Energy Baseline for Efficiency Verification in Yarn Industry: A Case Study

Todo H Simarmata[1], Aspita Dyah Fajarsari[1], Nico Juni Ferson[1] and Hari Kartiko[2]
[1]Ministry of Energy and Mineral Resources, Jakarta Timur, 13740, Indonesia
[2]PT.Indorama Synthetics, Purwakarta, 12950, Indonesia

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Correspondence email:
t.h.t.simarmata@gmail.com

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ABSTRACT

Energy consumption in the yarn manufacturing industry is significant due to electricity-intensive processes and auxiliary systems; energy intensity (kWh per kg of yarn) is a key indicator of efficiency and cost. To accurately evaluate savings from efficiency measures, the study developed a multiple linear regression (MLR) baseline model for a large polyester and synthetic yarn plant in West Java Indonesia. The model used historical 2022 data to relate energy use to production output and operational variables, enabling prediction of energy consumptionin the absence of improvements. Statistical analysis showed the regression was significant. The plant's energy intensity averaged ~3.4–4.1 kWh/kg, which is moderate compared with European benchmarks. Using the model as an energy performance indicator (EnPI), the 2023 monitoring year data were compared to baseline predictions to verify savings. The comparison revealed that energy-saving initiatives—such as improved motors and climate control—reduced actual energy use below the baseline, confirming real efficiency gains while accounting for factors like production level and weather. The case study demonstrates that MLR-based EnPI baselines provide a robust framework for moni-toring and verifying industrial energy savings and benchmarking performance.

Keywords : Energy Baseline, Energy Management, Energy Performance, Verification, Regression

INTRODUCTION

Energy performance in the yarn industry has become a critical focus over the past decade, driven by sustainability goals and cost pressures. Synthetic yarns (primarily polyester, polypropylene, nylon, etc.) dominate global textile production, comprising roughly two-thirds of textile fibers (Palacios-Mateo et al., 2021).

Manufacturing these yarns is energy-intensive, consuming electricity and thermal energy at various stages from polymer production to fiber extrusion and spinning. Energy intensity, often expressed as energy use per unit of output (e.g. kilowatt-hours per kilogram of yarn, kWh/kg), is a key performance indicator for benchmarking efficiency and environmental impact. High energy intensity not only raises production costs but also correlates with significant greenhouse gas emissions (Demirdelen et al., 2023; Palacios-Mateo et al., 2021)

Energy efficiency is a critical concern in the yarn manufacturing industry, not only for environmental reasons but also due to the significant share of energy in production costs. In typical yarn mills (e.g. spinning mills), energy costs can range from about 5–18% of total manufacturing costs (and even 10–25% in certain spinning processes) (Branchetti et al., 2019).

Reducing energy use through efficiency measures (such as installing efficient motors, improving climate control, etc.) can thus yield substantial cost savings. However, verifying these energy savings is challenging, because savings represent energy not used and cannot be measured directly (Medojevic et al., 2017).

A reliable approach is needed to quantify how much energy has been saved after an improvement, accounting for factors like production levels and weather that also affect consumption. This is where multiple linear regression (MLR) methods come into play. MLR-based models are widely used in industrial energy measurement and verification (M&V) to establish an energy baseline and validate savings against that baseline (Kelly Kissock & Eger, 2008) .

Yarn manufacturing (spinning) involves processes that are electricity-intensive, powering machinery like blowroom lines, carding machines, ring frames or rotors, winding machines, and extensive climate control (air conditioning and humidity control systems) to maintain fiber quality. A large portion of energy in a textile plant is consumed in the spinning stage – one analysis reported that spinning processes are responsible for approximately 93% of the total electricity consumption in the production of textile yarn. (Branchetti et al., 2019).

