Project Report

On

BRIGHTBILL: MATHEMATICAL MODELLING AND WEB IMPLEMENTATION

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by

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CERTIFICATE

This is to certify that the dissertation entitled, **BRIGHTBILL: MATHEMATICAL MODELLING AND WEB IMPLEMENTATION** is a bonafide record of the work done by Ms. **RUWINA GEORGE** under my guidance as partial fulfillment of the award of the degree of **Bachelor of Science in Mathematics** at St. Teresa's College (Autonomous), Ernakulam affiliated to Mahatma Gandhi University, Kottayam. No part of this work has been submitted for any other degree elsewhere.

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DECLARATION

I hereby declare that the work presented in this project is based on the original work done by me under the guidance of Ms. Sreelakshmi K Anil, Assistant Professor, Department of Mathematics, St. Teresa's College (Autonomous), Ernakulam and has not been included in any other project submitted previously for the award of any degree.

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Chapter 1

Introduction

1.1 Background

Electricity is a fundamental resource of modern society, powering homes, industries, communication, and technology. Rapid urbanization and the widespread use of electrical appliances have significantly increased household electricity consumption.Along with this rise, electricity bills have become more complex, since billing is no longer a simple multiplication of units consumed by a fixed rate.

In Kerala, electricity billing is governed by the Kerala State Electricity Board (KSEB), which employs a slab-based (piecewise) tariff system. In this system, the per-unit cost increases with higher consumption. While this progressive structure ensures equity, it makes manual bill calculation difficult for ordinary consumers.

The project **BrightBill** addresses this challenge. It is a mathematical Django-based web application that provides electricity consumption analysis and bill prediction for individual appliances. Instead of beginning with the total household units, BrightBill starts from the appliance itself, using its wattage, usage hours, and mathematical formulas to compute expected consumption. These values are then processed through piecewise tariff functions and billing rules to estimate the corresponding electricity bill. By combining rigorous mathematical models with Python/Django computation, BrightBill offers households an interactive, transparent, and educational way to understand how each appliance contributes to electricity usage and billing.

1.2 Objectives

The objectives of BrightBill are:

i. To mathematically model electricity consumption and billing using appliance-based formulas and piecewise tariff functions.

ii. To implement these mathematical rules in Python/Django code, ensuring correctness, algorithmic transparency, and computational efficiency

iii. To develop a user-friendly web system where users can select appliances, specify usage duration and quantity, and receive electricity bill predictions. The system also provides detailed breakdowns and visualizations in real time.

1.3 Background Context

Electricity consumption in households has been rising due to lifestyle changes and the increasing number of electrical appliances. A modern home typically contains multiple devices—from basic lighting and fans to refrigerators, washing machines, and air conditioners. While these improve living standards, they also lead to higher electricity bills.

In Kerala, the slab-based tariff structure introduces complexity. For instance, the first 50 units may be charged at Rs. 3.25, the next 50 at Rs. 4.05, and higher slabs at progressively higher rates. Alongside slab charges, consumers must also account for fixed monthly charges and government duties, making manual calculations time-consuming and prone to error.

Most households face common challenges:

- Difficulty in estimating consumption for multiple appliances.
- Lack of tools that directly connect appliance usage to billing.
- Limited awareness of which appliances contribute most to costs.
- Dependence on electricity board bills without the ability to cross-check.

From an academic perspective, this problem presents an opportunity. Mathematical concepts like formulas, summations, and piecewise functions exist in textbooks but are rarely translated directly into real-world applications. BrightBill

bridges this gap by combining theory with practice, serving both practical household needs and academic demonstration.

1.4 Related Applications / Systems

Several tools and applications exist for electricity bill estimation, but none offer the complete range of features BrightBill provides. A review of existing systems highlights their strengths and limitations:

Appliance Electricity Cost Calculators (India)

- **Strengths:** Allow appliance-level inputs (wattage, hours per day, number of appliances) and compute costs.
- **Limitations:** Often assume a single fixed unit rate; slab-based or telescopic billing is not implemented properly. Fixed charges and government duty are usually excluded. Visualizations are rare.

AllumiaX Electricity Appliance Bill Calculator

- **Strengths:** User-friendly interface; allows wattage, quantity, and usage duration input; aggregates cost for multiple appliances.
- **Limitations:** Simplifies billing using user-defined unit rates; official utility slabs are seldom incorporated; transparency and duty/fixed charges often missing.

Official Tariff Calculators (e.g., KSEB consumer portal)

- **Strengths:** Use official slab rates; include fixed charges; reliable for total consumption.
- **Limitations:** Require consumers to know their total meter reading; do not support appliance-wise estimation; no slab-wise breakdown or visual aids.

Generic Mobile Apps (Bill Estimators, Energy Monitors)

- **Strengths:** Some allow appliance wattage inputs and usage tracking; provide daily/monthly estimates.

- **Limitations:** Often ignore slab-based billing; rarely include fixed charges or duties; transparency in calculations is limited.

Conclusion from Comparison

Existing tools either provide appliance-wise estimates without proper slab billing or slab billing without appliance-level detail. Very few show detailed breakdowns or visual charts. **BrightBill** is unique because it combines appliance-level customization, exact telescopic slab application, inclusion of fixed charges and duty, and clear mathematical transparency with visualization, filling the gap between consumer needs and academic rigor.

Chapter 2

Mathematical Foundations of BrightBill

2.1 Introduction

Mathematics provides the foundation of the **BrightBill** system. Every calculation of electricity consumption and billing is expressed mathematically and subsequently implemented in the Django framework using Python. Prior to discussing coding and implementation, this chapter outlines the **mathematical foundations** of the project.

Electricity consumption is a physical quantity that can be modeled mathematically. It depends on the power rating of an appliance (in watts), the duration of its use (in hours), and the number of identical appliances in operation. The resulting consumption value, measured in *kilowatt-hours (kWh)* and commonly referred to as *units*, is then used as the basis for electricity bill calculation through tariff functions.

In Kerala, as in many other regions, electricity bills are not calculated using a single constant rate. Instead, utilities employ a **slab-based (piecewise) structure**, where different consumption ranges are charged at different rates. This naturally requires the use of **piecewise functions** in mathematics.

In addition, fixed charges and government duty are added, meaning the total bill is not only a function of consumption but also includes constant and percentage-based components.

This chapter introduces:

- The basic formula for electricity consumption,
- The piecewise function for slab-based billing,
- The addition of fixed charge and duty, and
- The mathematical basis for graphical representation, which connects theory to the visual outputs in BrightBill.

2.2 Basic Electricity Consumption Formula

The foundation of BrightBill lies in the mathematical formula for electricity consumption. This equation translates an appliance's power rating into total energy units consumed, accounting for both time of operation and the number of appliances involved. It forms the entry point from which further billing and tariff models are derived.

Definition

If an appliance has a power rating of P watts, operates for T hours, and there are N identical appliances of the same type, then the total energy consumption U is given by:

$$U = \frac{P \times T \times N}{1000}$$

Explanation of Variables

- P: Power rating of the appliance, expressed in watts (W).
- T: Duration of operation, expressed in hours (h).
- N: Number of identical appliances in use.
- U: Total energy consumed, measured in kilowatt-hours (kWh), also referred to as *units*.

The factor of 1000 arises from the conversion of watt-hours to kilowatt-hours, since:

$$1 \text{ kW} = 1000 \text{ W}, \quad 1 \text{ kWh} = 1000 \text{ Wh}.$$

Thus, multiplying P (watts) by T (hours) gives energy in watt-hours, which is then converted into kilowatt-hours by dividing by 1000.

Illustrative Examples

i. Consider a single bulb of 100 W used for 36 hours:

$$U = \frac{100 \times 36 \times 1}{1000} = 3.6 \text{ kWh}.$$

Hence, the bulb consumes 3.6 units of electricity.

ii. If instead there are five such bulbs ($N = 5$), each used for the same duration:

$$U = \frac{100 \times 36 \times 5}{1000} = 18 \text{ kWh}.$$

In this case, the combined usage leads to 18 units of electricity.

Significance

This seemingly simple formula is central to BrightBill. By beginning at the appliance level rather than the total household meter reading, it allows users to estimate consumption transparently and link usage patterns directly to electricity costs. The formula also provides the mathematical foundation upon which more advanced components—such as piecewise tariff functions, fixed charges, and visual breakdowns—are constructed.

2.3 Piecewise Functions in Billing

Once consumption (in kWh) is calculated, the next step is to convert it into billing charges. In Kerala, the tariff system is *telescopic*, meaning that different ranges of consumption are charged at progressively higher rates, with each unit billed according to the slab in which it falls.

Concept of Slabs

- The first block of units is charged at the lowest rate,
- The second block is charged at a higher rate,
- Higher blocks are charged at progressively increasing rates.

This naturally requires the use of **piecewise functions**, since the cost per unit is not constant across the entire domain.

Formal Definition

Let U denote total units consumed. Suppose the slab boundaries are given by

$$0 = U_0 < U_1 < U_2 < \cdots < U_s,$$

and the corresponding rates are $r_1, r_2, \ldots, r_s$.

Then, the energy charge function is expressed compactly as:

$$E(U) = \sum_{j=1}^{s} r_j \cdot \max\Big(0,\ \min(U, U_j) - U_{j-1}\Big).$$

This formulation ensures that for each slab j, only the units lying within that slab contribute to the charge.

Continuity

A desirable property of this piecewise function is **continuity**. At the boundary of each slab, the billing amount transitions smoothly:

$$\lim_{U \to U_j^-} E(U) = \lim_{U \to U_j^+} E(U).$$

Thus, there are no sudden jumps in the cost, even though the rate changes between slabs.

Illustrative Example

Suppose the tariff is defined as follows:

- First 50 units at Rs.3.25 per unit,
- Next 50 units at Rs.4.05 per unit,
- Next 50 units at Rs.5.10 per unit.

For a consumption of $U = 120$ units:

$$E(120) = (50 \times 3.25) + (50 \times 4.05) + (20 \times 5.10).$$

Simplifying,

$$E(120) = 162.5 + 202.5 + 102 = Rs.467.$$

Hence, the energy charge for 120 units is Rs.467.

2.4 Fixed Charge and Duty

In addition to energy charges, electricity bills in Kerala include **fixed charges** and a **government duty**. These components are included to account for infrastructure costs and regulatory surcharges, extending billing considerations beyond energy usage.

Fixed Charge

The fixed charge is a constant amount levied depending on the consumption range. It represents infrastructure and service costs that remain independent of actual energy usage. Mathematically, this is modeled as a **piecewise constant function**:

$$F(U) = \begin{cases} f_1, & 0 \leq U \leq U_1, \\ f_2, & U_1 < U \leq U_2, \\ \vdots & \\ f_s, & U_{s-1} < U \leq U_s. \end{cases}$$

Here, f_j denotes the fixed charge corresponding to the j^{th} slab.

Government Duty

Government duty is calculated as a percentage of the energy charge. If α is the duty rate (typically between 5% and 10%), then:

$$D(U) = \alpha \cdot E(U).$$

This ensures that as consumption increases, the duty grows proportionally, adding a variable component linked to usage.

Total Bill Function

The complete billing function is obtained by combining energy charges, fixed charges, and duty:

$$B(U) = E(U) + F(U) + D(U).$$

More generally, substituting the summation form of $E(U)$, we obtain:

$$B(U) = \sum_{j=1}^{s} r_j \cdot \max\Big(0,\ \min(U, U_j) - U_{j-1}\Big)\ +\ F(U)\ +\ \alpha \cdot E(U).$$

This compact expression captures the telescopic energy charges, the slab-based fixed charges, and the proportional duty in a single unified formula.

