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ARTICLE

Statistical Modeling and Energy Benchmarking of Electrical and Thermal Energy Consumption in an Indian Dairy Industry

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ABSTRACT: The energy consumed in dairy processing depends on product, process, and system parameters; therefore, energy prediction, identification of significant parameters, and benchmarking are essential for energy management. This study develops regression models to predict electrical, thermal, and specific energy consumption (SEC) in two Indian dairy plants using Pearson correlation, stepwise multiple linear regression with k-fold cross-validation, variance inflation factor (VIF) analysis, and residual diagnostics. The initial electrical energy model had an R^2 of 99.12% with severe multicollinearity (VIF ≈ 973.63). Stepwise regression eliminated the multicollinearity but left positive autocorrelation (Durbin–Watson statistic = 0.88), which the Cochrane–Orcutt procedure removed. The final model retained curd sales and capacity utilization (CU) as significant variables, with a 10-fold R^2 of 93.79%, a VIF of 2.05, and a Durbin–Watson statistic of 1.963. The final thermal energy model retained milk sales as the only significant variable (10-fold R^2 = 84.60%). The product-specific electrical SEC models for milk, curd, and butter-ghee retained CU as the significant variable, with R^2 values of 65.48%, 62.97%, and 63.93%, respectively. Because UHT milk was produced only in Plant-B, its electrical and thermal SEC models were fitted to Plant-B data alone and electrical SEC model had CU and thermal SEC model had curd and UHT sales as significant variables, with 10-fold R^2 values of 55.98% and 85.64%, respectively. Thermal SEC models for the other products were infeasible because thermal SEC in Plant-B varied too strongly with CU. Correlation analysis and graphs showed a significant negative correlation between CU and both electrical and thermal SEC. The electrical SEC of Plant-B was about 32% higher than that of Plant-A, whereas the thermal SEC difference was insignificant. Plant-B could save 410,313 kWh/year by improving its CU and energy intensity and adopting energy-efficient equipment similar to Plant-A. The study offers a statistically sound framework for dairy-industry energy management.

KEYWORDS: Dairy industry; energy consumption; specific energy consumption; regression modeling; energy efficiency; capacity utilization; multicollinearity; Cochrane–Orcutt; cross-validation

1 Introduction

As energy demand grows in industrial and agro-based production, the efficient management of energy use becomes increasingly necessary. This is especially true of energy-intensive food-processing industries. The dairy industry contributes substantially to food security and agro-economic development, but it requires

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large quantities of both electrical and thermal energy for refrigeration, milk reception and transportation, homogenization, pasteurization, hot water and steam production, product treatment, cold storage, packaging, and wastewater treatment [1–4]. Energy consumption is therefore an important component of production cost and is directly linked to the efficiency and economic performance of dairy-processing facilities. Rising electricity and fuel costs, together with the need to reduce the environmental impact of energy consumption, make energy management and performance evaluation even more urgent [1,5,6]. Effective methods are therefore needed to identify the main drivers of energy consumption and to quantify their roles.

Fig. 1 shows the typical flow of a dairy processing plant, which combines thermal and mechanical operations. Milk and milk products, such as curd, butter, ghee, and ultra-high-temperature (UHT) milk, are processed through a series of well-controlled steps to ensure product quality and safety. Mechanical operations require large amounts of electrical energy for pumping, homogenization, refrigeration, and other treatments, whereas thermal energy is used mainly for heating, pasteurization, evaporation, and steam generation [7,8]. Pasteurized milk production involves quality testing, filtration, standardization, homogenization, pasteurization, and refrigerated storage. Butter-ghee production additionally involves cream separation and thermal processing of the cream, and curd production involves high-temperature treatment followed by refrigerated storage [7,8]. The ultra-high-temperature treatment of milk is followed by aseptic packaging to extend its shelf life.

The distinctive feature of dairy processing is the simultaneous presence of thermal and mechanical processes with quite different energy-supply requirements. Dairy processing consists of milk reception, quality testing, filtration, standardization, homogenization, pasteurization, refrigeration, storage, and product-specific operations for curd, butter, ghee, and UHT milk production [7,8]. Electrical energy is required for pumping, refrigeration, homogenization, mixing, material handling, packaging, and other auxiliary equipment, while thermal energy is required for heating, pasteurization, product treatment, and the generation of hot water and steam [7,8].

The complex interaction among production volume, product mix, operating conditions, equipment loading, and utility performance produces energy behavior that is difficult to evaluate from total energy consumption alone. Specific energy consumption (SEC), defined relative to the volume of product produced, allows a more detailed analysis of the performance of a dairy-processing facility. Industrial energy consumption is conventionally assessed and predicted through engineering calculations, energy audits, statistical modeling, and energy-management methods. Regression analysis is a useful tool for the quantitative evaluation of the dependence of energy consumption on several production and operational variables, with relative transparency and clarity of the model [9–11]. Multiple linear regression (MLR) allows the simultaneous evaluation of several explanatory variables and their statistical relationships with the energy-consumption indicator. Such models can therefore provide valuable decision-support information for production planning, energy-consumption forecasting, benchmarking, and performance evaluation. The applicability of regression-based approaches to various energy-related problems has been shown in previous studies. In particular, Ardakani and Seyedaliakbar [12] used multivariate regression to examine the relationships among energy consumption, economic growth, and CO_2 emissions, while Bhanuprakash and Manish [13] noted the simplicity and clarity of linear regression for energy-consumption analysis. Statistical regression can thus yield a practical energy model, provided that its assumptions and diagnostics are properly considered.

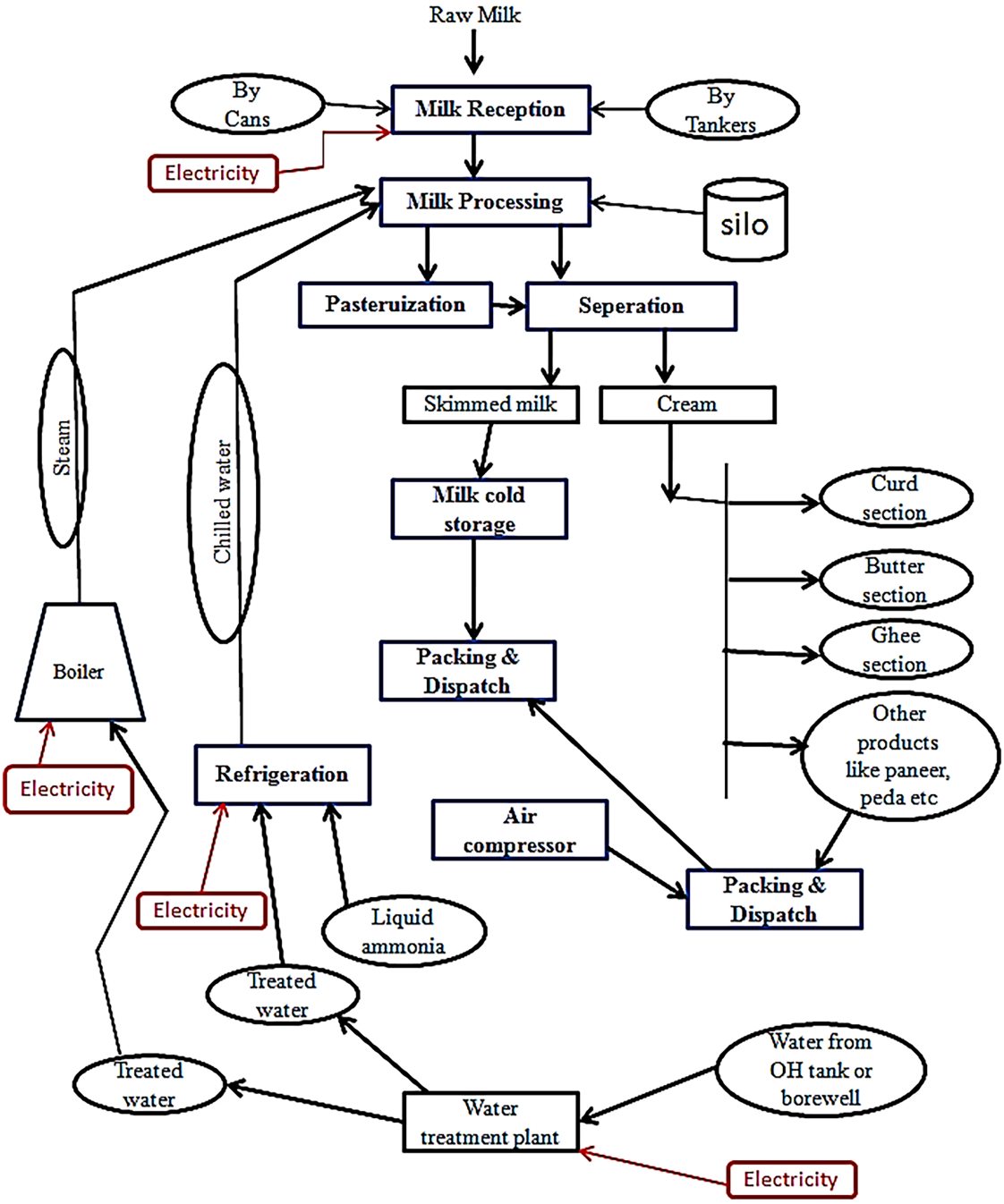


Figure 1: Overall process flow diagram.

Various statistical and machine-learning approaches have been applied in dairy-sector research. Moerkerken et al. [14] analyzed the determinants of energy efficiency in the Dutch dairy sector and identified technological, farm-size, and management-related factors as important components of energy performance. Shine et al. [15] used a support vector machine to predict the annual electricity consumption of dairy farms and showed the potential of machine-learning approaches for energy-consumption prediction. Żyłka et al. [16] developed regression-based models for electricity consumption in dairy wastewater treatment plants and revealed relationships between energy consumption and process variables such as wastewater

flow, ambient conditions, and organic load. Other studies have applied regression models to various dairy-related problems. For instance, Mbuthia et al. [17] used random regression models to analyze the impact of environmental conditions on milk production, while Kemitare et al. [18] used hierarchical multiple regression to analyze the relationships among value-chain practices, productivity, and trade performance. These studies illustrate the potential of statistical models for dairy-related problems. In recent years, regularized regression and machine-learning techniques have further expanded the possibilities for energy and production modeling. Mat et al. [19] showed that Elastic Net regularization is useful in the presence of correlated explanatory variables while retaining strong predictive properties. Çetiner and Çetiner [20] compared conventional regression methods with advanced machine-learning methods for predicting energy consumption and found that the advanced methods could offer better predictive performance but with less interpretability. Likewise, Asghar et al. [21] compared various regression and machine-learning methods for demand-side energy management and showed that predictive models can support energy-management applications. Rambabu et al. [22] compared linear and nonlinear machine-learning methods for predicting energy consumption and discussed the advantages and disadvantages of each. More recently, Sarswatula et al. [23] applied machine-learning models to more than 15,000 industrial energy-audit records of the U.S. Department of Energy to predict plant energy consumption, and Lee et al. [24] used multilayer perceptron and support vector regression algorithms to predict the electricity and liquefied natural gas consumption of food factories. In the dairy sector, Miserocchi et al. [6] proposed performance indicators and load profiles for the energy management of a cheese dairy plant in Italy, while Hernández Touset and Roche Delgado [3] assessed the thermal energy consumption of a fluid-milk plant and identified refrigeration and steam generation as the main areas for energy conservation. Devaru and Gopalakrishnan [25] developed a multiple linear regression model to predict the electrical energy consumption of lumber sawing, a wood-industry process, using product-, process-, and system-related parameters. They showed that an interpretable regression model can identify the relevant factors that affect industrial energy consumption and specific energy use.

An important methodological problem in applying regression models to industrial energy data is that the explanatory variables are often highly correlated. In a dairy processing plant, production volume, capacity utilization, product sales, energy intensity, and equipment loading may all vary, but they can also be correlated. Such relationships may lead to multicollinearity among the predictor variables. Although multicollinearity does not necessarily reduce the overall predictive ability of a regression model, it can make individual regression coefficients less precise and less stable, complicate the interpretation of the model, and affect the significance of individual predictors [10,11]. A high coefficient of determination alone is therefore not sufficient to ensure the adequacy and interpretability of an industrial energy-consumption model. To obtain a statistically defensible model, appropriate diagnostic procedures are required, namely variance inflation factor (VIF) assessment, variable selection, residual analysis, and model validation.

The existing literature also reveals a research gap in integrated energy modeling at the level of industrial dairy plants. Previous studies have focused on energy efficiency, energy consumption, or production performance using one or a few process variables, parameters of specific equipment, farm-level variables, or advanced prediction methods. According to the available literature, very little attention has been given to a unified and interpretable regression framework that incorporates product-, process-, and system-related variables for electrical and thermal energy consumption in large-scale dairy processing plants. Moreover, total energy consumption together with product-specific SEC can give a better picture of energy performance, because the former reflects the overall utility requirement, whereas the latter reflects production throughput. This is especially relevant when comparing plants with different production sizes or product mixes.

Capacity utilization is another critical factor. In industrial energy systems, most energy needs are relatively constant, while some depend on capacity. The energy required per unit of product may therefore vary as the level of production shifts, even if the basic process technology is unchanged. Capacity utilization may thus be a significant factor explaining SEC. Other plant characteristics, such as equipment configuration, product mix, operating practices, utility-system characteristics, and maintenance condition, can also cause differences among plants.

These relationships are explored under actual operating conditions in two industrial-scale dairy processing plants. Plant-level comparison can reveal differences in electrical and thermal SEC and provide useful benchmarking information. However, the plants may differ in installed capacity, product mix, equipment configuration, and operating practices; the comparison between plants should therefore be viewed as performance benchmarking, to a limited extent, rather than as a controlled experiment to determine the effect of one operational variable on another. In this context, regression analysis can detect statistical associations between energy performance and production or process variables, and comparative SEC analysis can reveal practical differences in plant performance.

Research Objectives

The main objectives of this study are:

1. To study the correlations among production-related variables, capacity utilization, and electrical and thermal energy consumption in the selected dairy processing plants.
2. To build multiple linear regression models to predict total electrical energy consumption, total thermal energy consumption, and the specific energy consumption (SEC) of individual products.
3. To identify significant predictor variables, build parsimonious regression models, and examine multicollinearity through variance inflation factor (VIF) analysis.
4. To assess the predictive ability and stability of the regression models using the coefficient of determination, predicted R^2, and 10-fold cross-validation.
5. To check for residual dependence using the Durbin–Watson statistic and residual autocorrelation analysis and, if first-order serial autocorrelation is found, to apply the Cochrane–Orcutt procedure to improve the statistical adequacy of the regression model.
6. To compare the electrical and thermal SEC of Plant-A and Plant-B and to assess, through benchmarking, the potential reduction in electricity use at Plant-B.

2 Methodology

The present study proposes a regression-analysis framework for developing an interpretable model of electrical and thermal energy consumption and product-specific SEC in two industrial dairy processing plants in India. The analysis incorporates product-related variables (milk, curd, butter-ghee, and UHT production), process-related variables (capacity utilization), and system-related energy-intensity indicators. The relationships among the variables are first analyzed using Pearson correlation, and multiple linear regression is then used to develop models of energy consumption and SEC. Because the initial models showed significant multicollinearity, VIF analysis and stepwise regression are used to obtain more stable and interpretable sets of predictors. Statistical diagnostics and residual analysis are then used to assess model adequacy.

The electrical and thermal SEC of the two plants are also compared, and their variation with production throughput and capacity utilization is studied. The behavior of electrical and thermal energy is examined separately because they are different forms of energy with different process and equipment requirements. The analysis also establishes a benchmark for evaluating the electrical-energy-saving opportunity that could

be realized if the lower-performing plant matched the performance of the better-performing one. This assessment does not make direct causal judgments about savings from higher capacity utilization alone; it is a scenario-based, or benchmarking, assessment.

The contribution of this study is therefore not merely a regression equation with a high R^2, but a statistically screened and interpretable framework for energy benchmarking in industrial dairy production. The framework incorporates product-, process-, and system-related variables in a single regression model, explicitly addresses multicollinearity through VIF assessment and variable selection, considers both total energy consumption and product-specific SEC, and combines statistical modeling with comparative plant-level benchmarking. The approach aims to give plant managers and energy engineers a practical tool for identifying significant influences on energy consumption and assessing energy-performance gaps, while taking appropriate care in interpreting the causal nature of the differences.

The present study is not intended to develop a new regression algorithm; rather, it builds on existing statistical methods and integrates them into a framework for interpretable energy modeling and benchmarking in dairy processing. Three sets of models are developed, for total electrical energy consumption, total thermal energy consumption, and product-specific SEC, using variables related to products, processes, and systems. To determine whether multicollinearity exists, correlation analysis and the variance inflation factor (VIF) are used, and stepwise regression is then performed to identify the relevant predictors. K-fold cross-validation is applied to the final models to investigate their predictive stability, and the Durbin–Watson statistic is used to examine residual dependence between successive monthly observations. Finally, the model outputs are combined with plant-level SEC benchmarking to estimate the electricity-saving potential under a "benchmark scenario". The contribution of this study is therefore the integration of statistical screening, interpretable regression modeling, model validation, residual diagnostics, and plant-level energy benchmarking using actual operating data from dairy processing plants.

To explore the relationships among production characteristics, capacity utilization, and electrical and thermal energy consumption, a quantitative, data-driven approach was applied to two industrial dairy processing plants [1,26,27]. Operational data were collected monthly for 12 months for each plant, giving a total of 24 observations.

The methodology (Fig. 2) involved data collection and pre-processing, formulation of operational and energy-performance parameters, regression modeling and variable selection, 10-fold cross-validation, and assessment of residual independence. Pearson correlation analysis was performed first to explore the linear relationships among the measured variables. Multiple linear regression (MLR) was then used to build models for total electrical energy consumption, total thermal energy consumption, and product-specific energy consumption (SEC). The variance inflation factor (VIF) was calculated to check for multicollinearity, and stepwise regression was used to obtain parsimonious models.

