	Integration interval	1
Integration Method	Numerical method used	Euler
Initial Time	Start year	0
Final Time	End year	15

Appendix B: Empirical Validation Case

B.1 Overview

This appendix documents the setup and data used for the empirical validation experiment described in Section 7.

B.2 Data Source

The validation uses EIA historical data spanning 2014 – 2024 (Electric Power Annual 2024) [21].

Table 7. Average Price of Electricity to Ultimate Customers: All Sectors. (Table 2.7.)

Year	Average Price (¢/kWh)	Average Price ($/MWh)
2014	10.44	104.4
2015	10.41	104.1
2016	10.27	102.7
2017	10.48	104.8
2018	10.53	105.3
2019	10.54	105.4
2020	10.59	105.9
2021	11.10	111.0
2022	12.36	123.6
2023	12.68	126.8
2024	12.94	129.4

Table 8. Sales of Electricity to Ultimate Customers: All Sectors. (Table 2.5.)

Year	Electricity Sales (Thousand MWh)	Converted Demand (MWh/Year)
2014	3,764,700	3.7647×10^9
2015	3,758,992	3.75899×10^9
2016	3,762,462	3.76246×10^9
2017	3,723,356	3.72336×10^9
2018	3,859,185	3.85919×10^9
2019	3,811,150	3.81115×10^9
2020	3,717,674	3.71767×10^9
2021	3,805,874	3.80587×10^9
2022	3,927,169	3.92717×10^9
2023	3,874,253	3.87425×10^9
2024	3,975,382	3.97538×10^9

B.3 Model Configuration

The modified model incorporating the historical EIA data is shown in Figure 19, with Yearly Price Data and Real-World Data representing the price data and consumption (demand) data over the period 2014 to 2024, respectively. The Lookup implementation in vensim's equation editor can be seen in Figure 20, with the model parameter values given in table 9.

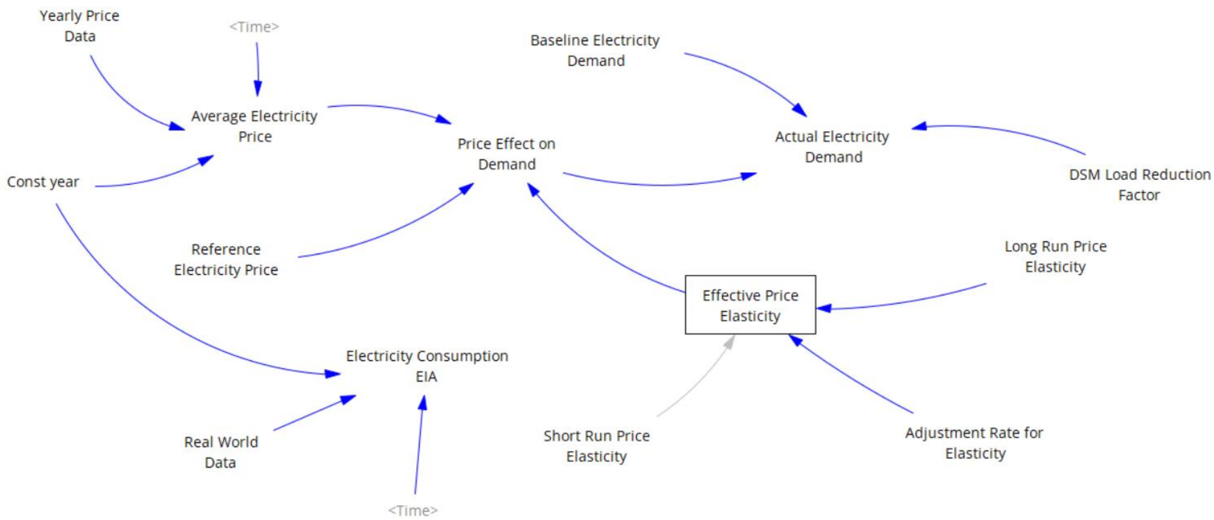

Figure 19. Price-Demand System Dynamics Model with historical price and demand data integrated via a lookup table.

Table 9. Baseline and Reference Values

Parameter	Value	Units	Description
Baseline Electricity Demand	3.7647×10^9	MWh/Year	Base demand at 2014 price
Reference Electricity Price	104.4	\$/MWh	Corresponding 2014 average price
Short Run Price Elasticity	-0.1	Dmnl	Initial elasticity value
Long Run Price Elasticity	-1.0	Dmnl	Equilibrium elasticity value
Adjustment Rate for Elasticity	0.2	1/Year	Rate of elasticity change
DSM Load Reduction Factor	0	Dmnl	Disabled for validation test

Figure 20. Yearly Price Data Lookup variable equation implementation via the Vensim equation editor tool, using data from table 7.

B.4 Time bounds and Integration technique

Table 10. Model Settings for validation case.

Parameter	Description	Value
Simulation Time	2014 - 2024	11 years
Time Step (DT)	Integration interval	1
Integration Method	Numerical method used	Euler
Initial Time	Start of dataset	2014
Final Time	End of dataset	2024