The key drivers of energy consumption in a yarn factory include: (1) Production Output: The amount of yarn produced (e.g. in kilograms or yarn count) has a direct impact on energy use. Machines draw power roughly proportional to throughput, so higher production generally means higher energy consumption, (2) Machine Operating Parameters: Machine speeds, load factors, and utilization rates influence energy usage. For instance, running more spindles or higher spindle speeds will consume more electricity, (3) Auxiliary Systems: Supporting systems such as compressed air, lighting, and particularly climate control (humidification and air-conditioning) can draw substantial energy. In many spinning mills, the air conditioning/chiller plant is a major consumer (one case found ~80% of the specific energy consumption was from AC and chilling systems (Sakti et al., 2021). Ambient conditions (outside temperature and humidity) affect how hard these systems must work, (4) Raw Material or Process Differences: Different fiber types (cotton vs. synthetic blends) or process routes can have different energy profiles. For example, open-end (rotor) spinning tends to use less energy per kg of yarn than ring spinning (Koc & Kaplan, 2007), so a shift in product mix could influence total energy use.

All these factors cause normal fluctuations in a plant's energy consumption. Thus, when an energy efficiency measure is implemented, simply comparing the utility bills "before vs after" can be misleading unless adjustments are made for these variables. A period of lower production or milder weather could appear as "savings" when in fact it's due to external factors. To accurately verify savings, we need a baseline model that correlates energy use with the relevant independent variables (production, weather, etc.), and then use that model to predict what energy would have been used had no efficiency changes been made. Multiple linear regression provides a robust statistical framework to build such a baseline model.

RESEARCH METHOD

Multiple linear regression (MLR) is a commonly used method for Measurement and Verification (M&V) of energy savings in industrial facilities. By modeling a plant's energy consumption as a function of key operational variables (production output, operating conditions, etc.), MLR provides a baseline to compare what energy use would have been without efficiency measures against actual post-implementation usage. An MLR baseline model for a yarn factory can be expressed generically as:

$E = \beta_0 + \beta_1 P_1 + \beta_2 P_2 + \beta_3 P_3 + \ldots + \varepsilon$ …………..(1)

where:

- **E** is the energy consumption over a certain period (e.g. kWh per day or per month).
- **P1, P2, P3** is the production specific output in that period (e.g. kilograms of yarn produced).
- **β0, β1, β2, β3** are the regression coefficients determined by fitting the model to historical data.
- **β0** is the intercept (the model's estimate of the energy use when all independent variables are zero), and β1, β2, β3, ... quantify how sensitive energy consumption is to each factor. For instance, β1 (coefficient on production) represents the **incremental energy consumption per unit of production** – effectively, how many kWh are needed for each additional kilogram of yarn output (Branchetti et al., 2019). **β0**, the intercept, represents the **base load** or fixed energy use of the facility when production is zero (e.g. energy for lighting, idling equipment, or baseline HVAC needs).
- **ϵ** is the error term, accounting for random fluctuations and factors not captured by the model.

A. *The Case Study*

The plant choosen as the case study is located in West Jawa Indonesia is the largest plant in ASEAN producing differentiated polyester products for high-value textiles. It started as a cotton spinning mill and later diversified into synthetic yarn and fibre production.

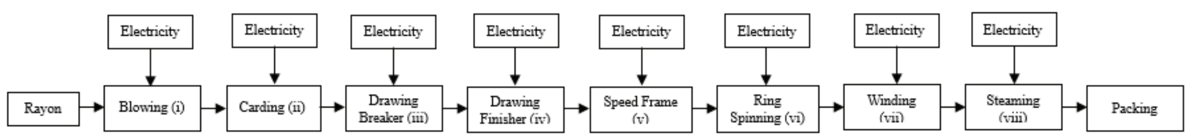

Figure 1. Typical Production Process (Sakti et al., 2021)