Residual independence was also checked using the Durbin–Watson (DW) statistic and the residual autocorrelation function (ACF), because the observations came from consecutive monthly operating periods. The Cochrane–Orcutt procedure was applied to regression models found to have first-order residual autocorrelation. The developed models were interpreted as statistical relationships among the observed operating conditions, not as causal effects.

The data comprised product parameters, process parameters, and system parameters. Product parameters included milk, curd, butter-ghee, and UHT production/sales, while the process parameter was capacity utilization. System parameters, such as electrical intensity (hp/100 L) and thermal intensity (MJ/100 L), were formulated with production scale, operational efficiency, and system performance in the dairy processing environment in mind [1,26,27]. Total electrical energy consumption (kWh) and total thermal energy

consumption (kJ) were collected along with these data. Before the regression analysis, the data were pre-processed to ensure consistency, completeness, and uniformity [9,10].

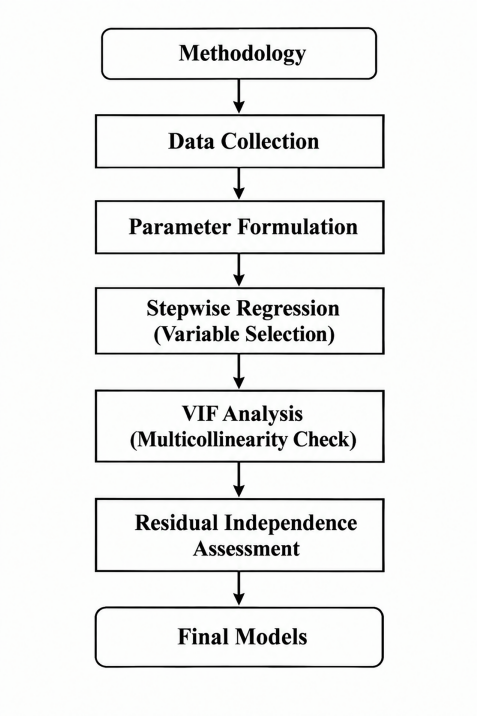


Figure 2: Flowchart of the methodology adopted for regression-based energy modeling and validation.

2.1 Data Collection

Observations were taken monthly from two industrial dairy processing plants for 12 months, giving 12 observations per plant and 24 observations in the combined data set (Table 1). The data collected comprised product quantities, capacity utilization, installed equipment capacities, total electrical energy consumption, and total thermal energy consumption.

Table 1: Operational data of dairy Plant-A and Plant-B.

Sl. No.	Plant	Total kWh	Milk Sales (L)	Curd Sales (L)	B&G Sales (L)	UHT Sales (L)	hp/100 L	Total kJ	MJ/100 L
1	A	553,600	16,080,137	1,614,400	644,700	0	0.5260	7,868,268,440	2.5
2	A	538,700	14,384,523	1,747,850	598,278	0	0.5260	8,039,289,000	2.5
3	A	536,600	14,600,792	1,831,075	609,079	0	0.5260	6,655,488,400	2.5
4	A	509,300	13,876,040	1,775,650	541,964	0	0.5260	7,072,564,100	2.5
5	A	517,100	14,321,966	1,699,750	519,121	0	0.5260	8,134,285,900	2.5
6	A	524,800	14,151,287	1,801,700	523,747	0	0.5260	8,627,537,000	2.5
7	A	499,200	12,239,277	2,005,300	408,227	0	0.5260	7,513,484,900	2.5
8	A	576,700	12,763,496	2,507,900	418,676	0	0.5260	6,661,095,000	2.5
9	A	578,500	12,147,554	2,763,400	365,610	0	0.5260	7,964,383,500	2.5
10	A	612,100	14,129,210	2,554,700	417,429	0	0.5260	8,506,259,300	2.5
11	A	584,955	14,962,075	2,097,050	545,765	0	0.5260	8,577,748,000	2.5
12	A	590,939	17,739,281	1,722,200	674,440	0	0.5260	7,906,902,800	2.5
13	B	307,150	2,454,698	266,242	158,756	2,220,678	0.5322	3,763,385,390	2.5
14	B	315,150	1,733,460	278,282	148,693	2,361,738	0.5322	3,492,351,670	2.5

(Continued)

Table 1 (continued)

Sl. No.	Plant	Total kWh	Milk Sales (L)	Curd Sales (L)	B&G Sales (L)	UHT Sales (L)	hp/100 L	Total kJ	MJ/100 L
15	B	316,450	2,377,533	297,289	179,530	2,468,341	0.5322	3,792,522,260	2.5
16	B	315,350	2,546,467	291,943	145,936	2,677,118	0.5322	4,150,014,130	2.5
17	B	302,950	2,810,826	259,213	139,926	2,488,459	0.5322	3,941,973,910	2.5
18	B	298,050	2,625,796	296,929	144,111	2,983,373	0.5322	3,490,570,790	2.5
19	B	271,900	2,226,083	359,649	115,325	2,372,613	0.5322	3,101,682,380	2.5
20	B	306,450	2,630,629	438,420	135,945	2,121,962	0.5322	3,219,388,590	2.5
21	B	308,650	2,726,207	455,997	152,115	2,292,146	0.5322	3,032,732,180	2.5
22	B	317,250	3,744,868	441,222	235,466	2,819,659	0.5322	3,431,788,640	2.5
23	B	338,300	3,401,179	371,344	171,643	3,032,574	0.5322	3,743,191,750	2.5
24	B	352,200	3,143,355	252,531	178,936	3,674,915	0.5322	4,041,452,080	2.5

Sl. No.	Total Sales	Capacity Utilization	Elec SEC Milk kWh/L	Ther SEC Milk kJ/L	Elec SEC Curds kWh/L	Ther SEC Curds kJ/L	Elec SEC B&G kWh/L	Ther SEC B&G kJ/L	Elec SEC UHT kWh/L	Ther SEC UHT kJ/L
1	18,339,237	0.76	0.024	357	0.072407	782	0.070185	1338	—	—
2	16,730,651	0.70	0.025	393	0.075195	861	0.072887	1472	—	—
3	17,040,946	0.71	0.025	319	0.073202	698	0.070955	1193	—	—
4	16,193,654	0.67	0.025	357	0.07311	783	0.070865	1338	—	—
5	16,540,837	0.69	0.025	407	0.07368	892	0.071419	1524	—	—
6	16,476,734	0.69	0.025	430	0.074259	942	0.071979	1611	—	—
7	14,652,804	0.61	0.026	414	0.076612	906	0.07426	1549	—	—
8	15,690,072	0.65	0.027	336	0.080042	736	0.077585	1258	—	—
9	15,276,564	0.64	0.027	407	0.080326	892	0.07786	1524	—	—
10	17,101,339	0.71	0.027	400	0.079393	875	0.076956	1496	—	—
11	17,604,890	0.73	0.026	397	0.0764	870	0.074055	1487	—	—
12	20,135,921	0.84	0.024	329	0.070855	721	0.06868	1232	—	—
13	5,100,374	0.34	0.038	439	0.112241	963	0.108796	1646	0.075366	976
14	4,522,173	0.30	0.041	429	0.121631	939	0.117897	1606	0.081671	952
15	5,322,693	0.35	0.036	413	0.108075	905	0.104758	1547	0.072568	917
16	5,661,463	0.38	0.034	429	0.10215	939	0.099014	1606	0.06859	952
17	5,698,423	0.38	0.034	418	0.100622	916	0.097533	1566	0.067564	928
18	6,050,209	0.40	0.030	334	0.089702	732	0.086949	1252	0.060232	742
19	5,073,670	0.34	0.032	356	0.096659	780	0.093692	1333	0.064903	790
20	5,326,956	0.36	0.036	365	0.106426	800	0.10316	1368	0.071461	811
21	5,626,465	0.38	0.034	323	0.100895	708	0.097798	1210	0.067747	718
22	7,241,215	0.48	0.028	289	0.08301	634	0.080462	1084	0.055738	643
23	6,976,740	0.47	0.031	323	0.091002	707	0.088209	1209	0.061105	717
24	7,249,738	0.48	0.030	323	0.089156	707	0.086419	1208	0.059865	716

Plant-A is rated at 800,000 L/day and has an installed motor capacity of 4208 hp and a boiler capacity of 20,000 MJ/h. It processes regular milk, curd, and butter-ghee (B&G). Plant-B has a rated production capacity of 500,000 L/day, an installed motor capacity of 2661 hp, and a boiler capacity of 12,500 MJ/h. Plant-B also produced UHT milk, in addition to regular milk, curd, butter, and ghee. Production capacity, installed equipment, and product portfolio were treated as characteristics of the individual plants.

The quantities of milk, curd, B&G, and UHT in each monthly observation were recorded according to the availability of these products at the plant. Total electrical energy consumption was measured in kWh and total thermal energy consumption in kJ. All collected data were subjected to consistency and completeness checks before statistical analysis.

The data set is not experimental; it reflects the actual monthly operating conditions. The relationships derived from the regression models and the differences between the two plants were therefore considered only within the range of the observed operating conditions and in light of the differences in plant configuration and product mix.

Equipment List

Tables 2 and 3 list the major equipment used in dairy Plant-A and Plant-B, with their ratings.

Table 2: List of major equipment used in dairy Plant-A, with their ratings.

Sl. No.	Equipment	Qty.	Rating
1	Air Compressor	04	106 hp
	Refrigeration Section		
2	Screw Compressor	03	351 hp
3	Vilter compressor motor	02	60 hp
4	Chilling Water pump motor	04	20 hp
5	Motor (condenser 1 fan), 15 hp	03	15 hp
6	VFD for Screw Compressor	03	335 hp
	ETP		
7	Air Blower motor	02	40 hp
8	Intermediate motor	02	10 hp
9	Sludge Sump motor	02	15 hp
10	Treated water pump motor	01	15 hp
	WTP		
11	Hydro soft pump Motor	03	15 hp
12	Hydro filter pump Motor	02	10 hp
13	Hydro RO pump Motor	03	15 hp
14	RO High pressure pump	02	20 hp
15	Filter feed pump	02	15 hp
	Milk Reception		
16	Tanker Unloading Pump Motor	02	10 hp
	CIP Section		
17	CIP Tanker Line	03	10 hp
	Process CIP		
18	Line-1	03	15 hp
	Milk Processing		
19	Cream Separator motor 20 KL	01	50 hp
20	Cream Separator motor 30 KL	01	34 hp
21	30 KL Homogenizer	—	268 hp
22	20 KL Homogenizer	—	177 hp
23	Booster motor pump milk	02	15 hp

(Continued)

Table 2 (continued)

Sl. No.	Equipment	Qty.	Rating
	PMST		
24	PMST to Product Section	03	10 hp
	Butter Section		
25	CBMM Motor 3Ø	03	15 hp
	Boiler		
26	VFD for ID Fan Boiler	02	74 hp
	Fuel Handling System		
27	Fan DE dusting	01	10 hp
	Boiler Operating System		
28	Feed pump	02	10 hp
29	Primary Forced draft fan back ward type	01	15 hp
30	Secondary Forced draft fan back ward type	01	12.5 hp
31	Wood Crushing motor	01	101 hp
32	Induced Draft Fan	01	74 hp
33	Crusher Motor	01	10 hp
34	Feed Water Pump	01	10 hp
	OLD Boiler		
35	ID Fan motor	01	20 hp
	Product		
36	Ghee Separator motor	01	10 hp

Table 3: List of major equipment used in dairy Plant-B, with their ratings.

Sl. No.	Equipment	Qty.	Rating/Capacity
	Tanker Bay, RMST, PMST, CIP and RCM		
1	3 Phase Induction Motor	06	7.5 hp
2	3 Phase Induction Motor	02	10 hp
3	3 Phase Induction Motor	01	15 hp
	Boiler Section		
4	Thermax Boiler	02	5 t
5	3 Phase Induction Motor	01	7.5 hp
6	3 Phase Induction Motor	01	30 hp
7	3 Phase Induction Motor	03	50 hp

(Continued)

Table 3 (continued)

Sl. No.	Equipment	Qty.	Rating/Capacity
	UHT		
8	3 Phase Induction Motor	02	7.5 hp
9	3 Phase Induction Motor	02	10 hp
10	3 Phase Induction Motor	03	15 hp
11	3 Phase Induction Motor	02	25 hp
12	3 Phase Induction Motor	01	30 hp
13	3 Phase Induction Motor	01	200 hp
	Processing Unit for Milk		
14	3 Phase Induction Motor	03	7.5 hp
15	3 Phase Induction Motor	02	15 hp
16	3 Phase Induction Motor	01	30 hp
17	3 Phase Induction Motor	01	268 hp
	ETP		
18	3 Phase Induction Motor	02	7.5 hp
19	3 Phase Induction Motor	02	40 hp
	WTP		
20	3 Phase Induction Motor	10	7.5 hp
21	3 Phase Induction Motor	02	15 hp
	Refrigeration		
22	3 Phase Induction Motor	02	7.5 hp
23	3 Phase Induction Motor	05	25 hp
24	3 Phase Induction Motor	02	40 hp
25	3 Phase Induction Motor	03	335 hp
	Air Compressor		
26	3 Phase Induction Motor	02	105 hp

2.2 Parameter Formulation

- Capacity utilization was computed to represent the operational loading of the plants:

  Capacity Utilization = Actual Production/Installed Capacity

- Electrical energy intensity is calculated as follows:

  hp/100 L = Total Installed Motor Capacity (hp)/Daily Production Capacity (Liters) × 100

- Thermal energy intensity is calculated as follows:

  MJ/100 L = Total Boiler Capacity (MJ)/Daily Production Capacity (Liters) × 100

These parameters link equipment capacity with production scale and serve as proxies for system efficiency.

Sample Calculation of System Parameters for Plant-A and Plant-B

1. Capacity Utilization: The capacity utilization is defined as:

   Capacity Utilization = Actual Production/Installed Capacity

   Sample for Plant-A (Month 1)

   Total production = 18,339,237 L/month

   Installed capacity = 800,000 L/day × 30 days = 24,000,000 L/month

   CUA = 18,339,237/24,000,000 = 0.764 ≈ 0.76

   Sample for Plant-B (Month 1)

   Total production = 5,100,374 L/month

   Installed capacity = 500,000 L/day × 30 days = 15,000,000 L/month

   CUB = 5,100,374/15,000,000 = 0.34

2. Electrical Intensity (hp/100 L)

   The electrical intensity is calculated as:

   hp/100 L = Total Installed Motor Capacity (hp)/Daily Production Capacity (L) × 100 (L)

   Plant-A

   Motor capacity = 4208 hp

   Production capacity = 800,000 L/day

   hp/100 LA = 4208/800,000 × 100 = 0.526

   Plant-B

   Motor capacity = 2661 hp

   Production capacity = 500,000 L/day

   hp/100 LB = 2661/500,000 × 100 = 0.5322

3. Thermal Intensity (MJ/100 L)

   The thermal intensity is calculated as:

   MJ/100 L = Total Boiler Capacity (MJ/h)/Daily Production Capacity (L) × 100 (L)

   Plant-A

   Boiler capacity = 20,000 MJ/h

   Production capacity = 800,000 L/day

   MJ/100 LA = 20,000/800,000 × 100 = 2.5

   Plant-B

   Boiler capacity = 12,500 MJ/h

   Production capacity = 500,000 L/day

   MJ/100 LB = 12,500/500,000 × 100 = 2.5

A Pearson correlation analysis was carried out to understand the relationships and potential interdependencies among the variables and to identify possible multicollinearity before the regression modeling [9]. Multiple linear regression (MLR) models were developed to establish the relationship between energy

consumption (the dependent variable) and the product, process, and system parameters (the independent variables). The regression model is represented in the general form as follows [9]:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \quad (1)$$

where Y represents the dependent variable (total energy consumption or specific energy consumption); X_i represents the independent variables; β_i represents the regression coefficients; and ε represents the error term.

In this study, regression models were developed for total energy consumption in kWh, for total energy consumption in kJ, and for product-wise specific energy consumption.

Because production variables are highly interdependent, multicollinearity among the independent variables was checked in the developed models using the variance inflation factor (VIF). To overcome multicollinearity and obtain stable regression coefficients, stepwise regression was adopted for variable selection, eliminating redundant variables.

The regression models obtained were tested diagnostically using residual analysis to check the regression assumptions. k-fold cross-validation was then used to assess model stability. Normality of residuals was checked using the Kolmogorov–Smirnov test, and residual plots were used to check homoscedasticity [9,10]. This methodological framework thus provides a robust approach for developing reliable and applicable models that help dairy processing plants understand and improve their energy-consumption patterns. Furthermore, graphical analysis was conducted on the variation of SEC with production and capacity utilization to provide better visual insight into energy-efficiency trends. A comparative study of the two dairy processing plants was also conducted to compare their production trends and SECs across different product lines.

2.3 K-Fold Cross-Validation

To determine the predictive stability of the developed regression models, ten-fold cross-validation was used. The 24 observations were divided into 10 approximately equal folds. In each iteration, nine folds were used for model fitting and the remaining fold for validation. This was repeated until every observation had been used once for validation.

The resulting out-of-fold predictions were used to obtain the cross-validated coefficient of determination ($(R^2_{CV})^2$), adjusted (R^2), and predicted (R^2) values.

The 10-fold cross-validation results were considered an evaluation of predictive stability. Because of the small sample size and the stepwise selection of variables, the cross-validation results were not used as a stand-alone test of causal validity but were considered together with the other model diagnostics.