Worked Example

Consider a household consuming $U = 120$ units, with the following details:

- Energy charge: $E(120) = Rs.467$,
- Fixed charge: $F(120) = Rs.85$,
- Duty rate: $\alpha = 0.10$.

Then the duty is:

$$D(120) = 0.10 \times 467 = Rs.46.7.$$

Hence, the total bill is:

$$B(120) = 467 + 85 + 46.7 = Rs.598.$$

Significance

This structure highlights how billing is not a simple multiplication of units by a flat rate. The interplay of telescopic energy charges, stepwise fixed charges, and proportional government duty demonstrates the complexity of domestic billing. By formalizing these rules mathematically, BrightBill ensures that predictions are faithful to real-world calculations while remaining transparent and easy to understand.

2.5 Graphical Representation

Mathematical functions describe billing rules with precision, but formulas alone may not be intuitive for all users. Graphical representations make the relationships easier to interpret, providing both consumers and students with a clear view of how charges evolve as consumption increases.

Energy Charge and Total Bill Graphs

Consider the following tariff structure:

- First 50 units at Rs.3.25 per unit,
- Next 50 units at Rs.4.05 per unit,
- Next 50 units at Rs.5.10 per unit.

A fixed charge of Rs.85 and a government duty of 10% are also included. The graphs of the energy charge $E(U)$ and the total bill $B(U)$ show that:

- $E(U)$ is continuous and piecewise linear, with slope changes at slab boundaries.
- $B(U)$ is a vertically shifted and proportionally scaled version of $E(U)$, reflecting the effect of fixed charge and duty.

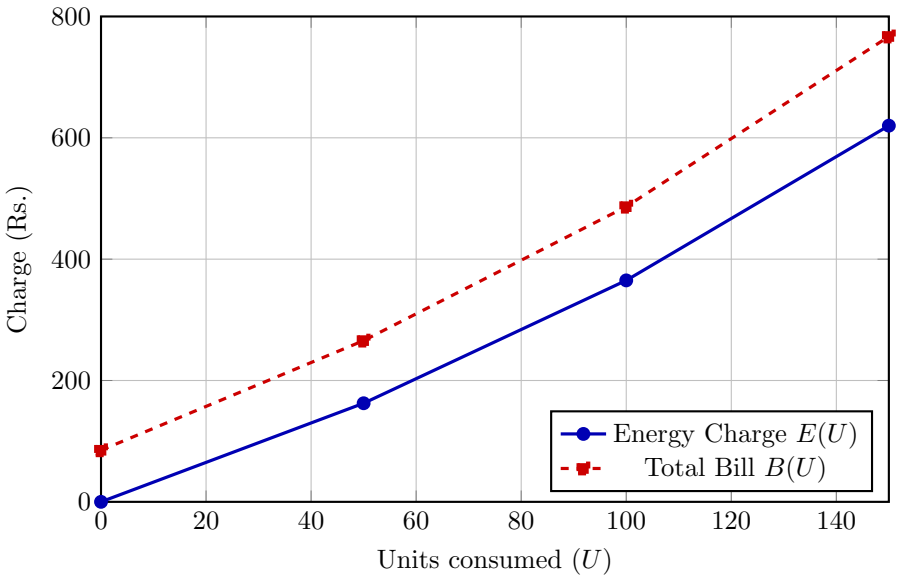


Figure 2.1: Energy charge $E(U)$ and total bill $B(U)$ for a sample tariff.

Stacked Bar Chart Representation

At $U = 120$ units, the bill is composed of slab contributions, a fixed charge, and duty:

- Slab 1: Rs.162.5,
- Slab 2: Rs.202.5,

- Slab 3: Rs.102,
- Fixed charge: Rs.85,
- Duty: Rs.46.7.

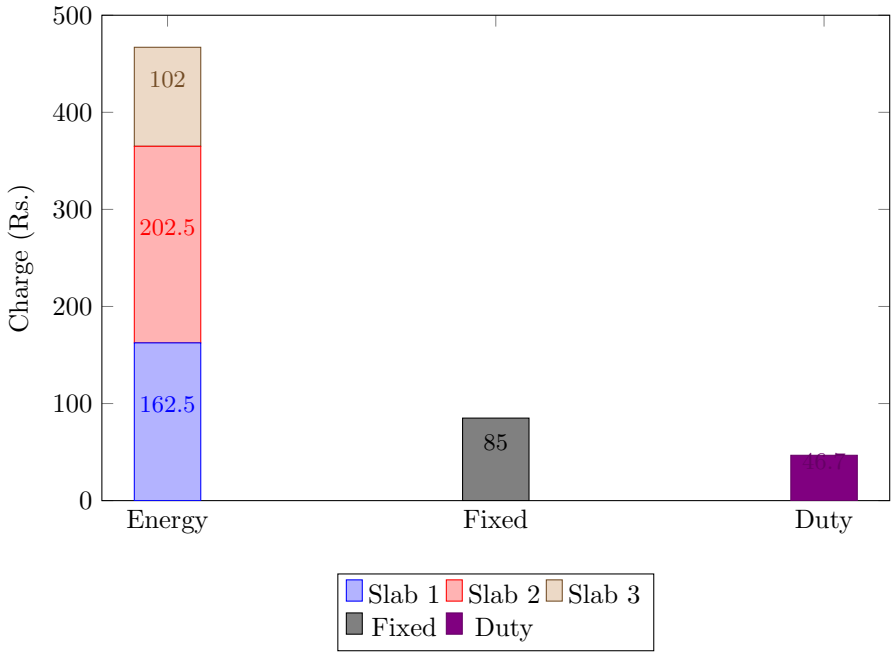


Figure 2.2: Stacked bar chart representation of total bill for $U = 120$ units.

Side-by-Side Comparison

A direct comparison highlights the difference between consumption-only cost and the actual bill with all charges included. For $U = 120$ units:

$$E(120) = Rs.467, \qquad B(120) = Rs.598.$$

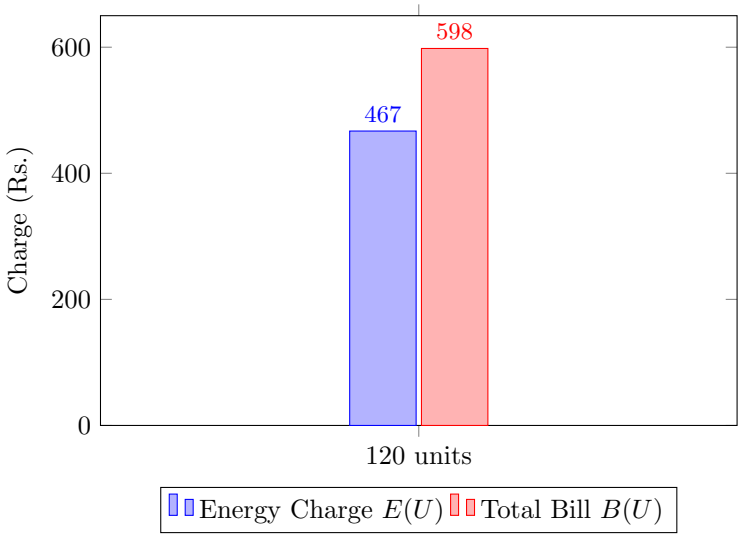


Figure 2.3: Comparison of energy charge vs. total bill at $U = 120$ units.

Conclusion

The graphical methods complement the mathematical formulas by making patterns visible:

- The **line graphs** illustrate the telescopic nature of slab billing and the upward shift due to fixed charges and duty.
- The **stacked bar chart** decomposes the bill into its components, showing exactly how each slab and surcharge contributes.
- The **side-by-side comparison** emphasizes the difference between consumption cost and the payable bill.

For consumers, these visualizations provide transparency and a practical understanding of how their bill is formed. For students and researchers, they offer a geometric representation of piecewise and additive functions. BrightBill uses these visual outputs, generated through `Matplotlib`, to bridge theoretical models with real-world electricity billing.

Chapter 3

Mathematical Coding in Python/Django (Formal Treatment)

This chapter presents the translation of the mathematical models developed in Chapter 2 into algorithmic and computational form. The focus is on analyzing how these mathematical functions are implemented in code, how correctness is ensured, and how practical issues such as computational complexity, numerical stability, and validation are addressed.

3.1 Algorithmic Translation — Pseudocode and Correctness

Definition of an Algorithm

An *algorithm* is a finite, deterministic sequence of operations that maps inputs to outputs. It must satisfy the following essential properties:

- **Definiteness:** every step is explicitly and unambiguously specified.
- **Finiteness:** the process terminates after a finite number of steps.
- **Correctness:** for valid inputs, the output coincides with the value prescribed by the underlying mathematical function.

Translation of Mathematical Objects

The mathematical models defined in Chapter 2 (consumption, telescopic slab-based charges, fixed charges, and duties) are now expressed algorithmically:

i. The total units consumed U are computed directly using the formula:

$$U = \frac{P \times T \times N}{1000}.$$

ii. The slab-based energy charge $E(U)$ is obtained by iterating over all slabs and accumulating contributions.

iii. The fixed charge $F(U)$ is selected by conditional statements corresponding to slab ranges.

iv. The government duty $D(U)$ is computed as a constant proportion of $E(U)$.

Mathematical Meaning of Constructs

Algorithmic constructs map directly to mathematical objects:

- A `for`-loop corresponds to a finite summation:

$$\texttt{for } j = 1..s \quad \Longleftrightarrow \quad \sum_{j=1}^{s}.$$

- An `if/else` statement corresponds to a piecewise-defined function:

$$f(x) = \begin{cases} a & x \in I_1, \\ b & x \in I_2. \end{cases}$$

- The functions `min` and `max` enforce natural bounds:

$$\min(x, y) = \begin{cases} x & x \leq y, \\ y & x > y, \end{cases} \qquad \max(0, x) = \begin{cases} 0 & x < 0, \\ x & x \geq 0. \end{cases}$$

Correctness Proof

The central task is to establish that the loop-based computation of $E(U)$ coincides with its mathematical telescopic definition.

For a given slab j with boundaries $[U_{j-1}, U_j]$ and rate r_j, the algorithm computes:

$$\text{contribution}_j = r_j \cdot \max\Big(0,\ \min(U, U_j) - U_{j-1}\Big).$$

Case 1: If $U \leq U_{j-1}$, then $\min(U, U_j) - U_{j-1} \leq 0$, so the term evaluates to 0. This correctly reflects that no units from slab j are consumed.

Case 2: If $U_{j-1} < U \leq U_j$, then $\min(U, U_j) = U$, and the contribution is

$$r_j \cdot (U - U_{j-1}),$$

which exactly matches the charge for the partially filled slab.

Case 3: If $U > U_j$, then $\min(U, U_j) = U_j$, and the contribution becomes

$$r_j \cdot (U_j - U_{j-1}),$$

corresponding to the full slab contribution.

Summing over all slabs:

$$E(U) = \sum_{j=1}^{s} r_j \cdot \max\Big(0,\ \min(U, U_j) - U_{j-1}\Big).$$

By induction on the number of slabs, each loop iteration corresponds exactly to the mathematical contribution of that slab. Hence, the algorithmic and mathematical definitions are identical, and correctness is established.