The yarn manufacturing process generally comprises eight sequential stages that convert raw fiber into finished yarn: (i) Mixing and Blowing: The process begins with the opening and blending of raw fibers sourced from multiple bales to achieve a homogeneous mix in line with product specifications. Using high-capacity mixing and blowing machines, compressed bales are opened, cleaned of contaminants, and thoroughly blended. This stage prepares the fibers into an aligned, continuous sheet (commonly referred to as a lap) for the subsequent process. (ii) Carding: During carding, the opened fibers are further individualized, combed, and aligned into a thin web, which is then condensed into a strand known as a sliver. Carding serves to straighten the fibers, remove residual impurities and short fibers, and produce a continuous sliver of predominantly parallel, longer fibers that provides the basis for uniform yarn quality. (iii) Drawing (Breaker Draw Frame): In the first drawing passage (breaker draw frame), multiple carded slivers are combined and drafted simultaneously. This drafting action attenuates the slivers while blending them and reducing variations in fiber mass per unit length. As a result, the breaker drawing stage markedly enhances sliver uniformity by averaging out thickness irregularities across the combined strand. (iv) Drawing (Finisher Draw Frame): The partially drawn sliver from the breaker stage is then processed through a second drawing passage, the finisher draw frame. Here, additional drafting and auto-leveling are applied to further improve evenness. This stage yields a highly uniform sliver with consistent linear density (weight per unit length), which is appropriate for the ensuing spinning operations. (v) Speed Frame (Roving): The uniform sliver is subsequently fed into the speed frame (roving frame), where it is further attenuated and imparted with a slight twist to form roving. Roving constitutes a relatively thick, low-twist intermediate yarn that is wound onto bobbins. This step provides the strand with sufficient strength and reduced thickness to withstand handling in the final spinning stage without excessive breakage. (vi) Ring Spinning (Ring Frame): In the ring spinning stage, the roving is converted into fine yarn. The roving is continuously drawn to the desired fineness in the ring frame and subjected to a higher degree of twist to generate a strong, coherent yarn. The spun yarn is then wound onto small bobbins known as cops. At this point, the yarn attains its specified count (fineness) and mechanical strength. (vii) Winding: Following spinning, yarn from multiple cops is rewound and consolidated onto larger packages, typically cones. The winding process often incorporates yarn clearing, during which defects and uneven portions are removed to ensure quality. By transferring the yarn onto cones, it is prepared in continuous lengths suitable for storage, transportation, and subsequent processes such as weaving or knitting. (viii) Steaming (Conditioning): In the final stage, the yarn packages are conditioned by exposure to steam in a controlled chamber to adjust and standardize their moisture content. Appropriate moisture conditioning is critical for maintaining yarn strength, flexibility, and weight consistency. The steam temperature and treatment duration are regulated according to the yarn's material characteristics and count. This conditioning step stabilizes the yarn structure, mitigates brittleness and static buildup, and ensures that the final product complies with required quality standards for end use or commercialization.

After completing the eight main processes above, the finished yarn cones are packed for shipment according to customer requirements. Packaging methods include stacking cones on pallets, packing in neutral or branded cartons, or using sacks, ensuring the yarn is protected and delivered in the requested format. This final step, while outside the spinning process itself, is essential for preserving yarn quality during transport and handling.

Energy consumption breakdown in a textile spinning mill: (2a) overall plant energy by use, and (right) production process energy by machinery stage. As shown in the charts, the production machinery dominates the energy usage in the textile plant, accounting for about 74% of total power consumption. In comparison, auxiliary systems for climate control (air conditioning in the plant and a chiller for cooling) take up roughly a quarter of the energy (13% and 12% respectively), while lighting and office AC are minimal uses. This indicates that the manufacturing process itself is the primary driver of electricity costs, although environmental control is also significant in spinning mills (maintaining temperature and humidity is critical for yarn quality).

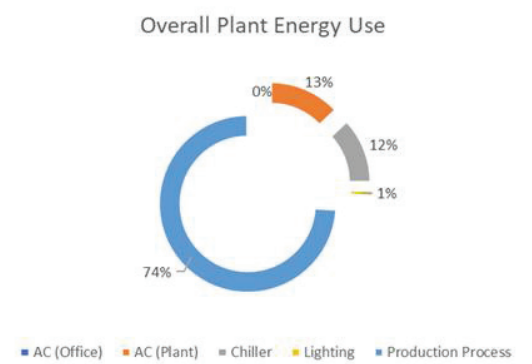

Figure **2**a. Overall Plant Energy Use ((Sakti et al., 2021))