2.4 Residual Independence Assessment

As part of the regression diagnostics, residual independence was evaluated because the data formed a sequence of monthly observations. The Durbin–Watson (DW) statistic was used to test for first-order residual autocorrelation in all regression models. A DW value close to 2 indicates little evidence of first-order autocorrelation, whereas values below 1.5 or above 2.5 suggest positive or negative residual dependence, respectively.

The residual autocorrelation function (ACF) was also used to further explore residual autocorrelation. Where first-order residual dependence was observed, the Cochrane–Orcutt procedure was applied to the

corresponding regression model: the first-order autocorrelation parameter was estimated, and the regression variables were corrected for serial correlation before the model was re-estimated.

The residual ACF was compared before and after the Cochrane–Orcutt transformation to check the effectiveness of the procedure in reducing first-order residual dependence. In the current study, the procedure was applied to the models in which first-order residual autocorrelation was found, as both a diagnostic and a corrective measure for residual dependence, and the first observation was deleted because of the transformation.

2.5 Cochrane–Orcutt Correction for Serial Correlation

1. Initially, ordinary least squares (OLS) was used to fit the regression model, and the Durbin–Watson statistic was calculated.
2. Estimation of autocorrelation coefficient (ρ): The first-order autocorrelation coefficient (ρ) was estimated from the Durbin–Watson statistic.

$$\rho = 1 - d/2 \,(d = \text{durbin-watson statistic}) \tag{2}$$

3. Variable transformation: The dependent and independent variables were transformed using the estimated ρ:

$$Yt* = Yt - \rho Yt - 1 \tag{3}$$

$$Xt* = Xt - \rho Xt - 1 \tag{4}$$

4. Model re-estimation: The regression model was re-fitted using the transformed variables.
5. Iterative correction: The estimation of ρ, the variable transformation, and the regression fitting were repeated until convergence was obtained (only one iteration was needed in the presented models).
6. Residual validation: The Durbin–Watson statistic was used to check for the absence of first-order serial correlation in the residuals of the converged model.
7. Final model: The final model contained the regression coefficients obtained after removing the autocorrelation.

3 Analysis and Results

The analysis consisted of correlation analysis, regression modeling, multicollinearity checks, residual diagnostics, model validation, and a comparison of electrical and thermal specific energy consumption (SEC). Residual independence was assessed using the Durbin–Watson statistic and residual autocorrelation analysis. The Cochrane–Orcutt procedure was used to correct first-order residual autocorrelation in the regression analysis.

3.1 Correlation Analysis

Pearson correlation analysis was used to explore the linear relationships among production, capacity utilization, electrical energy consumption, thermal energy consumption, and product-specific variables for Plants A and B. To identify the variables with significant associations with energy consumption and SEC, the analysis was carried out separately for each plant and for the combined data. These correlation results were then used to support the selection and interpretation of variables for the regression analysis.

3.1.1 Correlation Analysis of Plant-A

The correlation analysis of Plant-A showed that production throughput and capacity utilization significantly influence electrical and thermal energy performance in dairy processing operations [28]. Total electrical energy consumption showed a strong positive correlation with milk and curd sales because higher production requires greater use of refrigeration systems, pumps, homogenizers, separators, and packaging equipment [1]. Among all products, curd production exhibited the strongest influence on total electrical energy consumption.

Butter-ghee (B-G) production showed a weak and statistically insignificant correlation with total electrical energy consumption because of its smaller production volume and batch-based processing.

Milk sales were positively correlated with total thermal energy consumption, indicating higher energy consumption at higher production volumes. However, curd and butter & ghee sales did not show a significant correlation with total thermal energy consumption, which can be attributed to their smaller production volumes.

Capacity utilization positively influenced total electrical energy consumption, indicating increased utility loading during high-throughput operation. Electrical and thermal SEC showed a significant negative correlation with capacity utilization, indicating that the higher the capacity utilization, the lower the energy spent per unit of product [1,27].

A strong negative correlation existed between milk sales and butter-ghee sales, on the one hand, and both electrical and thermal SEC, on the other, confirming economies of scale in dairy processing systems [27]. Higher production throughput spreads the fixed utility loads associated with refrigeration systems, boilers, compressed-air systems, and CIP operations over larger production volumes, thereby reducing unit energy consumption.

Curd production had a positive influence on SEC because of the higher utility demand during incubation and fermentation operations. It should also be noted that curd sales were negatively correlated with milk sales; as milk sales decrease, curd sales increase, and electrical and thermal SEC rise because the milk production of the plant is reduced. Increased B&G production reduced electrical SEC, indicating efficient electrical utilization during high-volume fat-processing operations.

Although total electrical and thermal energy consumption were positively correlated with electrical and thermal SEC, respectively, capacity utilization was negatively correlated with both, indicating that the higher the capacity utilization, the lower the specific energy consumption.

Overall, the analysis confirmed that production throughput, utility loading, and product composition strongly influence energy performance in Plant-A. The correlation coefficients for Plant-A are presented in Table 4. The correlation analysis provides a preliminary evaluation of the associations among the variables, while possible serial dependence of the observations was checked in the regression analysis.

3.1.2 Correlation Analysis of Plant-B

The correlation analysis of Plant-B showed trends similar to those of Plant-A, with production throughput significantly influencing electrical and thermal energy behavior. Total electrical energy consumption was positively correlated with milk sales, butter-ghee sales, and UHT sales because higher production increased the use of refrigeration systems, milk-chilling equipment, pumps, homogenizers, separators, and utility infrastructure. Curd sales had a weak negative correlation with total kWh.

UHT milk production exerted the strongest influence on total electrical energy consumption because of the energy-intensive sterilization and aseptic packaging operations [2].

Table 4: Correlation results of Plant-A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Total kWh	1.00												
(2) Milk Sales	0.28	1.00											
(3) Curd Sales	0.57	−0.61	1.00										
(4) B&G Sales	−0.08	0.88	−0.83	1.00									
(5) hp/100 L	0.00	0.00	0.00	0.00	1.00								
(6) Total kJ	0.27	0.23	0.00	0.00	0.00	1.00							
(7) CU	0.45	0.98	−0.45	0.80	0.00	0.27	1.00						
(8) Elec SEC Milk	0.38	−0.76	0.94	−0.91	0.00	−0.02	−0.64	1.00					
(9) Ther SEC Milk	−0.20	−0.44	0.18	−0.50	0.00	0.73	−0.45	0.31	1.00				
(10) Elec SEC Curds	0.40	−0.75	0.94	−0.89	0.00	0.03	−0.63	0.97	0.35	1.00			
(11) Ther SEC Curds	−0.20	−0.44	0.18	−0.50	0.00	0.73	−0.45	0.31	1.00	0.35	1.00		
(12) Elec SEC B&G	0.40	−0.75	0.94	−0.89	0.00	0.03	−0.63	0.97	0.35	1.00	0.35	1.00	
(13) Ther SEC B&G	−0.20	−0.44	0.18	−0.50	0.00	0.73	−0.44	0.31	1.00	0.35	1.00	0.35	1.00

Note: Only the lower triangle is shown. CU = capacity utilization; Elec = electrical; Ther = thermal; SEC = specific energy consumption; B&G = butter and ghee.

Capacity utilization positively affected total electrical energy consumption, reflecting increased utility loading during high-throughput operation [1].

A strong negative correlation existed between milk, butter-ghee, and UHT sales and both electrical and thermal SEC, confirming improved energy-utilization efficiency at higher production throughput because fixed utility loads were distributed over larger production volumes. Curd production showed a strong negative correlation with thermal SEC but a relatively weak influence on electrical SEC because of stable utility demand.

Milk, butter-ghee, and UHT sales were positively correlated with total thermal energy consumption, and UHT sales showed the strongest correlation, indicating the thermally intensive nature of UHT production. In contrast, curd sales showed a significant negative correlation with total thermal energy consumption, which can be attributed to their smaller production volume.

Although total electrical energy consumption had a weak negative correlation with electrical and thermal SEC, and total thermal energy consumption had a positive correlation with thermal SEC and no correlation with electrical SEC, capacity utilization had a strong negative correlation with both electrical and thermal SEC, indicating that the higher the capacity utilization, the lower the specific energy consumption. This negative correlation between capacity utilization and electrical and thermal SEC is much stronger in Plant-B than in Plant-A because the capacity utilization in Plant-B is lower (below 50%).

Overall, the analysis demonstrated that production throughput, utility loading, and product composition significantly affect operational energy performance in Plant-B. The correlation coefficients for Plant-B are summarized in Table 5. The observed correlations were taken into account in the subsequent regression modeling, and residual autocorrelation was evaluated separately after model estimation.

3.1.3 Combined Correlation Analysis of Plants A and B

The combined correlation analysis of Plants A and B provided a comprehensive assessment of energy-utilization behavior in dairy processing systems. The integrated data set confirmed that production throughput, utility loading, and product mix significantly influence overall plant energy performance [1].

Table 5: Correlation results of Plant-B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Total kWh	1.00															
(2) Milk Sales	0.49	1.00														
(3) Curd Sales	−0.16	0.38	1.00													
(4) B&G Sales	0.58	0.69	0.20	1.00												
(5) UHT Sales	0.67	0.56	−0.29	0.42	1.00											
(6) hp/100 L	0.00	0.00	0.00	0.00	0.00	1.00										
(7) Total kJ	0.56	0.15	−0.74	0.21	0.49	0.00	1.00									
(8) CU	0.63	0.94	0.21	0.65	0.80	0.00	0.26	1.00								
(9) Elec SEC Milk	−0.16	−0.79	−0.27	−0.41	−0.68	0.00	−0.02	−0.85	1.00							
(10) Ther SEC Milk	−0.22	−0.71	−0.62	−0.43	−0.50	0.00	0.41	−0.75	0.81	1.00						
(11) Elec SEC Curds	−0.20	−0.83	−0.29	−0.43	−0.69	0.00	−0.02	−0.87	1.00	0.83	1.00					
(12) Ther SEC Curds	−0.22	−0.71	−0.62	−0.43	−0.51	0.00	0.41	−0.75	0.81	1.00	0.83	1.00				
(13) Elec SEC B&G	−0.20	−0.83	−0.29	−0.43	−0.69	0.00	−0.02	−0.87	1.00	0.83	1.00	0.83	1.00			
(14) Ther SEC B&G	−0.22	−0.71	−0.62	−0.43	−0.51	0.00	0.41	−0.75	0.81	1.00	0.83	1.00	0.83	1.00		
(15) Elec SEC UHT	−0.20	−0.83	−0.29	−0.43	−0.69	0.00	−0.02	−0.87	1.00	0.83	1.00	0.83	1.00	0.83	1.00	
(16) Ther SEC UHT	−0.22	−0.71	−0.62	−0.43	−0.51	0.00	0.41	−0.75	0.81	1.00	0.83	1.00	0.83	1.00	0.83	1.00

Note: Only the lower triangle is shown. CU = capacity utilization; Elec = electrical; Ther = thermal; SEC = specific energy consumption; B&G = butter and ghee.

Total electrical and thermal energy consumption exhibited strong positive correlations with milk sales, curd sales, and butter-ghee sales because increased production intensified the use of refrigeration systems, pumps, boilers, homogenizers, separators, packaging systems, and utility infrastructure.

Although UHT sales were positively correlated with total kWh and total kJ in Plant-B, they were not included in the combined analysis since it was not produced in Plant-A.

An interesting finding in the combined correlation analysis is that the electrical energy intensity variable (hp/100 L) was positively correlated with electrical SEC, which means that the higher the energy intensity of the plant, the higher the specific energy consumption.

Although total electrical energy consumption had a strong negative correlation with electrical SEC and total thermal energy consumption had a weak positive correlation with thermal SEC, capacity utilization had a strong negative correlation with electrical SEC and a weak negative correlation with thermal SEC, indicating that the higher the capacity utilization, the lower the specific energy consumption. Although the correlation between capacity utilization and thermal SEC is strong in the individual plants, the overall correlation is weak because of the large difference in correlation levels between the two plants.

The combined analysis further revealed strong negative correlations of milk, curd, and butter-ghee sales with electrical SEC, confirming economies of scale in dairy processing systems. Fixed utility loads associated with refrigeration systems, compressed-air systems, and CIP operations were distributed over larger production volumes, thereby reducing SEC at higher throughput levels. There was no significant correlation of milk, curd, or butter-ghee sales with thermal SEC, which can be attributed to the large difference between Plant-A and Plant-B in the correlations of thermal SEC with product sales. The combined correlation analysis gives an overall view of the linear relationships among the variables in the study. These associations were then analyzed using regression modeling, with multicollinearity and residual dependence tested separately to check the reliability of the models.

Overall, the analysis confirmed that production throughput, operational loading, and utility management significantly influence electrical and thermal energy performance in dairy processing systems. The combined correlation coefficients for Plants A and B are presented in Table 6.

Table 6: Combined correlation results for Plant-A and Plant-B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Total kWh	1.00												
(2) Milk Sales	0.97	1.00											
(3) Curd Sales	0.96	0.90	1.00										
(4) B&G Sales	0.91	0.97	0.80	1.00									
(5) hp/100 L	−0.97	−0.98	−0.95	−0.93	1.00								
(6) Total kJ	0.96	0.96	0.92	0.91	−0.97	1.00							
(7) CU	0.95	0.98	0.86	0.96	−0.94	0.93	1.00						
(8) Elec SEC Milk	−0.82	−0.87	−0.77	−0.85	0.84	−0.82	−0.92	1.00					
(9) Ther SEC Milk	0.05	0.02	0.10	−0.04	−0.10	0.23	−0.12	0.29	1.00				
(10) Elec SEC Curds	−0.82	−0.88	−0.77	−0.86	0.85	−0.82	−0.93	1.00	0.29	1.00			
(11) Ther SEC Curds	0.05	0.02	0.09	−0.04	−0.10	0.22	−0.12	0.29	1.00	0.29	1.00		
(12) Elec SEC B&G	−0.82	−0.88	−0.77	−0.86	0.85	−0.82	−0.93	1.00	0.29	1.00	0.29	1.00	
(13) Ther SEC B&G	0.05	0.02	0.09	−0.04	−0.10	0.22	−0.12	0.29	1.00	0.29	1.00	0.29	1.00

Note: Only the lower triangle is shown. CU = capacity utilization; Elec = electrical; Ther = thermal; SEC = specific energy consumption; B&G = butter and ghee.

3.2 Regression Models with All Variables

i. Prediction of Total Electrical Energy Consumption with all the variables

Milk, curd, butter & ghee (B&G), and UHT sales, along with energy intensity (hp/100 L) and capacity utilization, were considered in the multiple linear regression model for total electrical energy consumption. This model had a 10-fold cross-validated R^2 of 98.32% and can therefore be considered to have high explanatory and predictive power. However, the VIF values of the production-related predictors were high, with a maximum of 973.63, indicating a high level of multicollinearity among the predictors.

The regression analysis showed that milk sales, curd sales, UHT sales, capacity utilization, and electrical intensity (hp/100 L) were significant ($p < 0.05$) predictors of the total electrical energy consumption of the dairy processing plants. Curd sales had the largest coefficient in the regression equation and the lowest p-value. Capacity utilization was statistically significant for electrical energy consumption. The model satisfied the normality-of-residuals assumption according to the Kolmogorov–Smirnov test ($p > 0.05$). The Durbin–Watson statistic of 1.516 was satisfactory. The regression coefficients and statistical parameters of the developed model are summarized in Tables 7 and 8, and the corresponding residual plot is shown in Fig. 3.

Table 7: Regression results for total electrical energy consumption (kWh) as a function of product, process and system parameters.

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	−16,361,053	6,054,319	−2.70	0.015	—
Milk Sales	0.0554	0.0148	3.74	0.002	973.63
Curd Sales	0.1544	0.0254	6.08	0.000	63.43
B&G Sales	0.132	0.112	1.18	0.255	61.06
UHT Sales	0.0916	0.0261	3.51	0.003	157.47
hp/100 L	31,105,180	1,139,013	2.73	0.014	158.68
Capacity Utilization	−884,585	310,722	−2.85	0.011	338.42

Table 8: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fo ld R^2	Durbin–Watson
13,732.2	99.12%	98.80%	98.17%	15,950.7	98.32%	1.51619

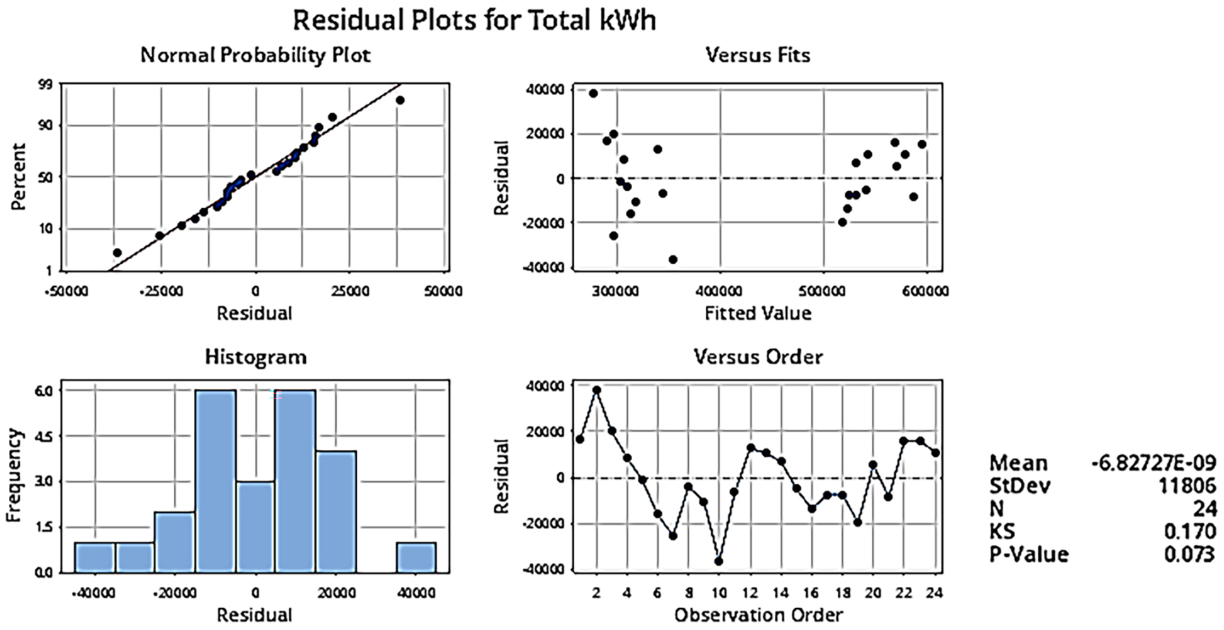


Figure 3: Residual diagnostic plots for Total kWh.