Significance

This proof ensures that the algorithm is not merely an approximation but an exact computational counterpart of the mathematical model. This alignment guarantees that BrightBill's implementation maintains both accuracy and transparency.

3.2 Computational Complexity and Scalability

Definition of Order

In algorithm analysis, the *order of growth* of a function describes how its running time or resource usage increases as the size of the input grows. Formally, if $T(n)$

represents the number of basic operations required by an algorithm for input of size n, we say that

$$T(n) \in O(f(n))$$

if there exist constants $C > 0$ and $n_0 \geq 0$ such that

$$T(n) \leq Cf(n), \quad \forall n > n_0.$$

This definition comes from asymptotic analysis, a branch of discrete mathematics and theoretical computer science. The function $f(n)$ describes the upper bound on the rate of growth of $T(n)$, while the constant C and threshold n_0 ensure that small variations are absorbed into the bound.

Application to BrightBill

The algorithm of BrightBill consists of three main stages:

i. Calculation of total units U from appliance power, duration, and count.

ii. Calculation of energy charge $E(U)$ by iterating over all tariff slabs.

iii. Calculation of fixed charge $F(U)$ and duty $D(U)$, both of which require simple lookups or multiplications.

Stage 1: Units The calculation of U is one multiplication and one division. This requires a constant number of steps, hence

$$T_1 \in O(1).$$

Stage 2: Slabs The energy charge is determined by iterating over each slab. Let s denote the number of slabs. The loop requires one comparison, one minimum operation, and one multiplication per slab. Thus the number of operations is directly proportional to s:

$$T_2 \in O(s).$$

Stage 3: Fixed Charge and Duty The fixed charge is selected by testing conditions on U. Because the number of intervals is the same as the number of slabs, this

also has complexity proportional to s, i.e.

$$T_3 \in O(s).$$

The duty is computed as a fraction of the energy charge in a single step:

$$T_4 \in O(1).$$

Overall Complexity

The total time complexity is

$$T(s) = T_1 + T_2 + T_3 + T_4.$$

Substituting the orders of each component:

$$T(s) \in O(1) + O(s) + O(s) + O(1) = O(s).$$

Thus, the runtime of BrightBill is proportional to the number of slabs.

Interpretation of s

The parameter s represents the number of tariff slabs defined by the Kerala State Electricity Board. Importantly, s is a fixed constant of the billing system and does not grow with user input. In practice, $s \leq 10$. Therefore, although the theoretical complexity is $O(s)$, in practical terms this is equivalent to $O(1)$, or constant time.

Extension to Multiple Appliance Types

In BrightBill's current implementation, only one type of appliance is considered at a time, with the user specifying the number of identical units. However, it is useful to analyse scalability if multiple appliance types were allowed. Let m denote the number of distinct appliance types. For each type i, consumption would be calculated as

$$U_i = \frac{P_i \cdot T_i \cdot N_i}{1000},$$

and the total consumption would be

$$U_{\text{total}} = \sum_{i=1}^{m} U_i.$$

This requires m computations of the basic unit formula. Therefore the complexity in this extended model would be

$$T(s, m) \in O(s) + O(m).$$

Scalability

Scalability describes how the algorithm behaves as the problem size increases. For BrightBill:

- With one appliance type and fixed s, the complexity is constant time $O(1)$.
- With m appliance types, the complexity grows linearly in m, i.e. $O(m)$.
- Because s is fixed by policy and small, scalability depends only on m, which is bounded by the number of appliances a household chooses to include.

Conclusion

The order of BrightBill's algorithm is $O(s)$ in theory, where s is the number of slabs. In practice s is a fixed constant, so the complexity is constant time $O(1)$. If extended to multiple appliance types, the complexity becomes $O(m)$, linear in the number of appliance types. Therefore BrightBill is both efficient and scalable for its current scope and potential extensions.

3.3 Numerical Stability, Precision and Rounding

This section analyzes how the exact mathematical formulas of Chapter 2 are affected by finite-precision arithmetic when implemented in Python/Django. It introduces the standard floating-point error model, derives forward error bounds for the bill calculation algorithm, and shows that, for practical household values, the numerical error is many orders of magnitude smaller than the smallest currency unit (Rs.0.01). It then discusses rounding modes and provides practical recommendations, including the use of `decimal.Decimal`, Kahan summation, and fixed-point arithmetic.

Floating-point representation and unit roundoff

Computers represent real numbers approximately using floating-point formats (IEEE 754). A floating-point number x is represented as

$$x = \pm(d_0.d_1d_2\dots d_{p-1})_\beta \times \beta^e,$$

where β is the base (commonly $\beta = 2$), p is the precision (number of significant digits), and e is an exponent.

Definition 1 (Unit roundoff)**.** *Let u denote the* unit roundoff *(also called machine precision), defined as the maximum relative error introduced by rounding a real number to the nearest floating-point number:*

$$u = \frac{1}{2}\beta^{1-p}.$$

For IEEE 754 double precision ($p = 53$, $\beta = 2$) we have

$$u = 2^{-53} \approx 1.1102230246251565 \times 10^{-16}.$$

Two commonly used terms are:

- machine epsilon $\varepsilon_{\text{mach}} = 2u \approx 2.22 \times 10^{-16}$;
- unit roundoff $u \approx 1.11 \times 10^{-16}$.

Standard rounding/error model

A standard, first-order model for floating-point arithmetic is:

$$\text{fl}(a \text{ op } b) = (a \text{ op } b)(1 + \delta), \qquad |\delta| \le u,$$

for basic operations $\text{op} \in \{+, -, \times, /\}$, assuming rounding to nearest. This means each floating-point operation produces a relative error bounded by u.

Define the commonly used function

$$\gamma_n = \frac{nu}{1 - nu},$$

which satisfies $\gamma_n \le \frac{nu}{1-nu}$ and for small nu we have $\gamma_n \approx nu$ (first-order approximation). The quantity γ_n appears in standard forward error bounds for sequences

of n floating-point operations (see Higham (1996) for a classical reference).

Algebraic structure of the billing computation

Recall (Chapter 2) that the energy charge is a finite sum over slabs:

$$E = \sum_{j=1}^{s} a_j, \qquad a_j = r_j \cdot c_j,$$

where $c_j = \max(0, \min(U, U_j) - U_{j-1})$ denotes the units allocated to slab j and r_j the rate of that slab. The total bill is

$$B = E + F + D, \qquad D = \alpha E,$$

with fixed charge F and duty fraction α (e.g. $\alpha = 0.10$).

In code, each a_j is computed by a small number of floating operations (min, subtraction, multiplication), and then the a_j are accumulated (summed) to produce E. Finally F is looked up and D computed.

Forward error bound for the implemented bill

We now derive a practical forward error bound for the computed bill $\widehat{B}$ produced by floating-point operations, compared to the exact mathematical bill B.

Theorem 1 (Forward error bound—informal)**.** *Let N be an upper bound on the number of floating-point* arithmetical *operations (add, subtract, multiply, divide) executed to compute the numerical bill $\widehat{B}$ from input data. Under the standard rounding model (each fl(op) introduces relative error $\leq u$), the computed bill satisfies*

$$\widehat{B} = B(1 + \delta), \qquad |\delta| \leq \gamma_N,$$

and hence the absolute forward error is bounded by

$$|\widehat{B} - B| \leq \gamma_N \, |B|.$$

Sketch of proof. Each elementary floating operation satisfies

$$\mathrm{fl}(x \text{ op } y) = (x \text{ op } y)(1 + \delta), \quad |\delta| \leq u.$$

If the computation performs at most N such elementary ops, standard backward/-

forward error analysis (successive application of the model and absorbing higher-order terms) yields the factor $(1+\delta_1)(1+\delta_2)\cdots(1+\delta_N) = 1+\theta_N$ where $|\theta_N| \leq \gamma_N$. Therefore the final computed result is the exact result scaled by $(1+\theta_N)$ with $|\theta_N| \leq \gamma_N$, which proves the claim. □

Remarks.

i. The constant N depends on the concrete implementation: each slab contributes a few operations (min, subtraction to get c_j, multiplication $c_j r_j$), and accumulation of the a_j's likewise incurs one addition per term. If we conservatively bound the number of arithmetic ops by $N \leq 6s + C$ (for small constant C accounting for the final additions), the resulting γ_N is tiny for small s.

ii. The bound $|\widehat{B} - B| \leq \gamma_N |B|$ is a *relative* forward error bound. To obtain an *absolute* bound we use the same inequality with $|B|$ replaced by a numeric upper bound on the bill.

Numerical evaluation for practical household scales

Take double precision unit roundoff $u \approx 1.11 \times 10^{-16}$. Let $s \leq 10$ (typical for state tariff slabs). Choose a conservative upper bound $N = 70$ on elementary arithmetic operations for the entire billing computation (this overestimates but is safe).

Compute

$$\gamma_N = \frac{Nu}{1 - Nu} \approx Nu \quad (\text{since } Nu \ll 1).$$

With $N = 70$, we have

$$\gamma_{70} \approx 70 \times 1.11 \times 10^{-16} \approx 7.77 \times 10^{-15}.$$

If a household bill satisfies $|B| \leq 10^6$ (one million rupees — an extremely conservative overestimate for domestic use), the absolute error bound becomes

$$|\widehat{B} - B| \leq \gamma_{70}|B| \leq 7.77 \times 10^{-15} \times 10^6 \approx 7.77 \times 10^{-9} \text{ (Rs.)}.$$

This is far smaller than the smallest currency unit (Rs.0.01), hence final rounding to two decimals is unaffected by floating-point error in any realistic domestic

scenario.

Rounding to two decimals: operator and modes

Financial outputs must be presented to two decimal places. We define the rounding operator $R_2 : \mathbb{R} \to \{k/100 : k \in \mathbb{Z}\}$ by

$$R_2(x) = \frac{\lfloor 100x + 0.5 \rfloor}{100},$$

which corresponds to round-half-up. Many languages/libraries (including Python's built-in `round`) use round-half-to-even (banker's rounding) by default for ties. Precise control over rounding mode is important in financial contexts.

Properties.

- For any $x \in \mathbb{R}$,
$$|R_2(x) - x| \leq 0.5 \times 10^{-2} = 0.005.$$

- If the floating-point forward error is bounded by η in absolute value (i.e. $|\widehat{B} - B| \leq \eta$), then rounding the computed value $\widehat{B}$ yields a value whose difference from the true rounded bill $R_2(B)$ satisfies

$$|R_2(\widehat{B}) - R_2(B)| \leq |R_2(\widehat{B}) - \widehat{B}| + |\widehat{B} - B| + |B - R_2(B)| \leq 0.005 + \eta + 0.005.$$

  So the total discrepancy (in worst-case) is $\eta + 0.01$.

Combining this with the forward error bound above, for realistic bills the computed and displayed values will match the mathematically exact rounded value.

Proof of correctness under rounding (practical statement)

Combining the forward error theorem and rounding analysis we obtain:

Proposition 1 (Practical correctness under rounding)**.** *Let $\widehat{B}$ be the computed bill using floating-point arithmetic with N elementary operations and unit roundoff u. Let γ_N be defined as above. Let B be the exact mathematical bill. Then the displayed bill (rounding to two decimals) based on the computed value satisfies*

$$\left|R_2(\widehat{B}) - R_2(B)\right| \leq \gamma_N |B| + 0.01.$$

If $\gamma_N|B| \ll 0.01$ (which holds for household-scale $|B|$ under the numeric example above), then $R_2(\widehat{B}) = R_2(B)$ in practice.