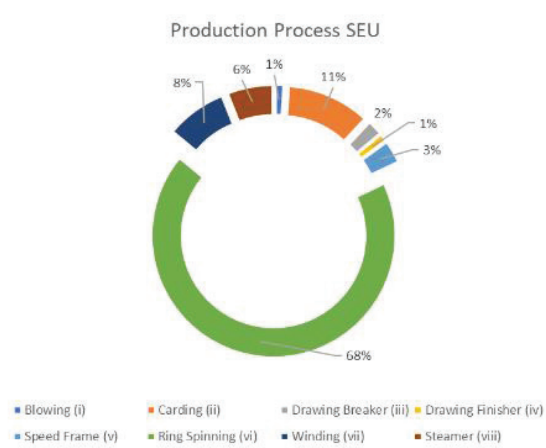

Figure 2b. Typical SEU energy consumption distribution ((Sakti et al., 2021))

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Within the production process segment, ring spinning is by far the most energy-intensive stage. According to the detailed breakdown, the ring spinning machines consume about 68% of the production-process energy — which equates to roughly half of the plant's total energy alone. The high energy demand is due to the large number of spindles running at high speeds continuously, and the power needed to overcome friction (in rings, travelers, and spindles) and drive the yarn winding. In the given data, ring spinning's energy usage vastly exceeds all other stages, identifying it as the primary target for energy efficiency improvements.

The carding department is the second most energy-consuming process, but at a much lower share than spinning. Carding accounts for about 11% of the production-process energy (~8% of total plant energy). Carding involves heavy drums and motors (and suction for fiber dust), so it draws significant power, though its contribution is far less than that of ring spinning.

Other process stages such as winding (approximately 8% of production energy) and the yarn conditioning steamer (~6%) also consume notable portions. Winding machines (autoconers) require power for high-speed yarn winding and operate suction for cleaning yarn.

The steamer uses thermal energy (and electrical controls) to produce steam and maintain vacuum, explaining its moderate share. Meanwhile, the preparatory steps — speed frame, drawing, and blow room — are comparatively low in energy consumption, together only accounting for a few percent of the production energy. In the chart, the speed frame (roving) is ~3%, the two drawing frames total ~3%, and blow room just ~1%. These machines, though essential, have lower motor loads or operate intermittently, so their impact on the overall energy profile is small.

In summary, the energy usage profile highlights ring spinning as the dominant energy consumer, with carding as a distant second. Winding and steaming are mid-level consumers, and all other processes use relatively little energy individually. The facility's utilities (air conditioning and chillers) also form a substantial secondary load. Therefore, any energy management efforts should focus first on the ring spinning frames, followed by carding and other significant machines, as well as optimizing the climate control systems.

B. *Data Collection*

Historical data of the plant's production in 2022 and 2023 was gathered. Data on production by different production line in the Spinning department (tons), total energy consumption of the plant (kWh/month) was collected. Based on these data, the SEC in each area was calculated.

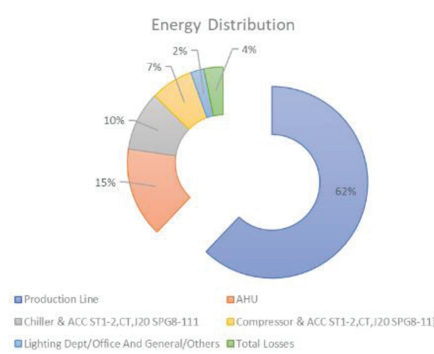

Figure 3. Energy Consumption Distribution of the Plant

The donut chart shows how electricity is allocated across different systems in a yarn-spinning facility. Production lines (spinning, winding and related equipment) account for about 62 % of the plant's energy consumption. This dominance is typical for textile mills: a study on cotton textile processing found that electricity makes up 93 % of the energy consumed in spinning and 85 % in weaving (Palamutcu, 2010), and that energy costs represent 8–10 % of total production cost. Polyester yarn production is similarly energy-intensive because polymerisation and melt-spinning require high temperatures and continuous machine operation.