Regression equation. Total kWh = −16,361,053 + 0.0554 Milk Sales + 0.1544 Curd Sales + 0.132 B&G Sales + 0.0916 UHT Sales + 31,105,180 hp/100 L − 884,585 Capacity Utilization.

ii. Prediction of Total Thermal Energy with all the variables

Milk, curd, B&G, and UHT sales, along with capacity utilization, were included in the multiple linear regression model for total thermal energy consumption. This model had a 10-fold cross-validated R^2 of 90.83%.

The model showed a high degree of multicollinearity, with VIF values ranging from 29.78 to 606.50. Its high explanatory power must therefore be interpreted with caution because of the high correlations among the predictors. The Durbin–Watson statistic of 1.950 was close to 2 and therefore satisfactory. The first thermal model was thus used only to investigate the overall relationship between the predictor variables and thermal energy consumption, and subsequent variable selection was used to obtain a more concise and interpretable model.

The regression analysis of total thermal energy consumption showed that milk sales significantly predicted ($p < 0.05$) the thermal energy demand of the dairy processing plants. Milk processing showed the greatest thermal energy demand because of steam-dependent activities such as pasteurization, sterilization, and cleaning in place (CIP). The model satisfied the normality-of-residuals assumption according to the Kolmogorov–Smirnov test ($p > 0.05$). The regression results for thermal energy prediction are presented in Tables 9 and 10, and the corresponding residual plot is shown in Fig. 4.

Regression equation. Total kJ = 3,727,100,109 + 1118 Milk Sales + 474 Curd Sales − 6344 B&G Sales + 1147 UHT Sales − 13,639,616,416 Capacity Utilization.

Table 9: Regression results for total thermal energy consumption (kJ).

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	3,727,100,109	1,177,277,339	3.17	0.005	—
Milk Sales	1118	476	2.35	0.030	606.50
Curd Sales	474	707	0.67	0.511	29.78
B&G Sales	−6344	4456	−1.42	0.172	58.24
UHT Sales	1147	1001	1.15	0.267	139.86
Capacity Utilization	−1.36396E+10	10,650,153,392	−1.28	0.217	240.49

Table 10: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
558,348,806	95.00%	93.61%	91.42%	654,863,277	90.83%	1.94974

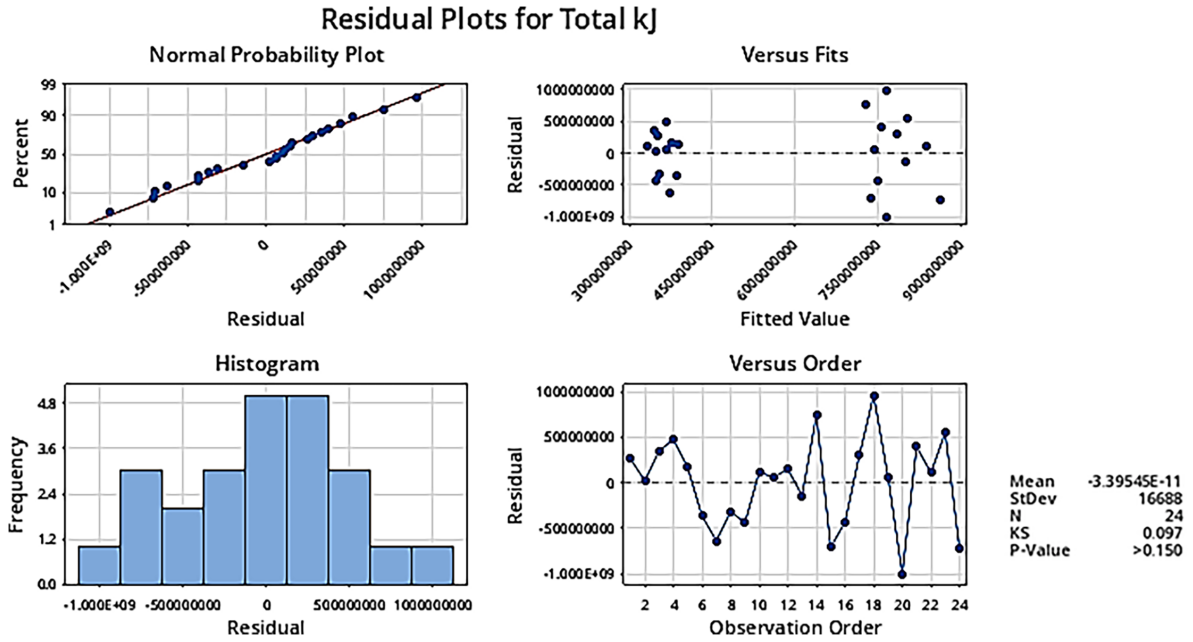


Figure 4: Residual diagnostic plots for Total kJ.

3.3 Multicollinearity Analysis and Selection of Variables

The variance inflation factor (VIF) was used to check for multicollinearity among the explanatory variables. In the first regression models, significant multicollinearity existed among the production-related variables because product sales, capacity utilization, and energy-related variables are operationally related. Stepwise regression was used to remove redundant predictors, retain only the statistically significant ones, and obtain more parsimonious models.

Stepwise regression with a strict *p*-value threshold of 0.01 was used for variable selection to reduce the number of redundant predictors and remove multicollinearity in cases where a threshold of 0.15 was not sufficient. The Cochrane–Orcutt procedure was employed specifically to reduce serial dependence (autocorrelation) in the regression errors.

After variable selection, the VIF values were re-examined for the final models. The results showed that multicollinearity decreased significantly compared with the original models.

i. *Stepwise regression model for Total Electrical Energy Consumption (kWh)*

Both curd sales and capacity utilization were statistically significant in the stepwise regression model of total electrical energy use ($p < 0.05$). The model had a 10-fold cross-validated R^2 of 97.65%. Variable selection reduced the severe multicollinearity of the initial full model, as the VIF values of the two retained predictors were both 3.96.

The high coefficient of capacity utilization is expected because it is a scale variable, and it should be interpreted only in conjunction with the other variables. A Durbin–Watson statistic of 0.882 suggests positive residual dependence among the monthly observations.

The Cochrane–Orcutt procedure was therefore applied to reduce this autocorrelation.

The model satisfied the normality-of-residuals assumption according to the Kolmogorov–Smirnov test ($p > 0.05$). The final regression coefficients obtained after stepwise variable selection are presented in Tables 11 and 12, and the residual analysis of the electrical energy model is illustrated in Fig. 5.

Table 11: Regression results for total electrical energy consumption (kWh) as a function of product, process and system parameters.

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	148,221	16,217	9.14	0.000	—
Curd Sales	0.07577	0.00807	9.40	0.000	3.96
Capacity Utilization	358,618	42,750	8.39	0.000	3.96

Table 12: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
17,464.5	98.23%	98.07%	97.71%	18,840.5	97.65%	0.881800

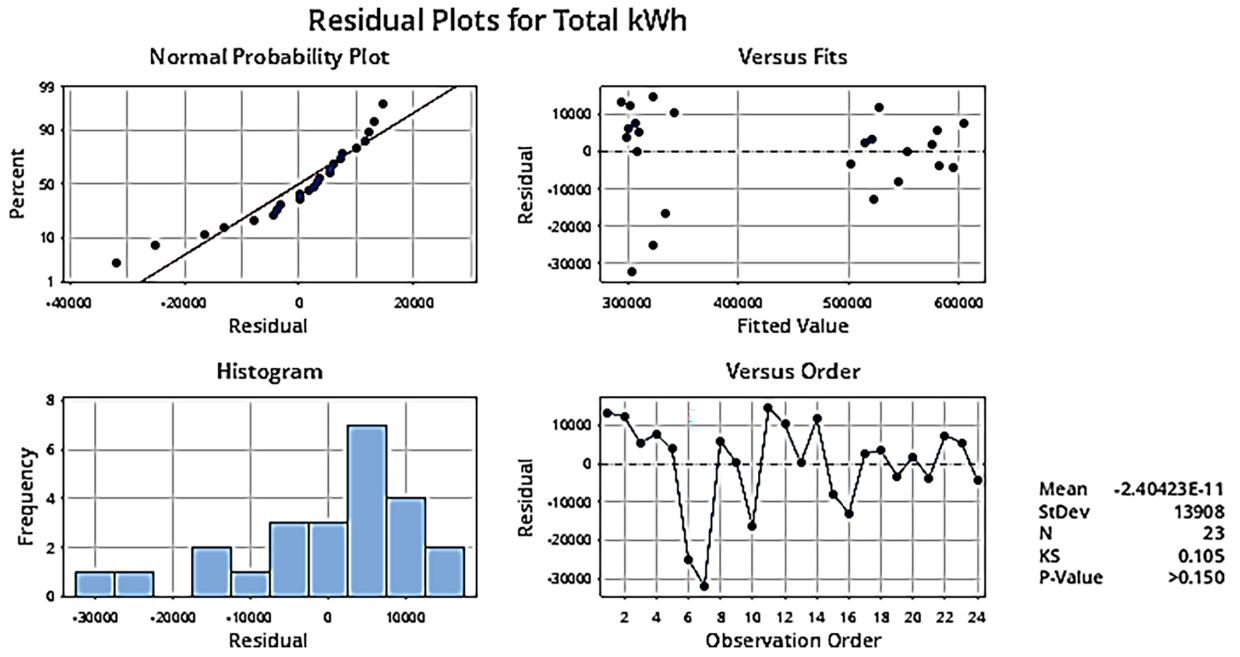


Figure 5: Residual diagnostic plots for Total kWh.

Regression equation. Total kWh = 148,221 + 0.07577 Curd Sales + 358,618 Capacity Utilization

ii. *Prediction of Total Electrical Energy Consumption (kWh) after applying Cochrane–Orcutt procedure*

Both curd sales and capacity utilization were statistically significant in the final model of total electrical energy consumption ($p < 0.05$). The model had a 10-fold cross-validated R^2 of 93.79% and a VIF of 2.05. After the Cochrane–Orcutt procedure was applied, the Durbin–Watson statistic of the final model improved to 1.963, which was satisfactory. The model satisfied the normality-of-residuals assumption according to the Kolmogorov–Smirnov test ($p > 0.05$). The regression coefficients are summarized in Tables 13 and 14, and the residual plot is presented in Fig. 6.

Table 13: Regression results for total electrical energy consumption (kWh) as a function of product, process and system parameters.

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	62,465	9467	6.60	0.000	—
Trans Curd Sales	0.07630	0.00957	7.97	0.000	2.05
Trans Capacity Utilization	366,147	46,854	7.81	0.000	2.05

Table 14: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
14,586.6	95.64%	95.20%	94.16%	16,224.5	93.79%	1.96305

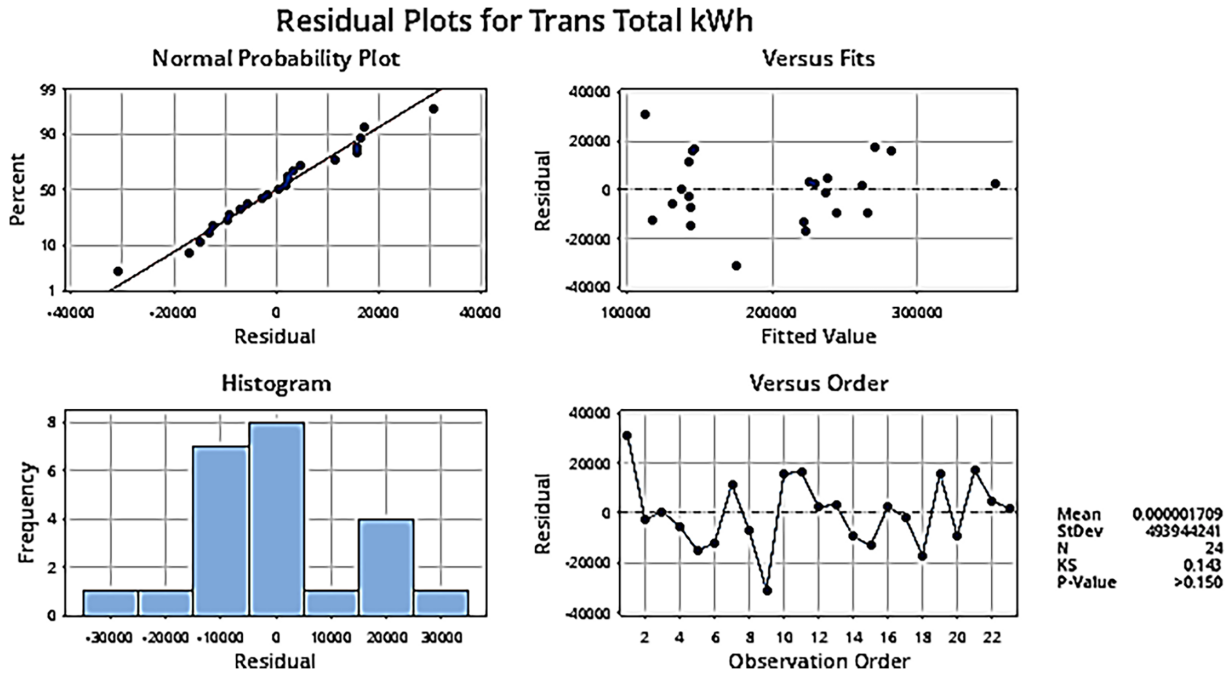


Figure 6: Residual diagnostic plots for Trans Total kWh.

Regression equation. Trans Total kWh = 62,465 + 0.07630 Trans Curd Sales + 366,147 Trans Capacity Utilization

iii. *Stepwise regression model for Total Thermal Energy Consumption (kJ)*

Stepwise regression analysis was carried out for total thermal energy consumption, with milk, curd, B&G, and UHT sales and capacity utilization as candidate variables. Milk sales was the only variable that remained significant after variable selection. The final model had a 10-fold cross-validated R^2 of 90.82% and a VIF of 1.00, which was satisfactory.

The equation that resulted: Total kJ = 2,701,557,195 + 352.7 Milk Sales

The selection of milk sales is consistent with the large thermal demand of milk-processing operations. The Durbin–Watson statistic was 1.439; the Cochrane–Orcutt procedure was therefore applied to improve it. The model satisfied the normality-of-residuals assumption according to the Kolmogorov–Smirnov test ($p > 0.05$).

The regression coefficients are summarized in Tables 15 and 16, and the residual plot is presented in Fig. 7.

Table 15: Regression results for total thermal energy consumption (kJ) incorporating production and operational variables.

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	2,701,557,195	220,340,388	12.26	0.000	—
Milk Sales	352.7	21.3	16.55	0.000	1.00

Table 16: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
615,752,922	92.57%	92.23%	91.06%	655,169,598	90.82%	1.43943

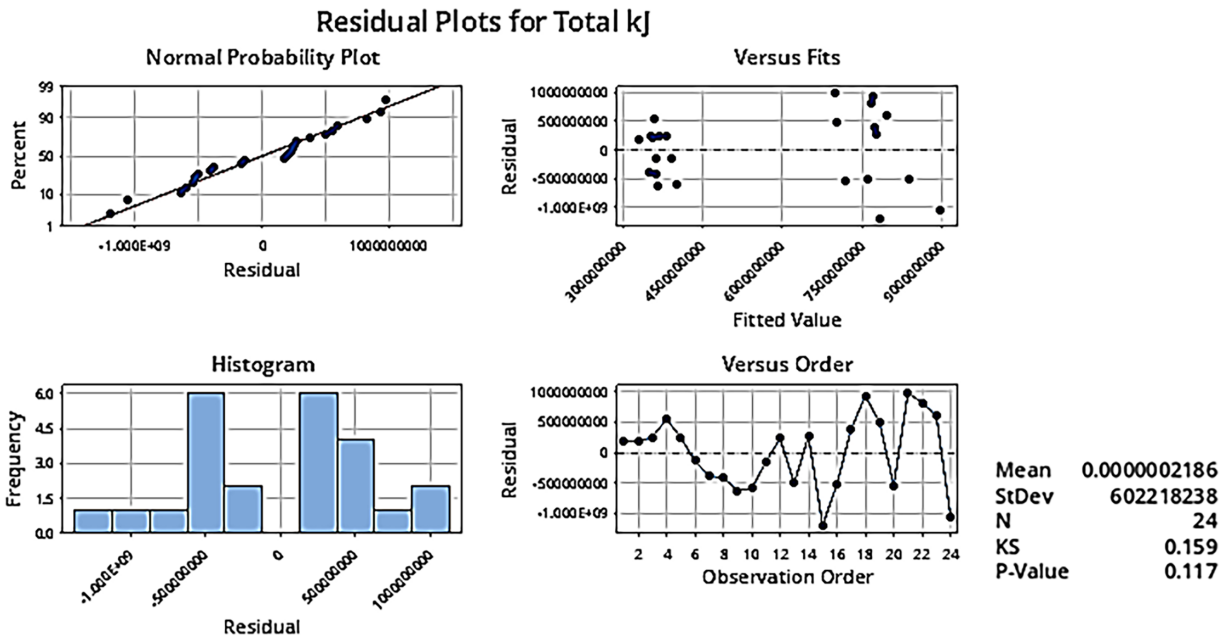


Figure 7: Residual diagnostic plots for Total kJ.

iv. *Prediction of Total Thermal Energy Consumption (kJ) after applying Cochrane–Orcutt procedure*

Only milk sales was statistically significant in the final model of total thermal energy consumption ($p < 0.05$). The model had a 10-fold cross-validated R^2 of 84.60% and a VIF of 1.00. After the Cochrane–Orcutt procedure was applied, the Durbin–Watson statistic of the final model improved to 1.756, which was satisfactory. The model satisfied the normality-of-residuals assumption according to the Kolmogorov–Smirnov test ($p > 0.05$). The regression coefficients are summarized in Tables 17 and 18, and the residual plot is presented in Fig. 8.