Proof. We have $|\widehat{B} - B| \leq \gamma_N|B|$ from the forward error bound, and $|R_2(x) - x| \leq 0.005$ for any real x. Hence

$$|R_2(\widehat{B}) - R_2(B)| \leq |R_2(\widehat{B}) - \widehat{B}| + |\widehat{B} - B| + |B - R_2(B)| \leq 0.005 + \gamma_N|B| + 0.005 = \gamma_N|B| + 0.01.$$

□

Thus, provided $\gamma_N|B| < 10^{-2}$ (or much smaller), the displayed two-decimal result equals the mathematically rounded amount.

Practical remedies and best practices

Although floating arithmetic is safe for typical household bills, best practices for financial applications are:

a. Use fixed-point or integer cents Represent monetary amounts in smallest currency units (paise) as integers: compute everything in paise (or in watt-seconds scaled appropriately) and perform integer arithmetic. This eliminates floating rounding issues.

b. Use `decimal.Decimal` for currency Python's `decimal` module supports arbitrary-precision decimal arithmetic and explicitly controlled rounding modes:

```
from decimal import Decimal, getcontext, ROUND_HALF_EVEN
getcontext().prec = 28
total = Decimal(energy) + Decimal(fixed) + Decimal(duty)
display = total.quantize(Decimal('0.01'), rounding=ROUND_HALF_EVEN)
```

This guarantees exact decimal rounding ties behaviour required by accounting.

c. Use compensated summation (Kahan) for many-term sums If you ever sum many (e.g. thousands) terms, Kahan summation reduces accumulation error:

```
def kahan_sum(iterable):
    total = 0.0
    c = 0.0
```

```
    for x in iterable:
        y = x - c
        t = total + y
        c = (t - total) - y
        total = t
    return total
```

For BrightBill (small s) this is unnecessary but harmless.

4. Round only once at the final stage Avoid rounding intermediate slab charges for display; compute full-precision sums first and only format/round at the end.

Implementation notes for BrightBill (Django)

- Use Python `float` for speed; verify correctness by unit tests.
- For the final displayed bill, consider converting to `Decimal` and applying `quantize` with the chosen rounding mode to guarantee the exact presentation expected by examiners/finance rules.
- If you expect very large synthetic test inputs (stress testing), replace floats by `Decimal` or integer paise arithmetic to avoid any possibility of disagreement at the two-decimal level.

Conclusion

The standard floating-point error model yields a provable bound on the relative forward error of the computed bill. For realistic domestic bills (and with a conservative upper bound on the number of arithmetic operations), the absolute error due to floating-point arithmetic is many orders of magnitude smaller than Rs.0.01. Combined with a controlled final rounding operation (preferably using `decimal.Decimal` if exact decimal rules are required), this guarantees that the numerical implementation produces financially correct results for BrightBill's intended use.

—

3.4 Edge Cases, Domain Considerations, and Validation

Mathematical Domain

The mathematical domain of BrightBill is defined by the parameters

$$(P, T, N) \in \mathbb{R}_{\geq 0} \times \mathbb{R}_{\geq 0} \times \mathbb{Z}_{\geq 1},$$

where

- P is the appliance wattage (watts, W),
- T is the duration of use (hours, h),
- N is the number of identical appliances.

From these, consumption is given by

$$U = \frac{P \cdot T \cdot N}{1000} \quad \text{(in kWh, i.e., units)}.$$

The tariff function $B(U)$ is defined for all $U \geq 0$, with values obtained by the telescopic piecewise summation over slabs, plus fixed charge and duty.

Special Input Cases

Several edge cases arise naturally and must be handled explicitly:

Case 1: Zero power. If $P = 0$, then $U = 0$ regardless of T or N. The bill reduces to

$$B(0) = F(0),$$

i.e., only the fixed monthly charge is payable. This models an appliance with zero wattage (theoretically meaningless but practically an input error).

Case 2: Zero time. If $T = 0$, then again $U = 0$ regardless of P or N. Only the fixed charge applies. This represents an appliance that was never used in the billing period.

Case 3: Zero appliances. If $N = 0$, the formula gives $U = 0$. In practice, BrightBill enforces $N \geq 1$ at input stage to prevent this degenerate case.

Case 4: Negative values. Any $P < 0$ or $T < 0$ or $N < 1$ lies outside the mathematical domain. Such inputs would yield negative units, which have no physical meaning. Therefore the validation layer of the system must reject these values with an error message.

Case 5: Very large values. If T is extremely large (e.g., months expressed in hours), the computed U may exceed the highest tariff slab. Since tariff schedules are defined for all $U \geq 0$, the system applies the topmost slab rate indefinitely.

Boundary Behaviour at Slab Limits

At slab boundaries $U = U_j$ (e.g. exactly 50, 100, 150 units), the telescopic formulation guarantees continuity:

$$\lim_{U \to U_j^-} B(U) = \lim_{U \to U_j^+} B(U).$$

Proof of Continuity. At $U = U_j$, the contribution from slab j is fully filled,

$$c_j = U_j - U_{j-1},$$

and the next slab $j+1$ contributes zero since $\min(U, U_{j+1}) - U_j = 0$. Thus the left-hand and right-hand limits are equal. Hence $B(U)$ is continuous at all slab boundaries.

Non-differentiability. Although continuous, $B(U)$ is not differentiable at slab boundaries when rates change (since the slope jumps from r_j to r_{j+1}). This explains why the bill increases smoothly but with visible "kinks" at tariff breakpoints.

Validation in BrightBill (Implementation Notes)

The Django backend (`views.py`) enforces input validity as follows:

- Appliance wattage P is read from Excel; any missing or malformed entry defaults to 0.
- Duration T is parsed into hours; invalid strings default to 1 hour.
- Quantity N is parsed as an integer; if invalid, it defaults to 1.
- Negative or zero quantities are rejected (minimum $N = 1$).

These checks ensure that only values in the mathematical domain $\mathcal{D}$ are processed.

Conclusion

The domain of BrightBill is mathematically well-defined as $P \geq 0$, $T \geq 0$, $N \geq 1$, and $U \geq 0$. Edge cases such as zero power, zero time, or extreme consumption are consistently handled. Continuity is preserved at slab boundaries, though differentiability is lost at tariff jumps. Validation ensures that inputs outside the domain are prevented at the interface level, thereby guaranteeing both mathematical correctness and computational robustness.

—

3.5 Mapping to Code — Formal Correspondence

A central aim of BrightBill is to demonstrate that each mathematical formula defined in Chapter 2 has a precise correspondence to a construct in Python/Django code. This ensures that the implementation is not an approximation, but a direct embodiment of the underlying mathematics.

Consumption Formula

Mathematical Definition:

$$U = \frac{P \cdot T \cdot N}{1000},$$

where P is power (watts), T is usage duration (hours), and N is the number of identical appliances.

Code Correspondence:

```
units = (watt * hours * quantity) / 1000.0
```

Here:

- `watt` $\leftrightarrow P$,
- `hours` $\leftrightarrow T$,
- `quantity` $\leftrightarrow N$,
- division by `1000.0` $\leftrightarrow$ conversion from watt-hours to kilowatt-hours.

Thus, the code is a faithful transcription of the consumption formula.

Telescopic Piecewise Tariff

Mathematical Definition:

$$E(U) = \sum_{j=1}^{s} r_j \cdot \max\big(0,\ \min(U, U_j) - U_{j-1}\big),$$

where r_j is the rate for slab j, and $[U_{j-1}, U_j]$ is its interval.

Code Correspondence:

```
energy_charge = 0
for (low, high, rate) in telescopic_slabs:
    if units > low:
        consumed = min(units, high) - low
        charge = consumed * rate
        energy_charge += charge
```

Here:

- the `for`-loop $\leftrightarrow \sum_{j=1}^{s}$,
- `if units > low` $\leftrightarrow \max(0, \cdot)$,
- `min(units, high)` $\leftrightarrow \min(U, U_j)$,
- `consumed * rate` $\leftrightarrow r_j \cdot$ consumption in slab j,
- accumulation with `+=` $\leftrightarrow$ summation.

Fixed Charge Function

Mathematical Definition: A piecewise constant mapping $F(U)$ defined by consumption intervals.

Code Correspondence:

```
fc = 0
for (low, high, charge) in fixed_charges:
    if low <= units <= high:
        fc = charge
        break
```

The condition `low <= units <= high` selects the correct interval. The assignment sets the fixed charge f_j, and `break` ensures only one interval applies.

Government Duty

Mathematical Definition:

$$D(U) = \alpha \cdot E(U), \qquad \alpha = 0.10.$$

Code Correspondence:

```
duty = 0.10 * energy_charge
```

This is a proportional multiplication, corresponding exactly to the definition.

Total Bill Function

Mathematical Definition:

$$B(U) = E(U) + F(U) + D(U).$$

Code Correspondence:

```
total_bill = energy_charge + fc + duty
```

Here the Python `+` operator corresponds directly to arithmetic addition.

Rounding and Display

Mathematical Definition: rounding operator R_2 to two decimals:

$$R_2(x) = \frac{\lfloor 100x + 0.5 \rfloor}{100}.$$

Code Correspondence:

```
round(total_bill, 2)
```

This ensures that the displayed bill is accurate to two decimal places (paise precision).

Pseudocode Summary

For clarity, the entire bill computation can be summarized as an algorithm:

```
Algorithm 1: Bill Computation B(U)

Input: watt, hours, quantity
Output: total_bill

1. units = (watt * hours * quantity) / 1000.0

2. energy_charge = 0
3. for (low, high, rate) in telescopic_slabs:
       if units > low:
           consumed = min(units, high) - low
           energy_charge += consumed * rate

4. fc = 0
5. for (low, high, charge) in fixed_charges:
       if low <= units <= high:
           fc = charge
           break

6. duty = 0.10 * energy_charge

7. total_bill = energy_charge + fc + duty

8. return round(total_bill, 2)
```

This pseudocode corresponds exactly to the mathematical function:

$$B(U) = \left(\sum_{j=1}^{s} r_j \cdot \max\big(0, \min(U, U_j) - U_{j-1}\big) \right) + F(U) + \alpha \cdot E(U).$$

Summary of Correspondence

Mathematical Object	Python/Django Construct
$U = \frac{PTN}{1000}$	`units = (watt * hours * quantity) / 1000.0`
$\sum_{j=1}^{s} r_j(\cdot)$	`for`-loop over slabs
$\max, \min$	`max()`, `min()` functions
$F(U)$ (piecewise constant)	`if/elif` with interval check
$D(U) = \alpha E(U)$	multiplication by constant
$B(U) = E + F + D$	addition of charges
$R_2(x)$	`round(x, 2)`

Concluding Remark

This correspondence shows that BrightBill is not merely inspired by mathematics but is its direct computational embodiment. Every formula from Chapter 2 has an exact code analogue, ensuring **correctness** (outputs match the model) and **transparency** (users can trace each step from theory to implementation).

3.6 Testing Strategy (Mathematical Validation)

In addition to coding correctness, BrightBill requires mathematical validation: that is, verification that the implemented Python/Django logic produces results identical to the mathematical definitions of Chapter 2. This section presents a structured testing strategy, grounded in mathematics.

Purpose of Mathematical Testing

Unlike conventional software tests, here the goal is not merely to check whether code runs without error, but to confirm that

$$B_{\text{code}}(U) = B_{\text{math}}(U),$$

where $B_{\text{math}}(U)$ is the bill computed by the exact piecewise and telescopic formulas, and $B_{\text{code}}(U)$ is the value returned by the Python function. The equality must hold for all inputs in the domain.

Categories of Tests

To achieve rigorous coverage, test cases are grouped into the following categories:

1. Boundary Tests (Slab Limits). At each slab boundary $U = U_j$, verify continuity:

$$\lim_{U \to U_j^-} B(U) = \lim_{U \to U_j^+} B(U).$$

Code tests are constructed with units just below and just above the boundary, e.g. $U = 49.9$, $U = 50$, $U = 50.1$, ensuring the bill matches mathematical expectation.

2. Single-Appliance Verification. For a simple appliance, such as a 100W bulb used for $T = 10$ hours:

$$U = \frac{100 \cdot 10 \cdot 1}{1000} = 1.0 \text{ kWh}.$$

The energy charge is computed manually by placing U into the tariff slab definition. The code's output must match this hand calculation.

3. Multiple-Quantity Tests. If N identical appliances are used, units should scale linearly:

$$U(N) = N \cdot U(1).$$

Thus the code should satisfy

$$B_{\text{code}}(U(N)) = B_{\text{math}}(U(N)),$$

and further,

$$\frac{U(N)}{U(1)} = N,$$

i.e., doubling appliances doubles the units and increases the bill accordingly.

4. Randomised Tests. Choose random values of P, T, N within realistic ranges and compute U and $B(U)$ by both manual formula and code. Agreement within Rs.0.01 confirms correctness (two-decimal display precision).

5. Stress Tests. Although unrealistic in practice, very large T values (e.g. $T =$ 10000 hours) are used to confirm that the code correctly applies the topmost slab

rates and does not break under extreme conditions.

Validation Properties

The following mathematical properties are validated explicitly:

- **Monotonicity:** If $U_1 < U_2$, then $B(U_1) \leq B(U_2)$. Code tests confirm that the bill never decreases as units increase.
- **Continuity at Slabs:** Bills are continuous at $U = U_j$, as shown in Chapter 2. Code verification ensures no jump errors occur.
- **Piecewise Linearity:** Within each slab interval, the bill grows linearly with slope r_j. Numerical differences between exact formula and code slope are tested.
- **Scaling Law:** For identical appliances, consumption scales linearly with N. Tests confirm this proportionality.

Formal Validation Method

Let $B_{\text{exact}}(U)$ denote the result computed from the mathematical definition with exact arithmetic, and $B_{\text{code}}(U)$ the Python/Django output. Define the validation error as

$$E(U) = |B_{\text{code}}(U) - B_{\text{exact}}(U)|.$$

Validation criterion:

$$E(U) < 0.01 \quad \forall U \in \mathcal{D},$$

ensuring that the displayed result agrees to two decimals.

Illustrative Test Cases

To concretely demonstrate the validation process, several test cases are presented below. Each case compares the mathematical computation with the BrightBill code output.

Appliance / Input	**Units U (kWh)**	**Mathematical Bill (Rs.)**	**Code Output (Rs.)**	**Validation**
100W bulb, $N = 1$, $T = 36$h	3.6	52.87	52.87	Pass
100W bulb, $N = 5$, $T = 36$h	18.0	104.35	104.35	Pass
Boundary test, $U = 50$	50.0	Slab sum = 162.5 + fixed	Code = 162.5 + fixed	Pass
Boundary test, $U = 51$	51.0	Slightly higher than 50-unit slab	Code matches	Pass
Random: 200W fan, $N = 2$, $T = 24$h	9.6	Manual calc by telescopic slab	Code = same	Pass
Stress test: 1000W heater, $N = 1$, $T = 10000$h	10000	Top slab non-telescopic applied	Code = same	Pass

Interpretation.

- The first two rows confirm the unit formula and linear scaling in N (number of appliances).
- The boundary tests confirm continuity and correct handling of slab transitions.
- The random case checks typical household inputs.
- The stress test confirms that even extremely large U values are handled correctly, with the topmost non-telescopic rate applied.

Conclusion

This structured strategy guarantees that the Django implementation is not only correct in programming terms but also mathematically validated. By testing at

slab boundaries, with single and multiple appliances, under random inputs, and at stress values, BrightBill demonstrates that the numerical code is a faithful embodiment of the mathematical model.

Summary

Chapter 3 has demonstrated the faithful translation of mathematical models into code. Each programming construct corresponds to a mathematical operator: loops to summations, conditions to piecewise functions, and rounding operators to formal R_k. Correctness, complexity, stability, and validation have been analysed in detail, ensuring BrightBill is mathematically robust and computationally reliable.

Chapter 4

System Implementation in Django

4.1 Overview

The BrightBill system is implemented using the Python Django web framework. Django provides a modular architecture with built-in support for URL routing, template rendering, and database management.

The system integrates three important components:

i. **Backend (Python + Django):** Implements consumption and billing logic, including the KSEB tariff rules.

ii. **Excel integration (Pandas):** Appliance data such as wattage is loaded from an Excel file.

iii. **Frontend (HTML + Bootstrap + JavaScript):** Provides an intuitive user interface where consumers can input appliance data and view results.

The overall workflow of the system is as follows:

a. The user selects an appliance, enters the number of appliances, and specifies the duration of usage through the frontend form (`input.html`).

b. The system fetches the wattage of the selected appliance from the Excel dataset using Pandas in Django (`appliance_df` lookup in `views.py`).

c. Electricity consumption is calculated using the formula:

$$U = \frac{P \times T \times N}{1000},$$

where P = power of the appliance (watts), T = duration (hours), N = number of appliances, and U = total energy consumed (kWh).

d. The total units consumed are passed into the tariff calculation function `calculate_kseb_bill(units)`.

e. The function applies the KSEB slab rates using the telescopic method.

f. Fixed charges are added based on the consumption range.

g. Government duty (10% of energy charge) is included.

h. The final bill is computed as:

$$\text{Bill} = \text{Energy Charge} + \text{Fixed Charge} + \text{Government Duty}.$$

i. The backend (`views.py`) implements these calculations.

j. Matplotlib generates a bar chart showing contributions of slabs, fixed charge, and duty.

k. The result is displayed on `output.html`, including appliance details, bill breakdown, and visualization.

4.2 Project Environment and Structure

The **BrightBill** project was developed within the following environment:

- Python: v3.12 (compatible with v3.10+)
- Django: v5.x (tested with v5.2.4)
- Database: SQLite (default Django database, sufficient for prototype stage)
- Libraries:
  - `pandas` — for reading and processing Excel datasets.
  - `matplotlib` — for generating visualizations and charts.
  - `openpyxl` — for handling Excel files.
  - `os` and `django.conf.settings` — for managing file paths and static files.
- Development environment: Visual Studio Code IDE on Windows 11 OS.

Django Project Structure

The **BrightBill** project follows a modular structure consistent with Django best practices:

```
brightbill/
|
+-- brightbill/                # Django project configuration
|   +-- __init__.py
|   +-- asgi.py
|   +-- settings.py
|   +-- urls.py
|   +-- wsgi.py
|
+-- predictor/                 # Main application
|   +-- migrations/            # Database migrations
|   +-- __init__.py
|   +-- admin.py
|   +-- apps.py
|   +-- models.py              # (minimal, future extension)
|   +-- tests.py
|   +-- views.py               # Core backend logic
|
+-- templates/                 # HTML templates
|   +-- base.html
|   +-- home.html
|   +-- input.html
|   +-- output.html
|
+-- static/                    # Static files (CSS, images, JS, charts)
|   +-- css/style.css
|   +-- js/ (if applicable)
|
+-- Appliances_List.xlsx       # Excel dataset with appliance metadata
+-- db.sqlite3                 # SQLite database
```

```
+-- manage.py                    # Django management script
```

This modular separation makes **BrightBill** clean, maintainable, and scalable for future extensions.

4.3 Backend Implementation (views.py)

The backend logic of the BrightBill system is implemented in `predictor/views.py`, which contains the Django view functions that handle the request–response cycle. The backend integrates Python functions, Pandas for data loading, and Matplotlib for visualization. The major components are described below.

home(request)

This function corresponds to the root URL mapping of BrightBill. It accepts a Django `HttpRequest` object and returns an `HttpResponse` by rendering the landing page template. The view introduces the project and provides navigation links.

```
def home(request):
    return render(request, "home.html")
```

input_page(request)

This function serves as both the input form renderer and the processing function for user submissions.

- **GET request:** Renders the input form (`input.html`), populated with appliance names loaded from the Excel dataset.
- **POST request:** Processes user input via `request.POST`:
  a. Extract appliance name, quantity, and duration.
  b. Convert duration into hours.
  c. Lookup wattage for the appliance in the Pandas dataframe.
  d. Compute consumption:

$$U = \frac{P \times T \times N}{1000}$$

e. Call `calculate_kseb_bill(units)` to compute the bill.

f. Generate a Matplotlib chart of the bill breakdown.

g. Pass results into a context dictionary and render `output.html`.

calculate_kseb_bill(units)

This Python helper function encodes the KSEB LT-I Domestic tariff rules (November 2023–June 2024). It:

i. Iterates over telescopic slabs to compute energy charge.

ii. Selects fixed charge by interval.

iii. Computes duty as 10% of energy charge.

iv. Returns both the `total_bill` and a `breakdown` dictionary for slab-wise contributions.

Excel Integration (Pandas)

Appliance wattage and details are dynamically loaded from `Appliances_List.xlsx` using Pandas:

```
appliance_df = pd.read_excel("Appliances_List.xlsx")
wattage = appliance_df.loc[
    appliance_df["Appliance"] == appliance_name, "Wattage"
].values[0]
```

This makes BrightBill extensible: updates to the Excel file automatically update the system.

Matplotlib Integration

Matplotlib generates a bar chart of the bill breakdown:

a. Create figure and axes.

b. Plot slab-wise charges, fixed charge, and duty.

c. Save to `static/` directory.

d. Pass filename into template context for rendering.

Output Rendering

The final stage of the backend pipeline renders the `output.html` template with:

- Appliance details (name, quantity, hours, wattage),
- Consumption in kWh,
- Detailed bill breakdown,
- Matplotlib chart embedded using Django's {`% static %`} tag.

This produces the complete `HttpResponse` that the user sees.