Table 17: Regression results for total thermal energy consumption (kJ) incorporating production and operational variables.

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	2,000,773,282	221,732,832	9.02	0.000	—
Trans Milk Sales	340.6	28.0	12.16	0.000	1.00

Table 18: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
609,530,302	87.56%	86.97%	85.00%	648,068,861	84.60%	1.75627

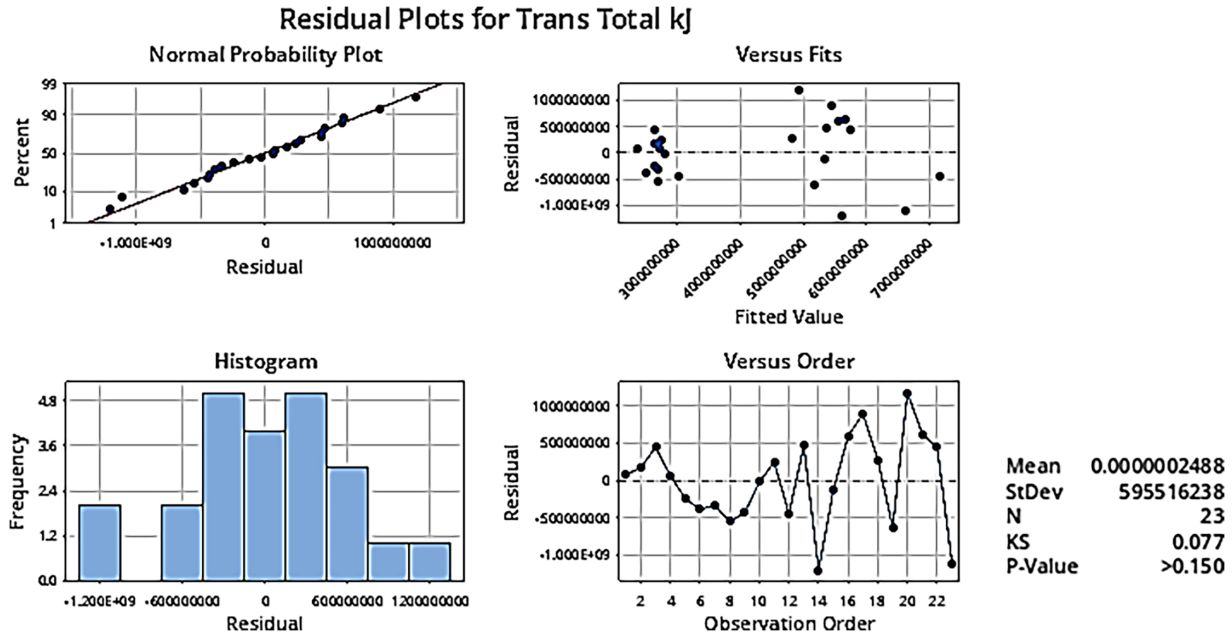


Figure 8: Residual diagnostic plots for Total kJ.

Method. Cross-validation: 10-fold; Stepwise selection of terms; α to enter = 0.01, α to remove = 0.01

Regression equation. Trans Total kJ = 2,000,773,282 + 340.6 Trans Milk Sales

v. *Electrical SEC—Milk*

The candidate predictors considered for the electrical SEC model of milk were milk sales, curd sales, B&G sales, UHT sales, capacity utilization, and energy intensity. The electrical SEC model for milk was

developed in the same way as the total electrical energy consumption model. Only capacity utilization was statistically significant in the final model of the electrical SEC of milk ($p < 0.05$). The model had a 10-fold cross-validated R^2 of 65.48% and a VIF of 1.00. After the Cochrane–Orcutt procedure was applied, the Durbin–Watson statistic of the final model was 1.885, which was satisfactory. The model satisfied the normality-of-residuals assumption according to the Kolmogorov–Smirnov test ($p > 0.05$). Capacity utilization has a negative relationship with electrical SEC, indicating that SEC decreases as capacity utilization increases. The regression coefficients are summarized in Tables 19 and 20, and the residual plot is presented in Fig. 9.

Table 19: Regression model for electrical specific energy consumption (SEC) in milk processing.

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	0.02130	0.00103	20.70	0.000	—
Trans Cap Utl1	−0.02471	0.00339	−7.28	0.000	1.00

Table 20: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
0.00161045	71.62%	70.27%	65.11%	0.00169720	65.48%	1.88511

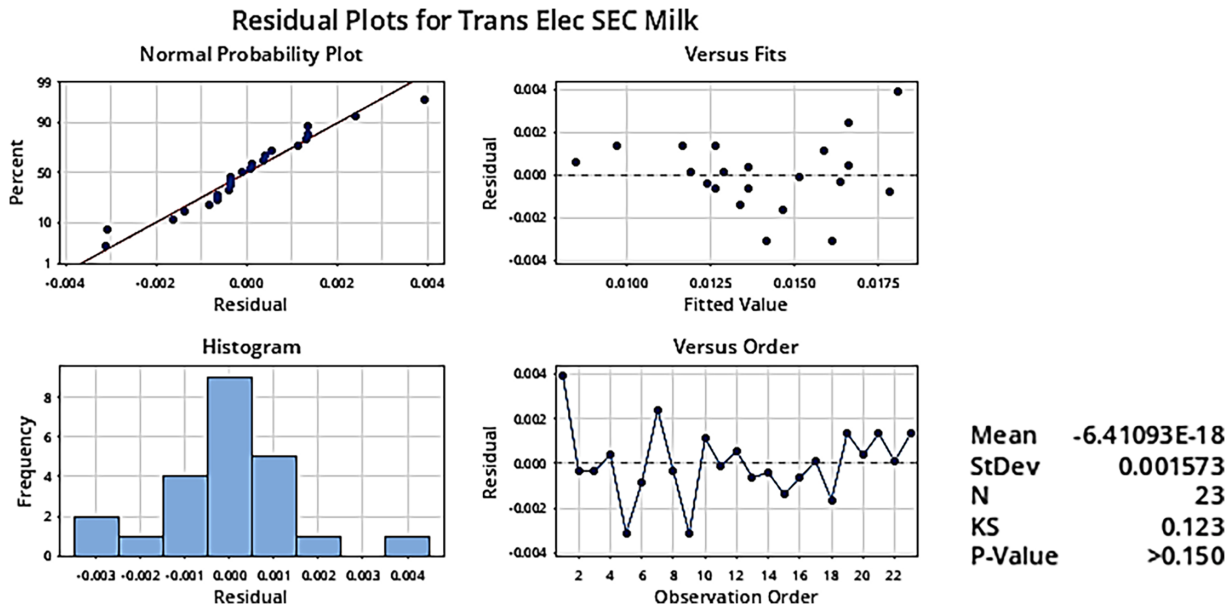


Figure 9: Residual diagnostic plots for Trans Elec SEC Milk.

Method. Cross-validation: 10-fold; Stepwise selection of terms; α to enter = 0.15, α to remove = 0.15

Regression equation. Trans Elec SEC Milk = 0.02130 − 0.02471 Trans Cap Utl1

vi. *Electrical SEC—Curds*

The candidate predictors considered for the electrical SEC model of curd were milk sales, curd sales, B&G sales, UHT sales, capacity utilization, and energy intensity. The electrical SEC model for curd was

developed in the same way as the total electrical energy consumption model. Only capacity utilization was statistically significant in the final model of the electrical SEC of curd ($p < 0.05$). The model had a 10-fold cross-validated R^2 of 62.97% and a VIF of 1.00. After the Cochrane–Orcutt procedure was applied, the Durbin–Watson statistic of the final model was 1.967, which was satisfactory. The model marginally satisfied the normality-of-residuals assumption according to the Kolmogorov–Smirnov test ($p = 0.043$). Capacity utilization has a negative relationship with electrical SEC, indicating that SEC decreases as capacity utilization increases. The regression coefficients are summarized in Tables 21 and 22, and the residual plot is presented in Fig. 10.

Table 21: Regression model for electrical specific energy consumption (SEC) in curd processing.

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	0.05891	0.00297	19.81	0.000	—
Trans Cap Utl2	−0.0715	0.0104	−6.89	0.000	1.00

Table 22: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
0.00481296	69.36%	67.90%	62.30%	0.00505553	62.97%	1.96796

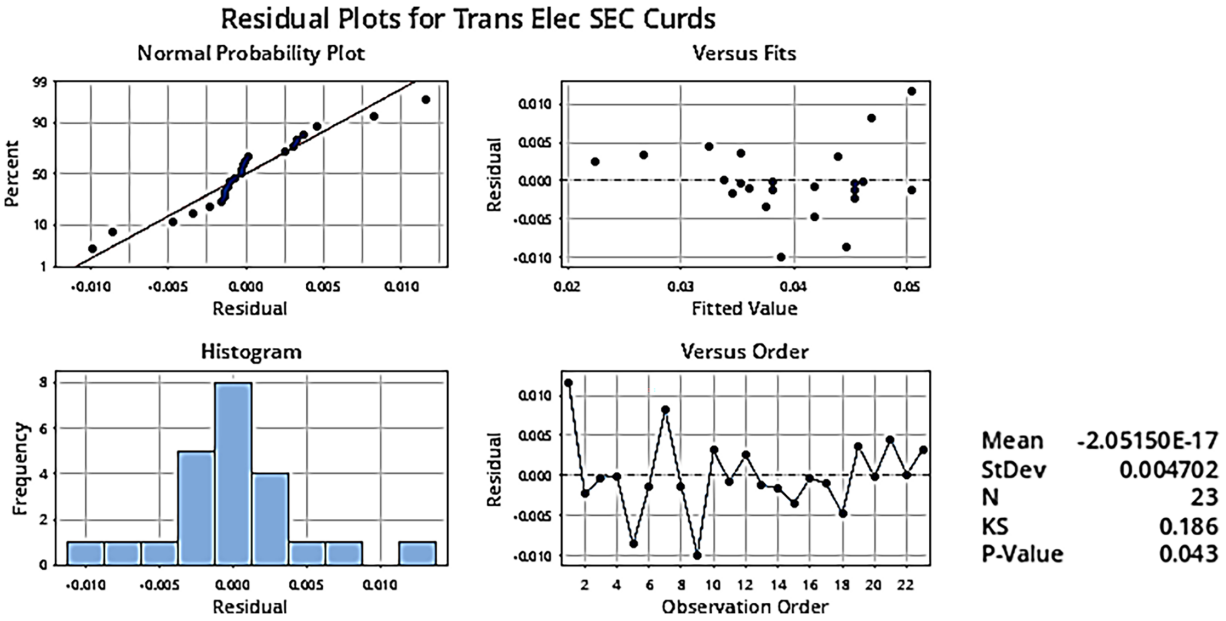


Figure 10: Residual diagnostic plots for Trans Elec SEC Curds.

Method. Cross-validation: 10-fold; Stepwise selection of terms; α to enter = 0.15, α to remove = 0.15

Regression equation. Trans Elec SEC Curds = 0.05891 − 0.0715 Trans Cap Utl2

vii. *Electrical SEC—Butter & Ghee*

The candidate predictors considered for the electrical SEC model of butter and ghee were milk sales, curd sales, B&G sales, UHT sales, capacity utilization, and energy intensity. The electrical SEC model for

butter and ghee was developed in the same way as the total electrical energy consumption model. Only capacity utilization was statistically significant in the final model of the electrical SEC of B&G ($p < 0.05$). The model had a 10-fold cross-validated R^2 of 63.93% and a VIF of 1.00. After the Cochrane–Orcutt procedure was applied, the Durbin–Watson statistic of the final model was 1.954, which was satisfactory. The model satisfied the normality-of-residuals assumption according to the Kolmogorov–Smirnov test ($p > 0.05$). Capacity utilization has a negative relationship with electrical SEC, indicating that SEC decreases as capacity utilization increases. The regression coefficients are summarized in Tables 23 and 24, and the residual plot is presented in Fig. 11.

Table 23: Regression model for electrical specific energy consumption (SEC) in butter-ghee processing.

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	0.05702	0.00283	20.16	0.000	—
Trans Cap Utl3	−0.06931	0.00986	−7.03	0.000	1.00

Table 24: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
0.00457752	70.16%	68.74%	63.27%	0.00480909	63.93%	1.95440

Regression equation. Trans Elec SEC B&G = 0.05702 − 0.06931 Trans Cap Utl3

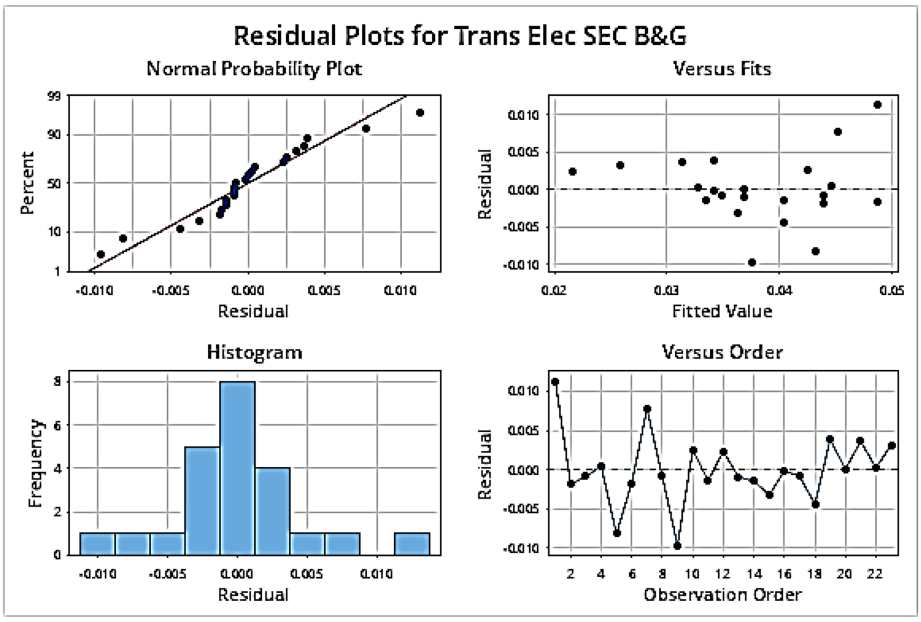


Figure 11: Residual diagnostic plots for trans elec SEC B&G.

viii. *Electrical SEC—UHT*

The candidate predictors considered for the electrical SEC model of UHT were milk sales, curd sales, B&G sales, UHT sales, and capacity utilization. UHT milk is produced only in Plant-B and no energy is allocated to UHT in Plant-A (Section 2.1); the UHT SEC was therefore modeled using only the 12

monthly observations from Plant-B, which keeps structural zeros out of the analysis. Stepwise regression retained capacity utilization as the only significant variable ($p < 0.05$). The ordinary least squares model showed positive first-order autocorrelation (Durbin–Watson statistic = 1.0339), which was corrected using the Cochrane–Orcutt procedure ($\rho = 0.483$; 11 transformed observations). The final model had a 10-fold cross-validated R^2 of 55.98%, a VIF of 1.00, and a Durbin–Watson statistic of 1.771. The residuals satisfied the normality requirement (Shapiro–Wilk $p > 0.05$). The negative coefficient of transformed capacity utilization (−0.1063; $p = 0.001$) indicates that electrical SEC decreases as capacity utilization increases, in agreement with the product-specific models for milk, curd, and butter & ghee. The regression coefficients are summarized in Tables 25 and 26, and the residual plot is presented in Fig. 12.

Table 25: Regression model for electrical specific energy consumption (SEC) in UHT processing (Plant-B only, n = 12).

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	0.05593	0.00484	11.57	0.000	—
Trans CU	−0.1063	0.0226	−4.70	0.001	1.00

Table 26: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
0.00332326	71.06%	67.84%	53.55%	0.00370724	55.98%	1.77140

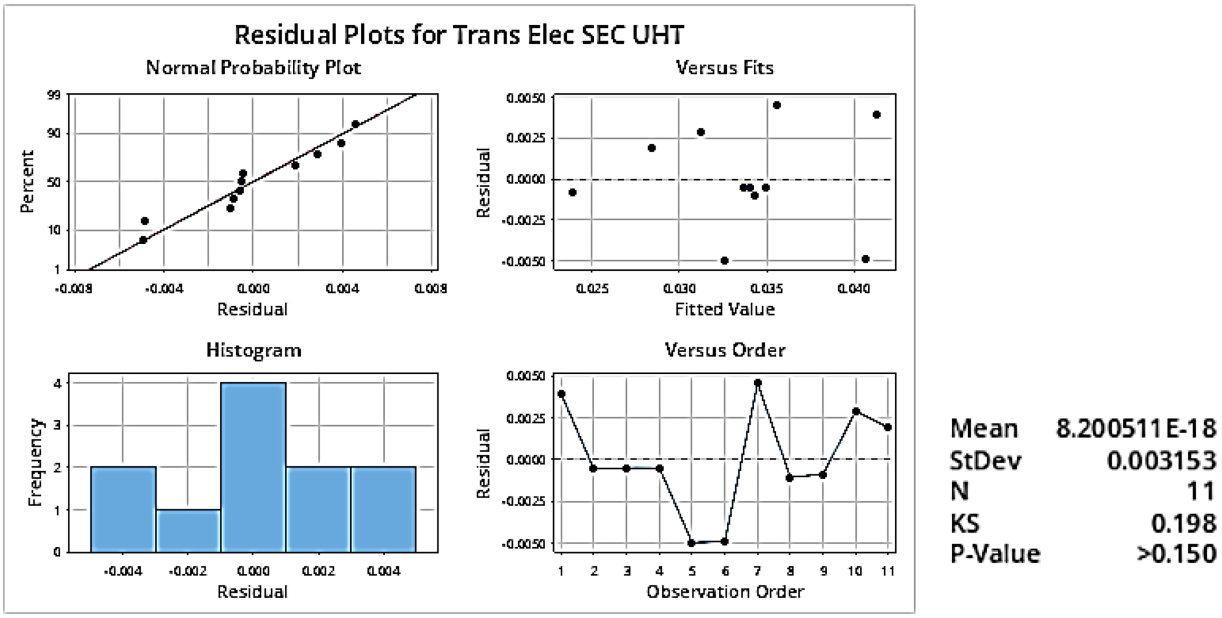


Figure 12: Residual diagnostic plots for trans elec SEC UHT (Plant-B only).