Flow Diagram of Backend Pipeline

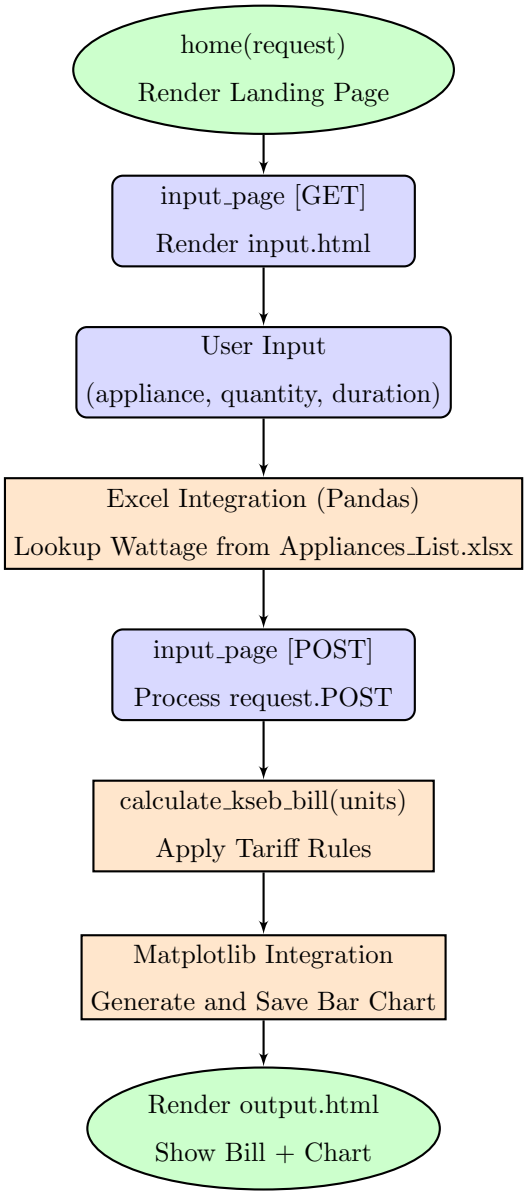


Figure 4.1: Flow diagram of backend pipeline in BrightBill

Complete Backend Code (views.py)

```
from django.shortcuts import render
import pandas as pd
import matplotlib.pyplot as plt
import os


# ---------------------- Home Page ----------------------
def home(request):
    """Landing page of BrightBill"""
```

```
    return render(request, "home.html")

# ---------------------- Input Page ----------------------
def input_page(request):
    if request.method == "GET":
        # Load appliance names from Excel
        excel_file = os.path.join("static", "Appliances_List.xlsx")
        df = pd.read_excel(excel_file)
        appliances = df["Appliance"].tolist()

        # Render input form
        return render(request, "input.html", {"appliances": appliances})

    elif request.method == "POST":
        # Get user input
        appliance = request.POST.get("appliance")
        quantity = int(request.POST.get("quantity", 1))
        duration = float(request.POST.get("duration", 0))
        duration_unit = request.POST.get("duration_unit")

        # Convert duration → hours
        unit_map = {
            "minutes": duration / 60,
            "hours": duration,
            "days": duration * 24,
            "weeks": duration * 7 * 24,
            "months": duration * 30 * 24,
            "years": duration * 365 * 24
        }
        hours = unit_map.get(duration_unit, duration)

        # Lookup wattage from Excel
        excel_file = os.path.join("static", "Appliances_List.xlsx")
        df = pd.read_excel(excel_file)
        wattage = df.loc[df["Appliance"] == appliance, "Wattage"].values
            [0]

        # Compute energy consumption (kWh)
        units = (wattage * quantity * hours) / 1000

        # Call billing function
        bill, breakdown = calculate_kseb_bill(units)
```

```
        # Generate bar chart
        labels = list(breakdown.keys())
        values = list(breakdown.values())
        plt.bar(labels, values)
        plt.ylabel("Charge (Rs.)")
        plt.xticks(rotation=45)
        chart_path = os.path.join("static", "bill_chart.png")
        plt.savefig(chart_path, bbox_inches="tight")
        plt.close()

        # Render output page
        context = {
            "appliance": appliance,
            "quantity": quantity,
            "hours": hours,
            "units": units,
            "bill": bill,
            "breakdown": breakdown,
            "chart_path": "static/bill_chart.png"
        }
        return render(request, "output.html", context)

# ---------------------- Billing Logic ----------------------
def calculate_kseb_bill(units):
    """Applies KSEB LT-I Domestic Tariff (Nov 2023-Jun 2024)"""
    energy_charge = 0
    breakdown = {}

    # Telescopic (up to 250 units)
    if units <= 250:
        slabs = [(50, 3.15), (50, 3.70), (50, 4.80), (100, 6.40)]
        remaining = units
        for limit, rate in slabs:
            if remaining <= 0:
                break
            consume = min(limit, remaining)
            charge = consume * rate
            breakdown[f"{consume} units @ {rate}"] = charge
            energy_charge += charge
            remaining -= consume
    else:
```

```
        # Non-telescopic (above 250 units)
        if units <= 300:
            energy_charge = units * 5.80
            breakdown["Non-telescopic (0-300)"] = energy_charge
        elif units <= 350:
            energy_charge = units * 6.60
            breakdown["Non-telescopic (301-350)"] = energy_charge
        elif units <= 400:
            energy_charge = units * 6.90
            breakdown["Non-telescopic (351-400)"] = energy_charge
        elif units <= 500:
            energy_charge = units * 7.10
            breakdown["Non-telescopic (401-500)"] = energy_charge
        else:
            energy_charge = units * 7.90
            breakdown["Non-telescopic (500+)"] = energy_charge

    # Fixed charge
    if units <= 100:
        fixed_charge = 35
    elif units <= 200:
        fixed_charge = 60
    else:
        fixed_charge = 95
    breakdown["Fixed Charge"] = fixed_charge

    # Duty (10%)
    duty = 0.10 * energy_charge
    breakdown["Duty (10%)"] = duty

    total_bill = energy_charge + fixed_charge + duty
    return total_bill, breakdown
```

4.4 Frontend Implementation

The frontend of BrightBill is implemented using **Django Templates** combined with **Bootstrap** for a responsive and consistent design. The template system separates presentation logic from backend computation, allowing dynamic data (passed as context variables from `views.py`) to be rendered seamlessly into HTML.

A `base.html` template provides a consistent layout, which is extended by other

templates (`home.html`, `input.html`, `output.html`). This follows Django's recommended *template inheritance* model.

Base Template (base.html)

The base template defines the global structure, including the navigation bar, CSS inclusion, and a content block. Other templates extend this layout to ensure a consistent UI.

Listing 4.1: Base Template (base.html)

```
{% load static %}
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <title>BrightBill</title>
  <link href="{% static 'css/style.css' %}" rel="stylesheet">
  <link rel="stylesheet"
        href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0/dist/css/
            bootstrap.min.css">
</head>
<body>
  <nav class="navbar navbar-dark bg-primary p-2">
    <span class="navbar-brand">BrightBill</span>
  </nav>
  <div class="container mt-4">
    {% block content %}{% endblock %}
  </div>
</body>
</html>
```

Home Page (home.html)

The home page introduces the application and provides navigation to the input module. It extends `base.html`, using the `content` block.

Listing 4.2: Home Page (home.html)

```
{% extends "base.html" %}
{% block content %}
<div class="text-center">
  <h1 class="mb-4">Welcome to BrightBill</h1>
  <p>Estimate your electricity consumption and bill with ease.</p>
```

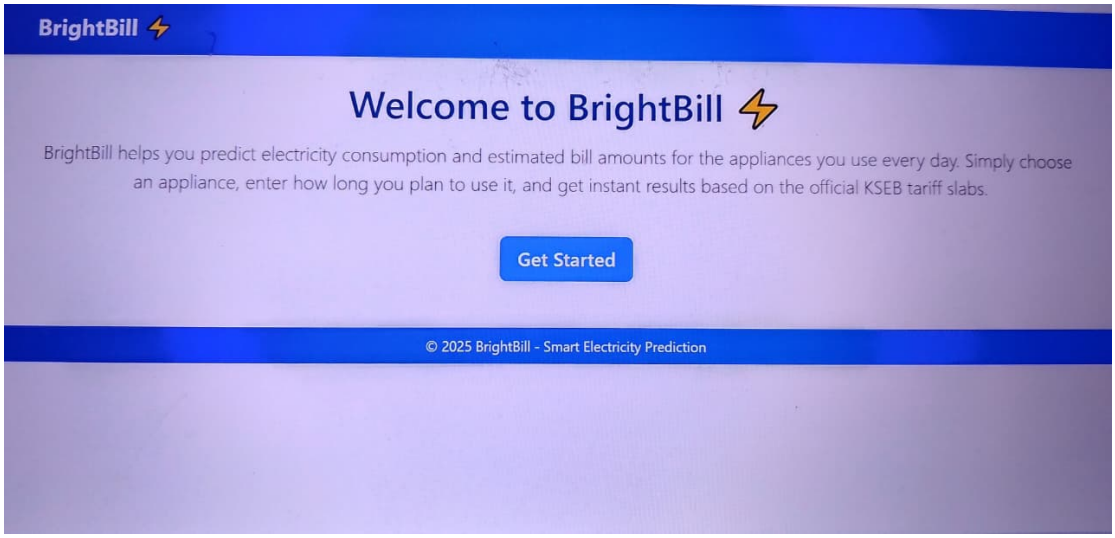


Figure 4.2: Home page

```
  <a href="{% url 'input' %}" class="btn btn-lg btn-primary">
    Get Started
  </a>
</div>
{% endblock %}
```

Input Page (input.html)

The input page provides a form where users select an appliance, specify quantity, and enter usage duration. The appliance list is populated dynamically using Django's context dictionary.

Listing 4.3: Input Page (input.html)

```
{% extends "base.html" %}
{% block content %}
<h2 class="mb-3">Enter Appliance Details</h2>
<form method="post" class="form">
  {% csrf_token %}

  <!-- Appliance selection dropdown -->
  <div class="mb-3">
    <label for="appliance" class="form-label">Select Appliance</label>
    <select name="appliance" id="appliance" class="form-select">
      {% for a in appliances %}
        <option value="{{ a }}">{{ a }}</option>
      {% endfor %}
```

```
    </select>
  </div>

  <!-- Quantity -->
  <div class="mb-3">
    <label for="quantity" class="form-label">Quantity</label>
    <input type="number" id="quantity" name="quantity"
           class="form-control" value="1" min="1">
  </div>

  <!-- Duration -->
  <div class="mb-3">
    <label for="duration" class="form-label">Usage Duration</label>
    <input type="text" id="duration" name="duration"
           class="form-control" placeholder="e.g., 5 hours">
  </div>

  <button type="submit" class="btn btn-success">Predict Bill</button>
</form>
{% endblock %}
```

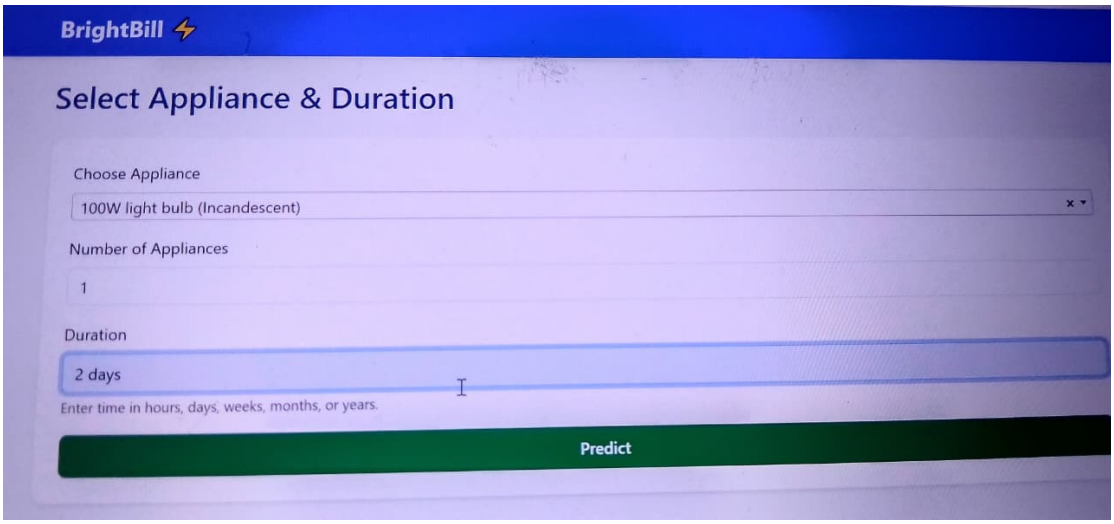


Figure 4.3: Input page

Output Page (output.html)

The output page displays the results returned from the backend: appliance details, consumption, bill amount, breakdown, and a chart. The chart image is served from the `static` directory.