Regression equation. Trans Elec SEC UHT = 0.05593 − 0.1063 Trans CU (Plant-B only; $\rho = 0.446$)

Thermal Specific Energy Consumption Models

ix. *Thermal SEC (Milk, Curd, Butter & Ghee—Combined Discussion)*

Milk sales, curd sales, B&G sales, UHT sales, and capacity utilization were selected as candidate predictors in the thermal SEC models of milk, curd, and butter & ghee. However, the stepwise procedure selected no statistically significant predictors for these three product-specific thermal SEC models. The variation in thermal SEC in the data set therefore could not be explained by the available production and utilization variables.

The stepwise regression did not select any variables to predict thermal SEC because the reduction in SEC for the same change in capacity utilization differs greatly between Plant-A and Plant-B. The regression results are presented in Figs. 13–15.

Regression Analysis: Ther SEC Milk versus Milk Sales, Capacity Utilization

* NOTE * There are no terms in the model.

Stepwise Selection of Terms

α to enter = 0.15, α to remove = 0.15
No terms can enter the model.

Figure 13: Regression results for thermal specific energy consumption (SEC) in milk processing.

Regression Analysis: Ther SEC Curds versus Curd Sales, Capacity Utilization

* NOTE * There are no terms in the model.

Stepwise Selection of Terms

α to enter = 0.15, α to remove = 0.15
No terms can enter the model.

Figure 14: Regression results for thermal specific energy consumption (SEC) in curd processing.

Regression Analysis: Ther SEC B&G versus B&G Sales, Capacity Utilization

* NOTE * There are no terms in the model.

Stepwise Selection of Terms

α to enter = 0.15, α to remove = 0.15
No terms can enter the model.

Figure 15: Regression results for thermal specific energy consumption (SEC) in butter-ghee processing.

x. *Thermal SEC—UHT*

The candidate predictors considered for the thermal SEC model of UHT were milk sales, curd sales, B&G sales, UHT sales, and capacity utilization. As with the electrical SEC, the model was fitted to the

12 monthly observations from Plant-B only because UHT is not produced in Plant-A. Curd sales and UHT sales were retained by the stepwise procedure, and both were statistically significant ($p < 0.001$). The model had a 10-fold cross-validated R^2 of 85.64%, a maximum VIF of 1.09, and a Durbin–Watson statistic of 1.698, so no autocorrelation correction was needed. The residuals satisfied the normality requirement (Shapiro–Wilk $p > 0.05$). The model had coefficients of both variables as negative, indicating that the thermal SEC of UHT decreased as UHT sales and curd sales increased. The regression coefficients are summarized in Tables 27 and 28, and the residual plot is presented in Fig. 16.

Table 27: Regression model for thermal specific energy consumption (SEC) in UHT processing (Plant-B only, n = 12).

Term	Coef.	SE Coef.	T-Value	*p*-Value	VIF
Constant	1773	109	16.33	0.000	—
UHT Sales	−0.000199	0.000029	−6.78	0.000	1.09
Curd Sales	−0.001284	0.000170	−7.57	0.000	1.09

Table 28: Validation statistics.

S	R^2	Adj. R^2	Pred. R^2	10-Fold S	10-Fold R^2	Durbin–Watson
41.0278	89.93%	87.69%	86.24%	42.4304	85.64%	1.69795

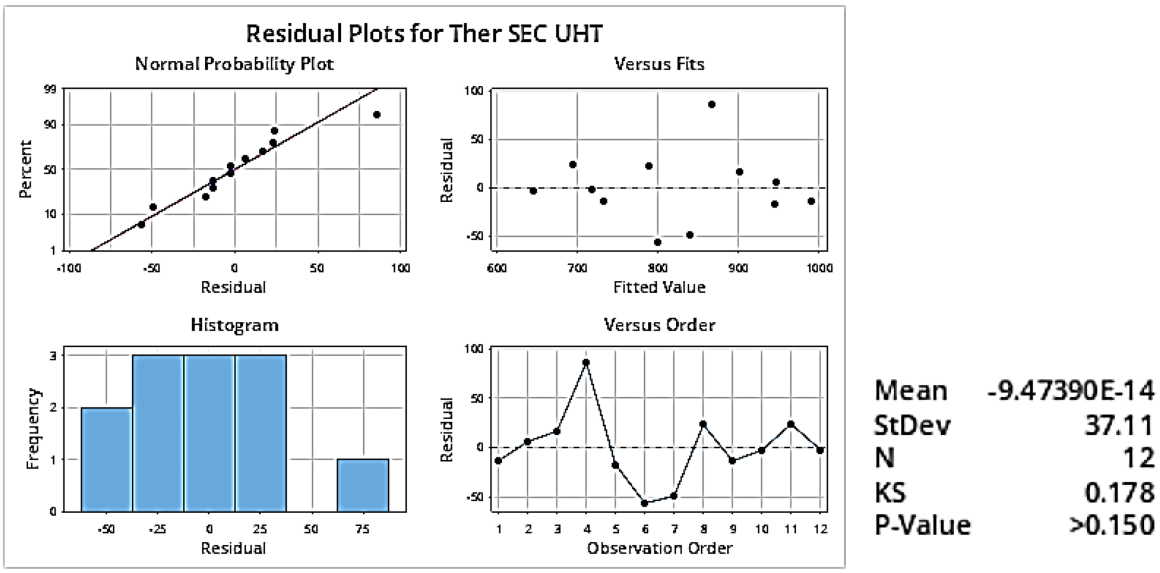


Figure 16: Residual diagnostic plots for ther SEC UHT (Plant-B only).

Regression equation. Ther SEC UHT = 1773 − 0.0001986 UHT Sales − 0.001284 Curd Sales (Plant-B only)

3.4 Comparative Analysis of Electrical and Thermal SEC between Plant-A and Plant-B

The specific energy consumption of the two plants showed that the electrical SEC of Plant-B was higher than that of Plant-A for milk, curd, and butter & ghee, by about 32.04%, 32.66%, and 32.76%, respectively. The differences in thermal SEC, however, were much smaller, ranging from 2.3% to 2.4%. A direct comparison of the plants is not possible for UHT because Plant-A does not process UHT milk.

The observed electrical SEC differences are the result of plant-level benchmarking and are not necessarily attributable to capacity utilization alone. Plant-A and Plant-B differ in production capacity, motor capacity, equipment configuration, and product line. These structural differences, together with other operating parameters not explicitly measured in this study, may contribute to the measured electrical SEC gap.

A comparative study of the electrical specific energy consumption (electrical SEC) and thermal specific energy consumption (thermal SEC) of the main dairy products processed in Plant-A and Plant-B was performed. The average SEC values are summarized in Table 29.

Table 29: Average electrical and thermal SEC values of Plant-A and Plant-B and the percentage difference between Plant-B and Plant-A.

Product	Plant-A Electrical SEC (kWh/unit)	Plant-B Electrical SEC (kWh/unit)	Percentage Difference (%)	Plant-A Thermal SEC (kJ/unit)	Plant-B Thermal SEC (kJ/unit)	Percentage Difference (%)
Milk	0.02550	0.03367	32.04	378.8	370.1	−2.35
Curd	0.07546	0.10010	32.66	829.8	811.0	−2.32
Butter & Ghee	0.07314	0.09710	32.76	1419	1386	−2.38
UHT	—	0.06723	—	—	821.8	—

Independent t-test analysis of the differences in electrical and thermal SEC between Plant-A and Plant-B:

Independent-sample *t*-tests were used to determine whether the observed differences in electrical and thermal SEC between Plant-A and Plant-B were statistically significant.

The results of the two-sample *t*-tests assuming unequal variances are summarized in Table 30. For electrical SEC, the differences between the plants were statistically significant for milk ($t = 7.29$, $p < 0.001$), curd ($t = 7.46$, $p < 0.001$), and butter & ghee ($t = 7.46$, $p < 0.001$). In contrast, the corresponding differences in thermal SEC were not statistically significant for milk ($t = -0.47$, $p = 0.644$), curd ($t = -0.47$, $p = 0.647$), or butter & ghee ($t = -0.46$, $p = 0.649$).

Table 30: Summary of two-sample *t*-test results assuming unequal variances.

Sl. No.	Test	T-Value	*p*-Value
1	Elec SEC Milk	7.29	0.000
2	Elec SEC Curd	7.46	0.000
3	Elec SEC B&G	7.46	0.000
4	Ther SEC Milk	−0.47	0.644
5	Ther SEC Curd	−0.47	0.647
6	Ther SEC B&G	−0.46	0.649

These results show a statistically significant difference between the plants in electrical SEC and no statistically significant difference in thermal SEC. The data used for the independent-sample *t*-tests are presented in Table 31. The t-values were calculated as Plant-B minus Plant-A, consistent with the percentage differences in Table 29, so a positive t-value indicates a higher mean for Plant-B.

The lower SEC in Plant-A is due to better capacity utilization, refrigeration efficiency, optimized loading of utilities, effective process integration, and better utilization of pumps, homogenizers, and chilling systems. The higher SEC in Plant-B, on the other hand, indicates higher auxiliary losses and relatively lower equipment-utilization efficiency.

Table 31: Data used for the *t*-test of the difference between the electrical and thermal SEC.

Plant-A Elec SEC Milk kWh/L	Plant-B Elec SEC Milk kWh/L	Plant-A Ther SEC Milk kJ/L	Plant-B Ther SEC Milk kJ/L	Plant-A Elec SEC Curds kWh/L	Plant-B Elec SEC Curds kWh/L	Plant-A Ther SEC Curds kJ/L	Plant-B Ther SEC Curds kJ/L	Plant-A Elec SEC B&G kWh/L	Plant-B Elec SEC B&G kWh/L	Plant-A Ther SEC B&G kJ/L	Plant-B Ther SEC B&G kJ/L
0.024	0.038	357	439	0.07241	0.11224	782	963	0.07018	0.1088	1338	1646
0.025	0.041	393	429	0.0752	0.12163	861	939	0.07289	0.1179	1472	1606
0.025	0.036	319	413	0.0732	0.10807	698	905	0.07095	0.10476	1193	1547
0.025	0.034	357	429	0.07311	0.10215	783	939	0.07087	0.09901	1338	1606
0.025	0.034	407	418	0.07368	0.10062	892	916	0.07142	0.09753	1524	1566
0.025	0.030	430	334	0.07426	0.0897	942	732	0.07198	0.08695	1611	1252
0.026	0.032	414	356	0.07661	0.09666	906	780	0.07426	0.09369	1549	1333
0.027	0.036	336	365	0.08004	0.10643	736	800	0.07759	0.10316	1258	1368
0.027	0.034	407	323	0.08033	0.1009	892	708	0.07786	0.0978	1524	1210
0.027	0.028	400	289	0.07939	0.08301	875	634	0.07696	0.08046	1496	1084
0.026	0.031	397	323	0.0764	0.091	870	707	0.07405	0.08821	1487	1209
0.024	0.030	329	323	0.07086	0.08916	721	707	0.06868	0.08642	1232	1208

There was no statistically significant difference between the thermal SEC of Plant-A and Plant-B, as shown in Table 30 ($p > 0.05$). The plants had similar thermal energy performance because pasteurization and steam-heating operations are generally uniform in dairy processing. The results show that the two plants have similar boiler efficiency, steam utilization, condensate recovery, and thermal process integration.

UHT processing was carried out only in Plant-B, so a direct comparison was not possible. In general, the comparative analysis confirmed that the electrical energy performance of Plant-A was better than that of Plant-B owing to better process integration, optimized operational loading, and utility management. Fig. 17 compares the electrical SEC of Plant-A and Plant-B.

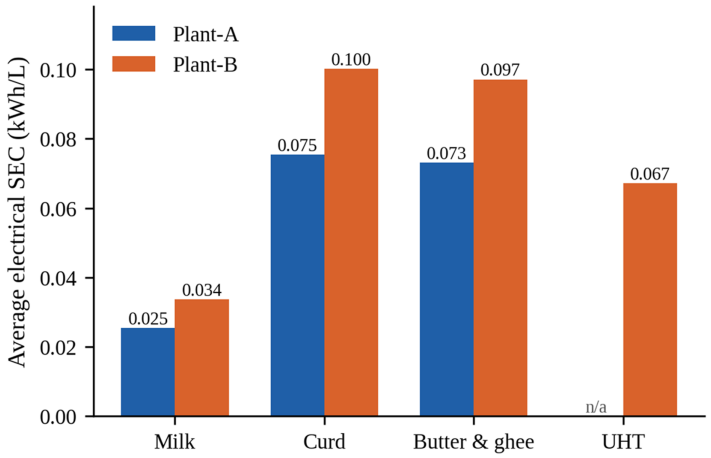


Figure 17: Comparison of average electrical SEC between Plant-A and Plant-B.

Smaller differences were observed in the thermal SEC analysis for dairy processing operations between Plant-A and Plant-B, showing similar thermal utility performance and steam-utilization efficiency. Initially, the thermal SEC of Plant-B was higher than that of Plant-A, but as capacity utilization increased, the thermal SEC of Plant-B dropped drastically, showing a negative correlation between capacity utilization and thermal SEC. The thermal SEC of Plant-B is highly sensitive to capacity utilization; hence, regression models for thermal SEC were not feasible. Fig. 18 compares the thermal SEC of Plant-A and Plant-B.

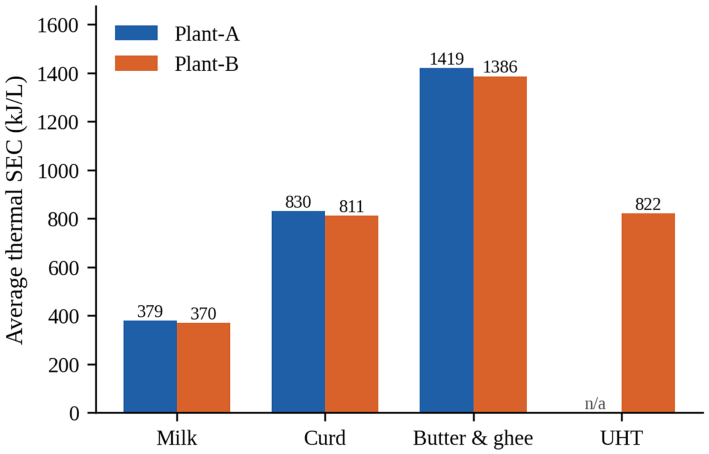


Figure 18: Comparison of average thermal SEC between Plant-A and Plant-B.

3.5 Benchmark-Based Electricity-Saving Potential for Plant-B

The difference in electrical SEC between Plant-A and Plant-B was used to approximate the potential electricity savings against a benchmark. The calculation is a hypothetical best-practice case that assumes that Plant-B achieves the same electrical SEC as Plant-A and operates the same number of annual production hours.

In this case, the potential electricity savings are estimated at about 265,853 kWh/year for milk, 98,783 kWh/year for curd, and 45,677 kWh/year for butter and ghee, adding up to about 410,313 kWh/year (Table 32). At an assumed electricity cost of ₹10 per kWh, this is worth about ₹41.03 lakh per year. With an emission factor of 0.95 kg CO_2/kWh, the avoided-emission potential is about 390 t CO_2/year.

Table 32: Comparison of average electrical specific energy consumption (SEC) and estimated electrical energy savings for Plant-B.

Plant	Average Milk Electrical SEC (kWh/L)	Average Curd Electrical SEC (kWh/L)	Average B&G Electrical SEC (kWh/L)
Plant-A	0.0255	0.07546	0.07314
Plant-B	0.0337	0.10010	0.09710
Δ_{SEC}	0.0082	0.02464	0.02396
Production Volume	32,421,101	4,009,061	1,906,382
Energy Savings	265,853	98,783	45,677

This estimate represents a potential for energy savings and should not be taken as a guaranteed saving. The Cochrane–Orcutt correction has been shown to improve the statistical properties of the regression model used to analyze the data, but it does not prove that the difference between Plant-A and Plant-B is due solely to the difference in capacity utilization. The SEC gap may also be due to differences in production capacity, motor capacity, equipment configuration, product portfolio, and operating conditions.

Hence, the estimated 410,313 kWh/year is an indicative improvement potential that must be verified and measured in the plant before it can be regarded as an achievable saving.