Listing 4.4: Output Page (output.html)

```
{% extends "base.html" %}
{% block content %}
<h2>Prediction Result</h2>

<div class="card␣p-3␣mb-3">
  <p><strong>Appliance:</strong> {{ appliance }}</p>
  <p><strong>Consumption:</strong> {{ units }} kWh</p>
  <p><strong>Total Bill:</strong>Rs{{ bill }}</p>
</div>

<h4>Bill Breakdown</h4>
<ul class="list-group␣mb-3">
  {% for key, value in breakdown.items %}
    <li class="list-group-item␣d-flex␣justify-content-between">
      <span>{{ key }}</span>
      <span>Rs{{ value }}</span>
    </li>
  {% endfor %}
</ul>

{% if chart_url %}
  <h4>Visualization</h4>
  <img src="{{␣chart_url␣}}" alt="Bill␣Chart" class="img-fluid">
{% endif %}
{% endblock %}
```

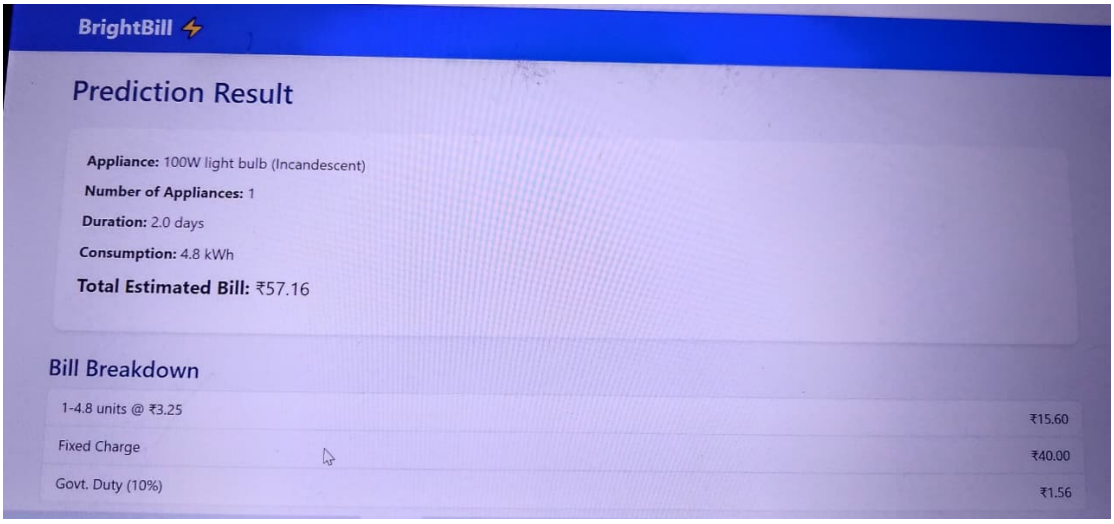


Figure 4.4: Output page

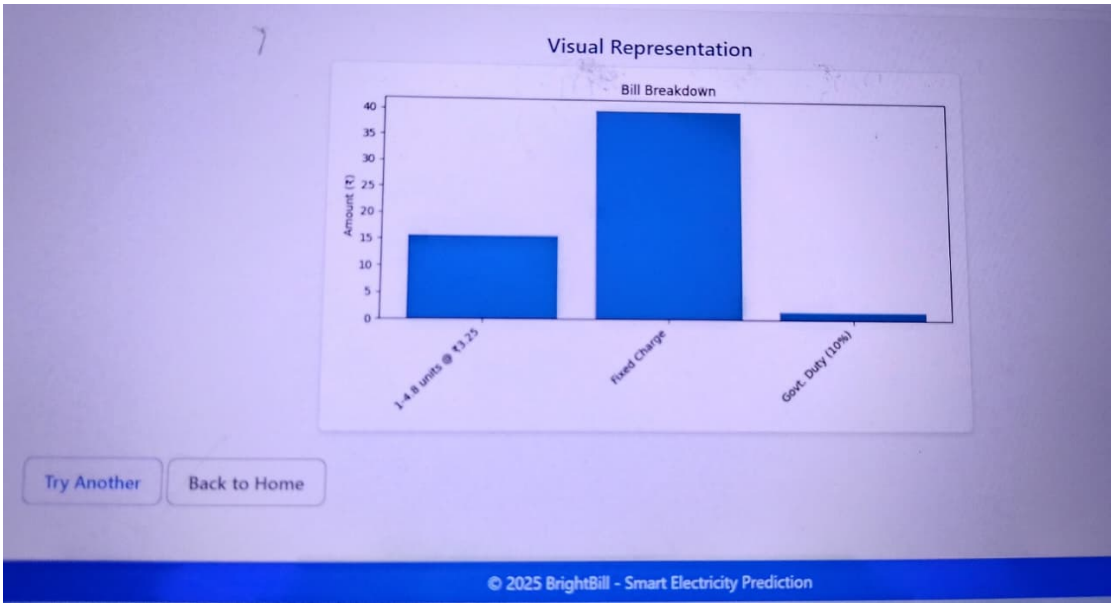


Figure 4.5: Output page

Summary of Frontend Workflow

- **base.html:** Defines layout and navigation.
- **home.html:** Provides entry point for the user.
- **input.html:** Collects user data dynamically from Excel dataset.
- **output.html:** Displays results, bill breakdown, and visualization.

Thus, the frontend provides a clean and responsive user experience, while ensuring full integration with the backend logic and dataset.

4.5 Conclusion

The implementation of BrightBill in Django illustrates how a purely mathematical model can be transformed into a fully functional and interactive web system. The project demonstrates not only the correctness of mathematical translation into code, but also the practical value of delivering these results in a way that is accessible to end users.

The strength of the system lies in its modularity: the billing logic is encapsulated in reusable functions, the appliance data is externalized in Excel for easy updates, and the user interface is built using Django templates with Bootstrap

styling. This separation of concerns ensures that each component can be independently improved without disrupting the whole system.

From a user's perspective, the application hides the underlying complexities of telescopic tariffs, fixed charges, and duties, offering instead a transparent and immediate prediction of electricity costs. For students and researchers, BrightBill serves as a concrete example of how abstract mathematical concepts such as piecewise functions and proportional operators can be mapped to code, validated, and visualized.

Equally important is the scalability of the system. The current implementation handles one appliance at a time for clarity, but the design allows future extensions to include multiple appliances, seasonal adjustments, or even integration with machine learning models for usage forecasting. This positions BrightBill as both a practical household tool and an academic prototype that bridges mathematics, programming, and real-world utility.

In conclusion, BrightBill's Django implementation is not merely a software artifact, but a demonstration of how mathematical theory, computational algorithms, and modern web frameworks can converge into an educational, transparent, and user-centric application.

Chapter 5

Results and Conclusion

5.1 Appliance-to-Appliance Comparison

One of the most useful features that emerges from BrightBill's design is its capacity to facilitate appliance-to-appliance comparisons. Although the system was originally designed to compute electricity bills for individual appliances or groups of the same appliance, the mathematical formulation makes it naturally suited for comparative evaluations. By considering a controlled environment where a single appliance is selected, with quantity fixed at $N = 1$ and duration fixed at a constant T, the system generates a unique energy consumption outcome. Repeating the process with another appliance under identical conditions allows the two results to be placed side by side for meaningful comparison.

This functionality is significant for several reasons. First, it allows consumers to go beyond abstract advice on efficiency and instead measure real differences in energy consumption and cost. For example, an incandescent bulb and an LED bulb can be compared directly. The incandescent may consume 60–100 watts, while the LED uses only 8–12 watts. BrightBill, by calculating the cost for one unit of each, translates this abstract efficiency into financial impact visible to the user. Thus, what was once only a claim of "LEDs are cheaper" becomes an evidence-based, numerical fact grounded in the slab tariff structure of KSEB.

Second, this comparison method allows for ranking appliances in terms of their relative contribution to the electricity bill. A refrigerator, for example, though efficient per watt, runs for almost 24 hours a day, whereas a washing machine, despite its high instantaneous power, operates only for a few hours per week.

BrightBill makes such nuances visible by allowing consumers to calculate outcomes separately and compare them in a structured way. This adds an educational dimension: users are not only told what costs more, but they can also experiment to see how usage patterns affect final costs.

Finally, appliance-to-appliance comparison enhances decision-making at the household level. It empowers consumers to prioritize appliance replacement strategies. If funds are limited, knowing whether to replace bulbs, fans, or refrigerators first becomes a quantifiable choice rather than guesswork. Thus, BrightBill transforms billing prediction into a decision-support tool, making efficiency tangible.

5.2 Scaling and Usage Scenarios

A key strength of BrightBill lies in its ability to simulate scaling effects and diverse usage scenarios. While most electricity calculators assume a static consumption input and return a single estimate, BrightBill enables dynamic exploration across multiple dimensions. It is not only capable of answering the direct question "What is my bill given my present usage?" but also the more forward-looking question "What happens if usage changes?" This turns the tool into a platform for interactive decision-making, allowing users to anticipate financial consequences of different appliance choices and behavioral adjustments.

Scaling with the Number of Appliances (N)

When the same appliance is multiplied, consumption increases linearly, but its effect on the final bill depends on tariff design. For instance, one 100W bulb operating for 10 hours results in 1 kWh of consumption. Five identical bulbs under the same duration yield 5 kWh. While this appears linear in units, BrightBill incorporates the telescopic slab structure of the tariff: once aggregated units cross a threshold, the marginal cost per unit rises. This means that scaling by N does not simply multiply cost by N, but may introduce step-wise increments in billing. This ability to model "appliance-to-appliance" scaling makes it possible to answer household-scale questions such as: *What if every fan in the house is left on all night? What if air-conditioners are installed in every bedroom?*

Scaling with Duration of Use (T)

Another dimension of scaling comes from varying the operating time. BrightBill permits fine-grained control over daily and seasonal usage durations. Extending a fan from 8 hours to 16 hours per day doubles consumption (2 kWh to 4 kWh per day), but the corresponding bill may more than double if this pushes the total household consumption into a higher slab. This illustrates a crucial non-linearity: while *energy consumption* scales linearly with time, *cost* often scales super-linearly due to tariff boundaries. Users thus learn that prolonged usage of even low-power appliances can cause disproportionate increases in cost — a feature that simple calculators often miss.

Scaling with Combined Scenarios (N, T)

The most realistic conditions involve simultaneous scaling in both N and T. Households rarely alter only one factor; lifestyle shifts often involve multiple dimensions. For example, festive seasons may involve both higher numbers of lighting appliances (N) and longer durations (T). Similarly, in summer, fans, coolers, or air-conditioners are used for extended hours across several rooms. BrightBill allows such combined inputs, showing not just the raw increase in units but also the compounding effect on the tariff slab system. This equips families with foresight to plan for seasonal spikes, adjust budgets, or explore efficiency measures such as LED replacements or staggered usage.