Step 1. Average Electrical SEC (Specific Energy Consumption)

The average electrical SEC values from the data set are given in Table 32:

Total Energy Savings = 265,853 + 98,783 + 45,677 = 410,313

Step 2. Electrical Energy Savings Calculation

Formula

Energy Savings (kWh) = $(SEC_B - SEC_A) \times$ Production Volume

Step 3: Annual Cost Saving

Assume electricity tariff: Electricity Cost = ₹10 per kWh

Therefore,

Annual Cost Saving = 410,313 × 10 = ₹4,103,130 ≈ ₹41.03 lakhs/year

Annual Cost Saving = ₹41.03 lakhs/year

The estimated annual electricity-saving potential of 410,313 kWh/year is based on a benchmarking scenario derived from the difference in SEC measured in the two plants. It should therefore be understood as a potential saving that may be achieved, not as a saving that was actually realized through energy-efficiency measures.

Step 4: CO_2 Emission Savings Calculation

For Indian grid electricity, a commonly used emission factor is: 0.95 kg CO_2/kWh

Annual CO_2 Savings = 410,313 × 0.95 = 389,797 kg CO_2/year = 390 t CO_2/year

As summarized in Table 33, based on the benchmark, Plant-B could save about 410,313 kWh of electricity annually. This benchmark scenario does not imply that increasing capacity utilization is the only way to achieve the expected savings.

Table 33: Summary of the benchmark-based annual energy, cost, and CO_2 savings for Plant-B.

Parameter	Value
Annual Energy Saving	410,313 kWh/year
Electricity Tariff	₹10/kWh
Annual Cost Saving	₹4,103,130/year
Annual Cost Saving (Approx.)	₹41.03 lakh/year
Annual CO_2 Savings	390 t CO_2/year

3.6 Effect of Production Rate and Capacity Utilization on Specific Energy Consumption (SEC) of Plant-A and Plant-B

The electrical SEC for milk, curd, and butter & ghee was negatively associated with capacity utilization. The models explained 71.62%, 69.36%, and 70.16% of the variation in electrical SEC, respectively, while their 10-fold cross-validated R^2 values were 65.48%, 62.97%, and 63.93%. The results suggest that, within the range of the observations, capacity utilization was a significant statistical predictor of electrical SEC. The Plant-B-only UHT model showed the same pattern: capacity utilization explained 71.06% of the variation in electrical SEC (10-fold cross-validated R^2 = 55.98%), although this model rests on only 12 monthly observations.

However, there is no direct evidence that a drop in capacity utilization directly leads to a drop in equipment efficiency. SEC is a mathematical ratio of consumed energy to produced output; a mathematical decrease in SEC can be achieved by increasing production output while keeping the fixed or semi-fixed electrical loads relatively stable. It is therefore possible that the observed association is due to operator behavior as well as to the mathematical composition of the SEC indicator.

In the plant-level comparison, the electrical SEC of Plant-A was lower than that of Plant-B. However, the two plants differ in production capacity, motor capacity, equipment configuration, product portfolio, and operating conditions. Hence, no single capacity-utilization effect can be isolated at the plant level.

The Cochrane–Orcutt correction addresses the problem of serial dependence in regression residuals, but it does not imply a causal relationship between capacity utilization and SEC. In this study, it was used only to correct the first-order residual dependence identified in the total electrical and thermal energy models and in the Plant-B UHT electrical SEC model.

No predictor was retained for the thermal SEC of milk, curd, or butter & ghee, which implies that the available production and capacity-utilization variables were not sufficient to explain the variation in thermal SEC. A more detailed thermal SEC model would require additional process-level parameters, such as steam demand, boiler operating conditions, condensate recovery, process temperature requirements, and equipment operating conditions. In contrast, the Plant-B-only UHT thermal SEC model retained UHT sales and curd sales as significant predictors (R^2 = 89.93%; 10-fold cross-validated R^2 = 85.64%), but, as with the UHT electrical SEC model, it is based on only 12 observations and should be regarded as indicative.

Capacity Utilization

Figs. 19 and 20 show the monthly capacity utilization of both dairy plants, and Table 34 lists the actual values. As shown in Table 34, Plant-A has a much higher capacity utilization, varying between 0.611 and 0.839. The trend in Fig. 19 shows that operation is relatively stable, with some fluctuations followed by a significant increase in the later months. This indicates good use of the installed capacity and a predictable production schedule. As capacity utilization increases, process efficiency increases and specific energy consumption decreases because part-load operation is minimized. Plant-B, on the other hand, exhibits lower and more fluctuating utilization, with values between 0.301 and 0.483, as given in Table 34. Fig. 20 reveals fluctuations in the trend, especially in the first few months, and a gradual increase toward the end of the period. The reduced utilization indicates underloading of the equipment and inefficient operation, which contributes to the higher specific energy consumption. In general, the comparison of the two plants shows that capacity utilization is a vital factor that influences energy efficiency. Plants with high and stable utilization levels are more likely to achieve maximum energy performance, whereas low utilization results in higher energy intensity because of operational inefficiencies.

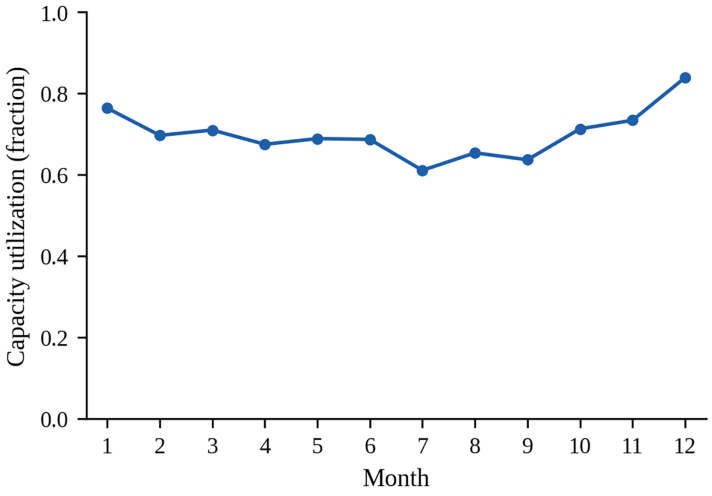


Figure 19: Monthly variation of capacity utilization for Plant-A, showing stable operation and higher utilization levels.

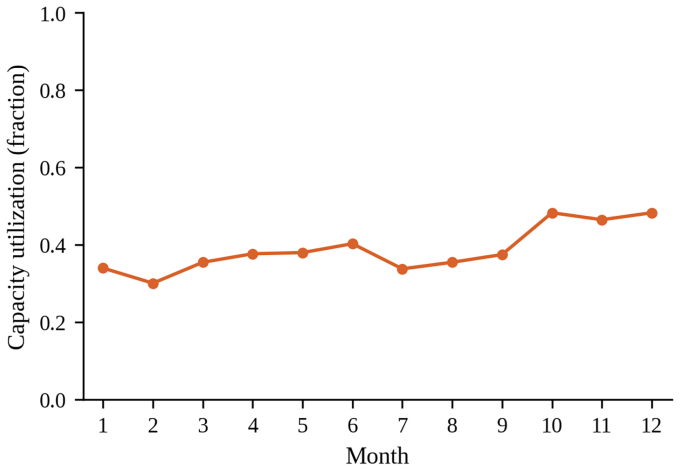


Figure 20: Monthly variation of capacity utilization for Plant-B, indicating lower and fluctuating utilization patterns.

Table 34: Monthly capacity utilization values for Plant-A and Plant-B.

Sl. No.	Plant-A Capacity Utilization	Plant-B Capacity Utilization
1	0.764	0.340
2	0.697	0.301
3	0.710	0.355
4	0.675	0.377
5	0.689	0.380
6	0.687	0.403
7	0.611	0.338
8	0.654	0.355
9	0.637	0.375
10	0.713	0.483
11	0.734	0.465
12	0.839	0.483

The comparison of production throughput and specific energy consumption (SEC) clearly shows the energy performance of Plants A and B for milk, curd, butter and ghee (B&G), and UHT processing operations, as shown in Figs. 21–27.

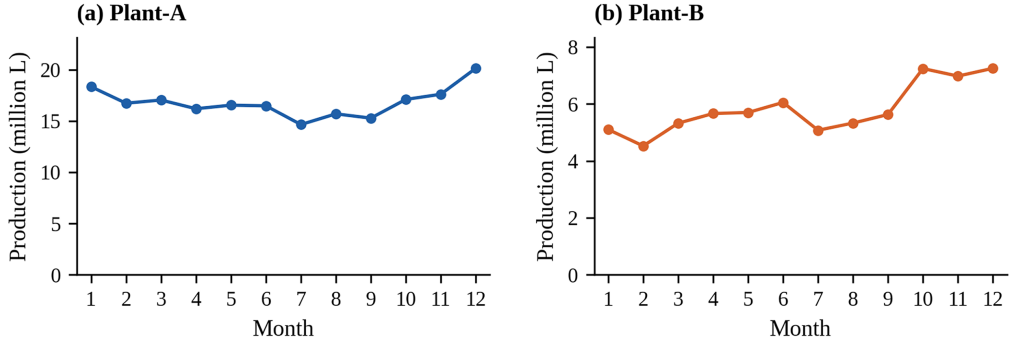


Figure 21: Monthly variation in total production of (**a**) Plant-A (**b**) Plant-B.

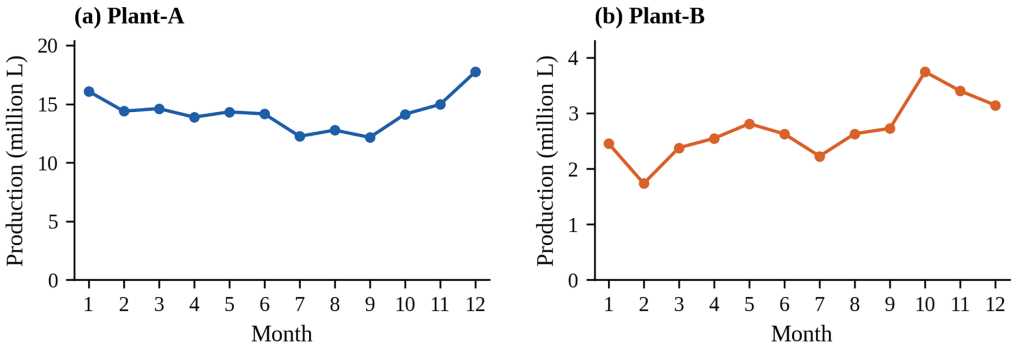


Figure 22: Monthly variation in milk production of (**a**) Plant-A (**b**) Plant-B.

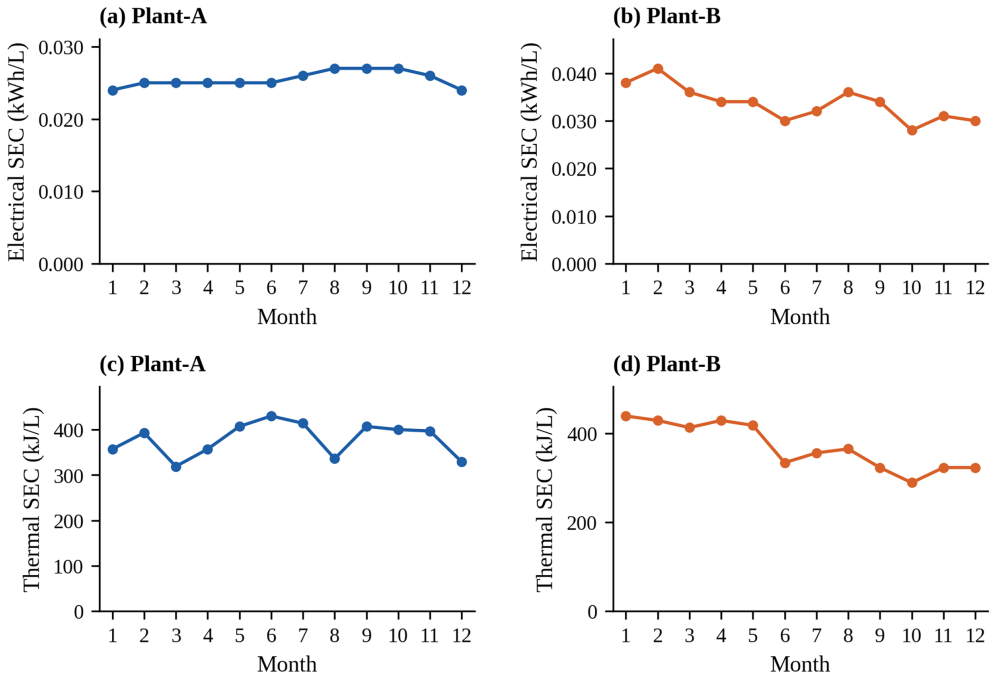


Figure 23: Monthly variation in electrical SEC (**a**,**b**) and thermal SEC (**c**,**d**) for milk processing in Plant-A (**a**,**c**) and Plant-B (**b**,**d**).

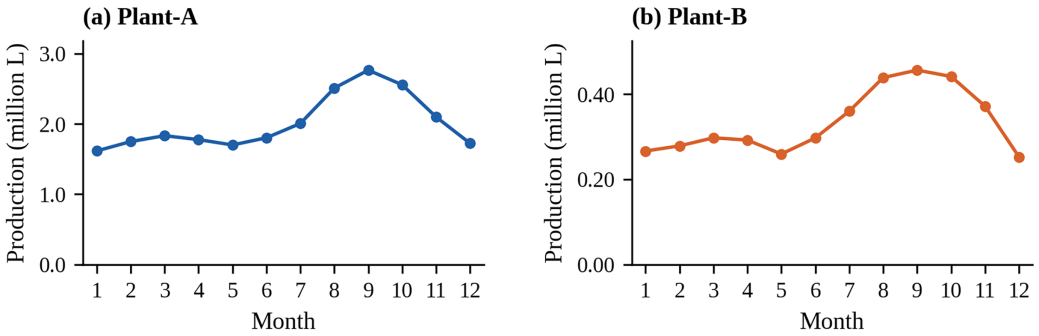


Figure 24: (Continued)

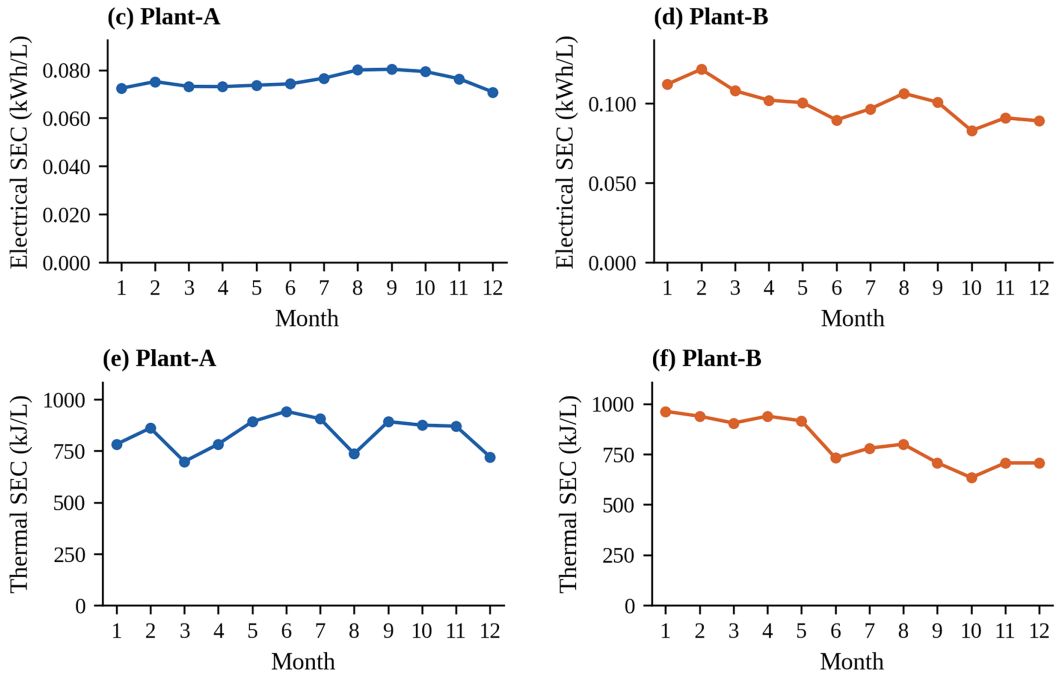


Figure 24: Monthly variation in curd production (**a**,**b**), electrical SEC (**c**,**d**), and thermal SEC (**e**,**f**) for Plant-A (**a**,**c**,**e**) and Plant-B (**b**,**d**,**f**).

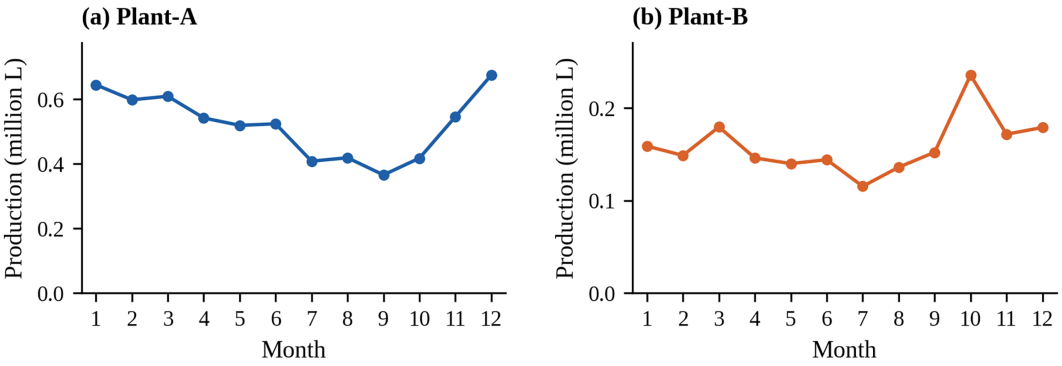


Figure 25: Monthly variation in butter and ghee production of (**a**) Plant-A and (**b**) Plant-B.