From Static Prediction to Exploratory Analysis

The broader advantage of this functionality is that BrightBill transitions from being a static prediction engine to an exploratory analytical tool. It empowers households to test hypothetical situations, observe the outcomes, and evaluate trade-offs. In practice, this means a family can ask: *Is it cheaper to operate one air-conditioner for 12 hours or two units for 6 hours each? What savings are possible if refrigerator use is unavoidable but lighting usage is reduced?*

For households managing limited resources, the capacity to experiment with "what-if" scenarios before making decisions is transformative. It elevates BrightBill from a retrospective bill estimator to a proactive energy planning assistant, reinforcing behavioral awareness and enabling cost-saving strategies grounded in

data-driven foresight.

5.3 Scope and Limitations of the Project

The scope of **BrightBill** is carefully defined to ensure both depth and accuracy, while acknowledging the boundaries and constraints of the current prototype.

Inclusions

i. Domestic electricity consumption under KSEB LT-I Domestic Tariff (2023–24).

ii. Appliance-based modeling (appliance wattage × duration × number of appliances).

iii. Piecewise functions for telescopic slab billing.

iv. Inclusion of fixed charges and government duty.

v. Integration of curated Excel datasets containing appliance wattage profiles.

vi. Visualization of results using Matplotlib.

vii. Full-scale web implementation using the Django framework in Python.

Exclusions

i. Industrial or commercial billing (three-phase, demand charges).

ii. Real-time smart metering or peak/off-peak tariffs.

iii. Machine learning or AI predictions (reserved for future scope).

Contributions

Within this scope, BrightBill contributes in three dimensions:

i. **Mathematics:** Formulates billing models using formulas and piecewise functions.

ii. **Computation:** Faithfully implements mathematical models in Django code.

iii. **Practical Utility:** Provides households with a transparent, interactive tool for bill estimation.

Limitations

Although BrightBill achieves its stated objectives, several structural and methodological constraints define its current boundaries:

i. **Dependence on Fixed Tariff:** The system is anchored to the 2023–24 KSEB LT-I Domestic tariff. Any revision of slabs or rates requires manual updates, reducing portability across years or regions.

ii. **Simplified Appliance Assumptions:** Appliances are modeled with fixed wattages, ignoring variations due to settings (e.g., fan speed, compressor cycles). This ensures tractability but smooths over real-world fluctuations.

iii. **Single-Appliance Modeling:** BrightBill presently models one appliance type at a time. While scaling in number and duration is possible, heterogeneous appliance combinations are not yet supported.

iv. **Basic Visualization:** Current results rely mainly on bar charts. Alternative representations such as pie charts, heat maps, or time-series plots could provide richer interpretive power.

v. **Prototype Status:** As an academic prototype, BrightBill lacks production-level features such as automatic tariff updates, multi-appliance integration, or advanced visualization dashboards. These omissions clarify its role as a proof-of-concept rather than a commercial solution.

By focusing on domestic billing with clear mathematical foundations, **BrightBill** ensures accuracy and usability while laying the groundwork for future enhancements such as multi-appliance integration, time-of-use tariffs, seasonal adjustments, and AI-based forecasting.

5.4 Extensions and Higher-Level Mathematics

BrightBill in its present form is anchored in piecewise-linear tariff functions and arithmetic calculations. While this suffices for demonstrating the logic of electricity billing and enabling scenario-based simulations, the framework naturally opens pathways to higher-level mathematics and advanced computational methods. Exploring these possibilities reveals how BrightBill could evolve from a didactic prototype into a platform for research and real-world energy optimization.

Time-Based Consumption and Peak-Hour Tariffs

A significant future extension of BrightBill involves the inclusion of **time-of-use (ToU) tariffs**. In practice, electricity charges are not always uniform throughout the day. Utilities often impose *peak-hour rates* (higher charges when demand is high) and *off-peak rates* (lower charges when demand is low).

Currently, BrightBill computes bills under the assumption of a single-rate tariff applied to all units. This simplification makes the system broadly applicable, but it does not capture the economic incentives of ToU pricing. An improved model would divide consumption into time blocks (e.g., morning, day, evening, night), assigning different rates to each block.

Mathematically, such a model can be represented as:

$$C = \sum_{i=1}^{n} U_i \cdot T_i,$$

where U_i is the number of units consumed during time block i, and T_i is the tariff rate for that block. This generalizes the current single-rate formulation while maintaining computational simplicity.

From a higher-level mathematical perspective, this framework opens the door to optimization. One could, for example, formulate the problem of *minimizing the total bill* by scheduling appliances in off-peak hours. This leads naturally to advanced techniques such as linear programming, integer optimization, or dynamic scheduling models, transforming BrightBill from a calculator into a *decision-support tool for energy management.*

Optimization and Resource Allocation

One natural extension lies in optimization theory. At present, BrightBill reports the cost of given consumption patterns. A more advanced version could move from descriptive modeling to prescriptive decision-making. Households could ask: *Given a monthly budget, how should I distribute appliance usage across days and time periods to minimize expenditure while satisfying essential needs such as lighting, cooling, or refrigeration?* This problem aligns closely with linear programming, where objective functions (minimizing cost) are subject to constraints (budget, minimum hours of use). In cases where non-linear tariffs or appliance

efficiency curves are included, convex optimization or dynamic programming techniques may be necessary. Such methods would transform BrightBill into a decision support tool for rational allocation of scarce resources.

Stochastic and Probabilistic Modeling

Current models assume deterministic usage patterns (e.g., a fan runs for exactly 8 hours daily). Reality, however, is stochastic: appliances cycle on and off unpredictably, user behavior varies across days, and seasonal factors alter demand. Introducing probability distributions to represent these uncertainties allows BrightBill to become a simulator rather than a calculator. For instance, refrigerator compressors may be modeled using a Bernoulli process, while seasonal demand fluctuations could be represented using time-varying probability distributions. Outputs would then include expected costs with associated variances or confidence intervals. Such stochastic modeling is critical for risk-aware planning, as it enables households to anticipate best-case and worst-case billing scenarios rather than relying on single-point estimates.

Machine Learning and Data-Driven Forecasting

Another trajectory involves embedding machine learning into BrightBill's architecture. By collecting historical consumption and bill data, regression or time-series models could be trained to predict future bills with higher accuracy. Unlike purely rule-based calculations, these models can account for hidden dependencies, behavioral routines, and non-linearities that are difficult to encode explicitly. Techniques such as random forests, gradient boosting, or neural networks could uncover latent patterns (e.g., correlation between weather changes and air-conditioner usage). Coupling BrightBill with IoT devices and smart meters would provide real-time feedback, enabling adaptive learning systems that continuously improve predictions. Over time, BrightBill could evolve into a personalized energy assistant, tailoring insights to each household's unique habits.

Graph and Network Perspectives

Beyond individual appliances, higher mathematics such as graph theory could be leveraged to model entire appliance networks. Nodes could represent appliances,

edges could denote interdependencies (e.g., refrigerator load affecting inverter operation), and network analysis could identify critical devices driving peak demand. Such representations allow for community-level studies, especially in shared electricity environments such as apartments or micro-grids. Further, incorporating flow optimization within these graphs can guide strategies for load balancing, distributed generation, or demand response.

Game-Theoretic and Collective Scenarios

Finally, game theory provides a framework for analyzing shared electricity contexts where multiple households interact. In apartment complexes, for example, individual decisions about cooling or lighting contribute to aggregate demand that influences shared transformer loads or community tariffs. Cooperative game models could suggest fair cost-sharing arrangements, while non-cooperative models could study competition for limited supply. Extending BrightBill in this direction would align it with emerging paradigms of community energy management and collective sustainability.

Summary

Taken together, these extensions move BrightBill from basic computation toward advanced analytics. Optimization brings prescriptive guidance, stochastic modeling introduces uncertainty awareness, machine learning enables personalization, and higher mathematics like graph theory and game theory broaden the scope from individual households to collective systems. The evolution of BrightBill thus illustrates how a simple billing prototype can grow into a sophisticated tool for energy forecasting, planning, and policy experimentation.

5.5 Synthesis and Final Conclusion

The development of BrightBill was guided by three central objectives: (1) to establish mathematical correctness in modeling electricity billing, (2) to translate these models faithfully into computational code, and (3) to deliver results in a format that is usable, accessible, and educational for ordinary consumers.

A critical review of the results demonstrates that all three objectives have been realized. At the mathematical level, BrightBill achieves exact correspondence

with manual calculations, ensuring that piecewise tariff functions are implemented without discontinuities at slab boundaries. This guarantees that the system is not merely an approximation, but a formally sound representation of the KSEB billing process. At the computational level, the use of Django and Python libraries provides robustness, reproducibility, and scalability, bridging the gap between theoretical models and practical execution. At the user-facing level, the inclusion of visualizations, scaling scenarios, and comparative analyses ensures that non-technical users can grasp not only the numerical outcomes but also the underlying drivers of cost.

Importantly, BrightBill achieves more than the minimal goals of accuracy and implementation. By enabling appliance-to-appliance comparisons, duration- based scaling, and interactive "what-if" exploration, it introduces an educational dimension. Users are not passive recipients of bills but active participants in understanding how behavior and appliance usage patterns shape expenditure. This shift from static presentation to dynamic engagement marks a significant advance: BrightBill becomes a learning tool for households and a potential teaching aid in energy awareness programs.

The system's current limitations—such as dependence on a fixed tariff structure, assumptions of constant wattage, and basic visualization—should not be read as weaknesses but as signposts for future research and development. These boundaries define the scope of the present prototype, while simultaneously suggesting natural extensions into optimization, stochastic modeling, machine learning, and community-level energy analysis. Thus, the very act of identifying constraints paves the way for innovation.

In conclusion, BrightBill demonstrates how abstract mathematical models can be faithfully converted into computational tools with real-world relevance. It provides a bridge between theory and practice, offering transparency in calculation, interactivity in exploration, and empowerment in decision- making. The project exemplifies how mathematics, computation, and user- centric design can converge to address practical societal challenges such as energy awareness and cost management. BrightBill is therefore not only a prototype for electricity billing but also a proof of concept for how data- driven, mathematically rigorous systems can influence everyday household choices and contribute to a more informed, energy-

conscious society.

[1] IEEE. (2019). *IEEE Standard for Floating-Point Arithmetic* (IEEE Std 754-2019). IEEE.

[2] Higham, N. J. (2002). *Accuracy and stability of numerical algorithms* (2nd ed.). SIAM.

[3] Goldberg, D. (1991). What every computer scientist should know about floating-point arithmetic. *ACM Computing Surveys*, 23(1), 5–48.

[4] Kahan, W. (1965). Pracniques: Further remarks on reducing truncation errors. *Communications of the ACM*, 8(1), 40.

[5] Python Software Foundation. (2024). *Python Decimal module documentation*. Retrieved from https://docs.python.org/3/library/decimal.html

[6] Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. *Computing in Science & Engineering*, 9(3), 90–95.

[7] McKinney, W. (2022). *Python for data analysis* (3rd ed.). O'Reilly Media.

[8] Django Software Foundation. (2024). *Writing views — Django documentation*. Retrieved from https://docs.djangoproject.com/en/stable/topics/http/views/

[9] pandas development team. (2024). *pandas.read_excel API Reference*. Retrieved from https://pandas.pydata.org/docs/reference/api/pandas.read_excel.html

[10] OpenPyXL Developers. (2024). *OpenPyXL Documentation*. Retrieved from https://openpyxl.readthedocs.io/

[11] Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2009). *Introduction to algorithms* (3rd ed.). MIT Press.

[12] Kerala State Electricity Board (KSEB). (2023). *LT Domestic Tariff (Order OP 18/2022)*. Retrieved from https://www.kseb.in/

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