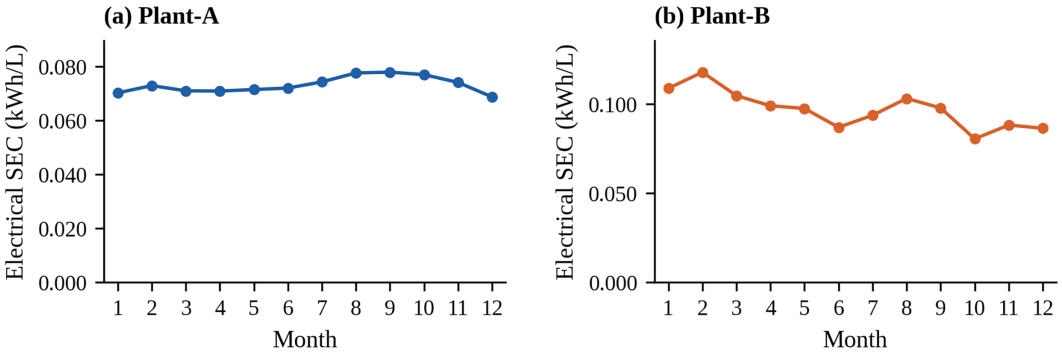


Figure 26: (Continued)

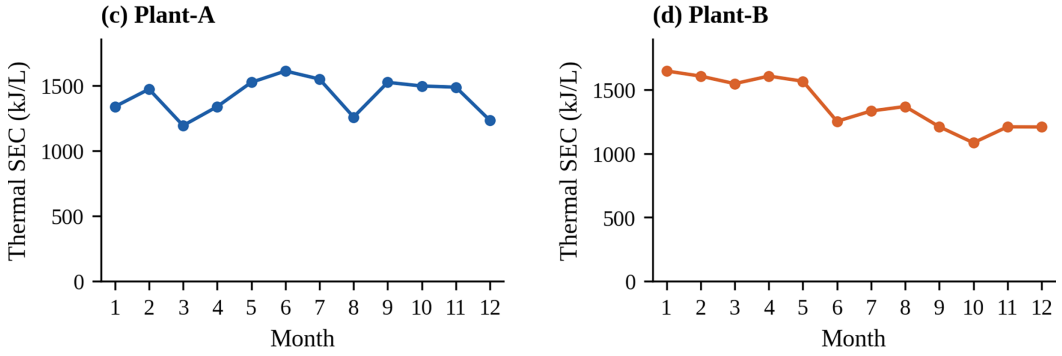


Figure 26: Monthly variation in electrical SEC (**a**,**b**) and thermal SEC (**c**,**d**) for butter and ghee processing in Plant-A (**a**,**c**) and Plant-B (**b**,**d**).

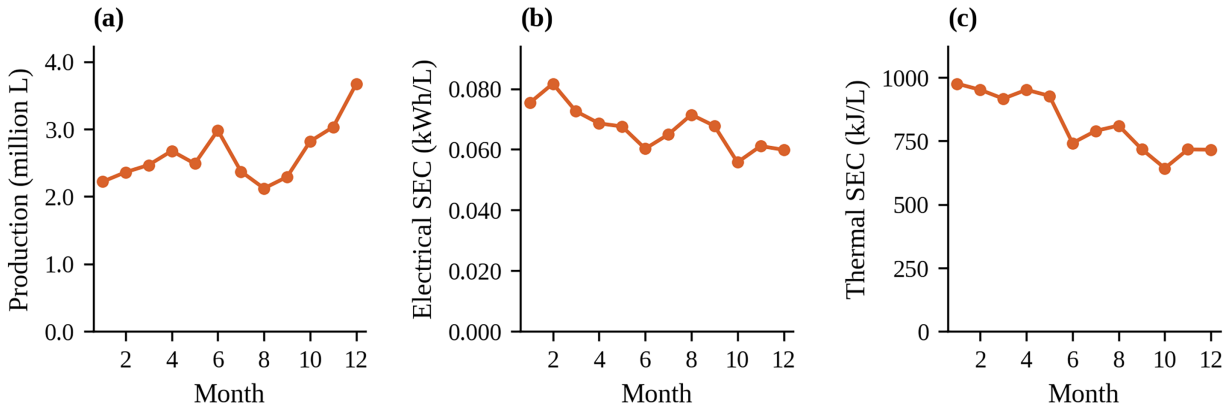


Figure 27: Monthly variation in (**a**) UHT production, (**b**) Electrical specific energy consumption (SEC), and (**c**) Thermal specific energy consumption (SEC) in Plant-B.

For milk processing, Plant-A showed less variation in production than Plant-B. In both plants, electrical and thermal SEC depended on production, decreasing as production increased. The thermal SEC of Plant-B was highly dependent on production, was more sensitive than that of Plant-A, and decreased drastically as production volume increased.

Curd and butter-ghee production showed the same dependency for both types of SEC. Finally, UHT production showed a larger decrease in thermal SEC than in electrical SEC as production increased.

In general, electrical SEC decreased with increasing production regardless of the product, which shows its dependency on capacity utilization. At the same time, thermal SEC was highly dependent on the production rate and changed drastically in Plant-B compared with Plant-A.

Initially, the thermal SEC of Plant-A was lower than that of Plant-B. The difference between the two plants narrowed as the production rate increased. However, the initially higher thermal SEC of Plant-B gradually decreased to lower values as the production rate increased.

4 Discussion

In the current study, an in-depth analysis of electrical and thermal energy consumption in dairy processing systems was performed using regression-based modeling. The study reveals that electrical and thermal energy consumption are influenced by specific product, process, and system parameters. This study used several complementary diagnostics, rather than R^2 alone, to assess model performance. Pearson

correlation analysis, model validation with k-fold cross-validation, VIF analysis, stepwise regression for variable selection, the Durbin–Watson statistic, and the Cochrane–Orcutt procedure were used to build robust and reliable models.

Milk, curd, and butter & ghee had no statistically significant predictors in the thermal SEC models. Initially, the thermal SEC of Plant-B was higher than that of Plant-A, but as capacity utilization increased, the thermal SEC of Plant-B dropped drastically, showing a negative correlation between capacity utilization and thermal SEC. The thermal SEC of Plant-B is highly sensitive to capacity utilization; hence, regression models for thermal SEC were not feasible.

For UHT milk, which is processed only in Plant-B, the models were fitted to the 12 monthly Plant-B observations. The electrical SEC of UHT decreased as capacity utilization increased (Table 25; coefficient = −0.1063, p = 0.001), and the Cochrane–Orcutt-corrected model had a 10-fold cross-validated R^2 of 55.98% and a Durbin–Watson statistic of 1.771 (Table 26). This is consistent with the scale effect observed for milk, curd, and butter & ghee. Unlike the other products, the thermal SEC of UHT could be modeled, with UHT sales and curd sales as significant predictors and a 10-fold cross-validated R^2 of 85.64% (Tables 27 and 28). Both coefficients were negative, meaning that the thermal SEC of UHT fell as throughput increased. The negative curd-sales coefficient is unlikely to represent a direct process effect on UHT and may instead reflect the spreading of shared boiler and steam load over a larger total throughput, so it should be interpreted cautiously.

Furthermore, the graphical analysis of SEC variation shows that electrical SEC decreases with increasing production and capacity utilization, illustrating the existence of scale efficiency in dairy operations and the influence of energy intensity (hp/100 L) and energy-efficient equipment. Plant-A has new equipment with energy-efficient technologies, such as variable-frequency drives (VFDs) on air compressors, multistage compressors on chillers, and energy-efficient motors [27]. The plant-level benchmarking analysis revealed that the electrical SEC of Plant-B was higher than that of Plant-A for milk, curd, and butter & ghee by around 32%–33%, whereas the thermal SEC differed by only around 2%–3%. The independent-sample t-tests revealed statistically significant differences in electrical SEC and no statistically significant difference in thermal SEC. This indicates that the observed difference in plant-level electrical SEC may be attributed to differences in plant capacity utilization, energy intensity, and energy-efficient equipment.

Therefore, Plant-B could achieve estimated electricity savings of 410,313 kWh/year if it improved its capacity utilization and energy intensity and used energy-efficient equipment similar to that of Plant-A.

Overall, the results indicate that improving capacity utilization is a vital approach for maximizing electrical and thermal energy efficiency in dairy processing plants [1]. The use of energy-efficient equipment is expected to reduce energy consumption, as seen in the electrical SEC of Plant-A. The regression models developed in this study provide a valuable perspective on energy-consumption behavior and a framework for energy-performance optimization in the dairy industry [2].

A comparative analysis of Plant-A and Plant-B showed that Plant-A had better energy performance, with higher capacity utilization and better operational loading of utilities and process equipment. In Plant-A, because the motors operated closer to their rated load, motor efficiency increased as relative fixed losses, such as friction, windage, and magnetic losses, decreased, as shown in the motor efficiency curve in Fig. 28a [29]. Partial loading of motors and boilers resulted in comparatively low operational efficiency in Plant-B, which led to high specific energy consumption (SEC), as shown in the motor and boiler efficiency curves in Fig. 28a,b [29,30]. As a result, Plant-A was more efficient in electrical energy use, and its associated CO_2 emissions were lower than those of Plant-B. The results suggest that better equipment utilization is one

of the most important factors for achieving better overall energy efficiency and energy sustainability in the dairy processing industry [1].

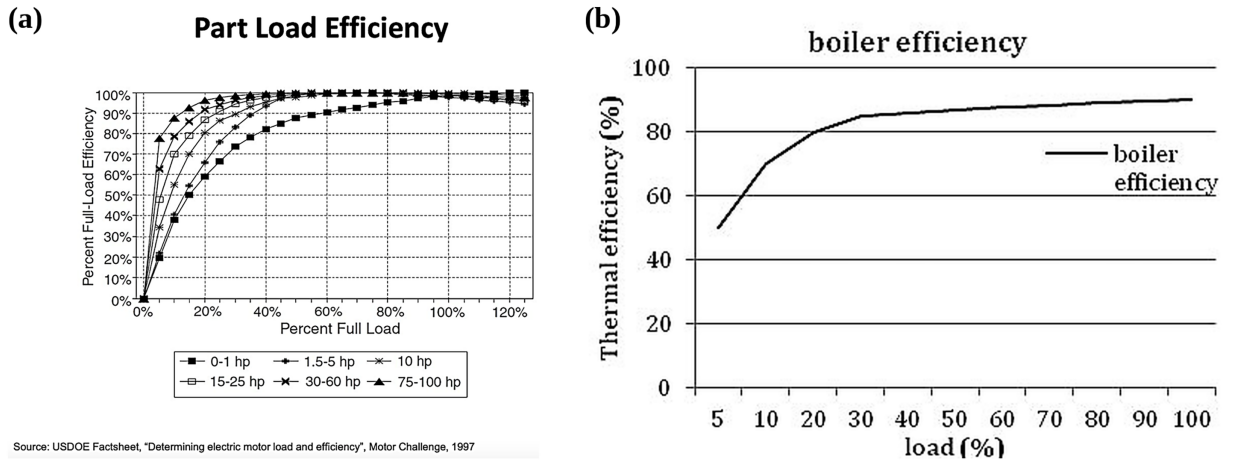


Figure 28: (**a**) Motor efficiency curve [29]; (**b**) Boiler efficiency curve [30].

The main strengths of the present study are the use of actual monthly operating data from two industrial-scale dairy processing plants, the simultaneous consideration of product-, process-, and system-related variables, the explicit assessment of multicollinearity before final model selection, and the evaluation of the final models using k-fold cross-validation and residual diagnostics. The combination of regression modeling with product-specific SEC benchmarking also provides an interpretable framework for comparing energy-performance differences between plants under actual operating conditions. In addition, the benchmark-based energy-saving assessment translates the observed SEC difference into an operationally interpretable energy, cost, and emission-saving potential.

Several limitations should be considered when interpreting the results. First, the analysis was based on 24 monthly observations from two dairy processing plants, which limits statistical power and may increase the sensitivity of stepwise variable selection to the available observations. Second, capacity utilization and SEC are mathematically related through production volume, so their statistical association may partly reflect the formulation of the indicators rather than an independent causal effect of capacity utilization on equipment efficiency. Third, equipment-level operating data, including individual motor loading, refrigeration-system performance, and boiler efficiency, could not be quantified independently at the required temporal resolution; instead, information available in the literature was used to infer possible outcomes. Future studies should therefore employ longer time-series data sets and, where sufficient observations are available, explicitly account for temporal dependence and equipment-level operating conditions. Fourth, UHT milk is produced only in Plant-B, so the UHT SEC models rely on 12 monthly observations from a single plant and should be regarded as indicative.

5 Conclusion

In this study, an integrated regression-based framework was developed to analyze the electrical and thermal energy consumption and the product-specific energy consumption (SEC) of dairy processing plants using monthly operational data. Multiple linear regression was combined with Pearson correlation analysis, stepwise variable selection, VIF evaluation of multicollinearity, 10-fold cross-validation, and residual diagnostics to obtain statistically interpretable and predictive energy models. The framework combines product,

process, and system variables to model the total electrical and thermal energy use of the plants and the product-specific SEC under actual operating conditions.

The plant-level benchmarking indicated that the electrical SEC of Plant-B was around 32%–33% higher than that of Plant-A for the compared products, whereas the thermal SEC differed by less than 3%, with no significant difference. The lower electrical SEC of Plant-A is a plant-level benchmarking result and may be linked to differences in loading, equipment configuration, process integration, and utility-management practices. The electricity-saving potential of Plant-B under the benchmark scenario was estimated at 410,313 kWh/year, equivalent to about ₹41.03 lakh/year at ₹10/kWh and about 390 t CO_2/year at 0.95 kg CO_2/kWh. These are indicative benchmarking values and not necessarily savings that can be guaranteed by improving capacity utilization alone.

The final electrical energy consumption model had curd sales and capacity utilization as significant variables, with a 10-fold R^2 of 93.79%, a VIF of 2.05, and a Durbin–Watson statistic of 1.963. The final thermal energy model had milk sales as the significant variable, with an R^2 of 84.60%. The product-specific electrical SEC models for milk, curd, and butter & ghee had capacity utilization as the significant variable, with R^2 values of 65.48%, 62.97%, and 63.93%, respectively. The electrical and thermal SEC models of UHT, fitted to Plant-B data only because UHT is not produced in Plant-A, and had capacity utilization (electrical) and curd and UHT sales (thermal) as significant variables, with 10-fold R^2 values of 55.98% and 85.64%, respectively. Thermal SEC models for the other products were infeasible because thermal SEC varied too strongly with capacity utilization in Plant-B.

The results should be interpreted with some caution because of several limitations. The analysis relied on observations from only two dairy processing plants, which limited statistical power, and stepwise variable selection may have been sensitive to the available observations. Furthermore, the mathematical dependency between capacity utilization and SEC can affect their observed statistical association. In addition, detailed equipment-level operating parameters were not available at the desired temporal resolution. Future investigations should therefore use longer time-series data and include detailed measurements of motor loading, refrigeration performance, boiler efficiency, and other utilities. Such data would help to better assess the mechanisms behind plant-level energy differences and support more robust recommendations for energy savings.

The main scientific contribution of this study is the combination, within a single study, of interpretable regression modeling, control of multicollinearity, cross-validation, residual autocorrelation assessment and correction, product-specific SEC analysis, and plant-level benchmarking to analyze energy consumption in dairy processing. The proposed framework is a meaningful general model for estimating energy consumption and specific energy consumption in the dairy processing industry.

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Availability of Data and Materials: The datasets used and analyzed during the current study are available from the corresponding author upon request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

Term/Symbol	Unit	Definition
SEC	kWh/L or kJ/L	Specific energy consumption
R^2	—	Coefficient of determination
Adj. R^2	—	Adjusted coefficient of determination
Pred. R^2	—	Predicted coefficient of determination
CV R^2	—	Cross-validated coefficient of determination
MLR	—	Multiple linear regression
VIF	—	Variance inflation factor
DW	—	Durbin–Watson statistic
ACF	—	Autocorrelation function
RMSE	—	Root mean square error
MAE	—	Mean absolute error
p	—	Probability value for statistical significance testing
SE	—	Standard error of the estimated coefficient
t	—	t-statistic
α	—	Significance criterion used for variable selection
ρ	—	First-order residual autocorrelation parameter used in the Cochrane–Orcutt transformation
CU	—	Capacity utilization (actual production/installed capacity; dimensionless)
B&G	—	Butter and ghee
UHT	—	Ultra-high-temperature
10-fold CV	—	10-fold cross-validation
Trans.	—	Transformed variable used in the Cochrane–Orcutt procedure
kWh	kWh	Kilowatt-hour
kJ	kJ	Kilojoule
hp	hp	Horsepower
CO_2	—	Carbon dioxide
L	L	Litre
Total kWh	kWh	Total electrical energy consumption
Total kJ	kJ	Total thermal energy consumption
Milk Sales	L/month	Monthly quantity of milk processed/sold
Curd Sales	L/month	Monthly quantity of curd processed/sold
B&G Sales	L/month	Monthly quantity of butter and ghee processed/sold
UHT Sales	L/month	Monthly quantity of UHT milk processed/sold
hp/100 L	hp/100 L	Electrical intensity based on installed motor capacity per 100 L of production
MJ/100 L	MJ/100 L	Thermal intensity based on thermal-system capacity per 100 L of production

(Continued)

(continued)

Term/Symbol	Unit	Definition
S	—	Standard error of the regression
Coef.	—	Estimated regression coefficient
p-value	—	Probability value associated with the statistical test of a regression coefficient
OLS	—	Ordinary least squares
Plant-A	—	Dairy processing plant A considered in the study
Plant-B	—	Dairy processing plant B considered in the study

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