The AHU (air-handling unit) segment (15 %) reflects the need to control temperature and humidity. Cotton fibres are sensitive to moisture; maintaining relative humidity around 60–65 % prevents yarn breakage and static, so substantial energy is spent conditioning air. Chillers and air-conditioning systems add another 10 %, illustrating that cooling is vital for both polyester and cotton lines to dissipate heat from high-speed motors.

Compressed air systems, used for cleaning, pneumatic transport and actuating machinery, contribute 7 % of energy use. A recent case study on yarn manufacturing noted that energy costs vary by raw material and process: for 20-tex carded open-end cotton yarn, energy costs range from 5–18 % of total mill costs, while ring-spinning and rotor-spinning lines can reach 10–25 % (Branchetti et al., 2019). The same study emphasised the importance of separating auxiliary energy uses (e.g., compressors) from production consumption to create meaningful benchmarks.. Proper maintenance of compressed-air networks is crucial, as leaks and idle operation can waste energy.

Lighting, office equipment and miscellaneous general uses account for 2 %. Though relatively small, adopting LED fixtures and occupancy sensors can yield quick savings. The total losses slice (4 %) represents energy lost as heat in motors, transformers and distribution systems. Regular servicing and upgrading to high-efficiency motors can help reduce these losses.

Overall, the chart highlights that most energy is consumed on the production floor, with sizeable shares devoted to HVAC and compressed air. Literature on textile-sector energy use recommends collecting detailed consumption data, segregating production and auxiliary loads, and benchmarking against best-practice factories to identify improvement opportunities, for a plant producing both polyester and cotton yarn, monitoring how each fibre type influences machine settings and energy demand can inform targeted efficiency measures.

C. Energy Performance Indicator

The line chart tracks the Energy Performance Indicator (EnPI) for the yarn-spinning plant over January 2022 – December 2023. The EnPI measures the electric energy consumed per kilogram of yarn (kWh /kg).

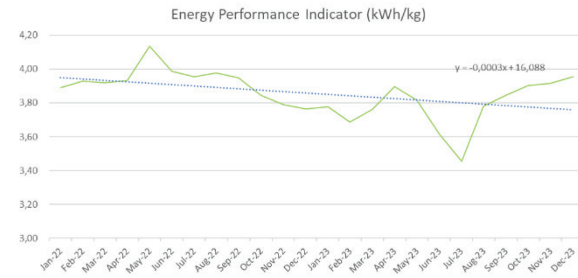

Figure 4. Energy Performance Indicator in kWh per kilogram

The EnPI hovers around 3.9 kWh /kg, peaking at ≈4.1 kWh /kg in May 2022. A gradual decline occurs, with specific energy consumption dropping below 3.8 kWh /kg by March 2023. The indicator briefly rises above 3.9 kWh /kg in May 2023 before plunging to ≈3.4 kWh /kg by July 2023, suggesting either a temporary improvement in energy efficiency (e.g., equipment upgrades or a shift toward lower-energy polyester yarn) or reduced production.

After the dip, energy intensity climbs steadily, reaching ≈4.0 kWh /kg by December 2023, likely reflecting increased production of finer or combed cotton yarns that require more energy to spin. Overall, the EnPI fluctuates within a relatively narrow band (≈3.4–4.1 kWh /kg), indicating that the plant maintains consistent control over its energy use per unit of product. However the chart shows a downward trend during year 2022 till 2023.

D. Energy Baseline

We use the linest function of Excel to determine the base line fitted model as :

$$y \approx 2.804SPG10+11.137SPG9+1.201SPG8+0.837ST2+4.825J20-3.941CT-5.625ST1+4{,}458{,}439 \quad \text{...(3)}$$

Table 1. Linest Table

	SPG10	SPG9	SPG8	ST2	J20	CT	ST1	b
m_n	2.804	11.137	1.201	837	4.825	(3.941)	(5.625)	4.458.439
SE_n	7.078	7.558	2.576	3.851	937	16.233	11.518	2.262.648
R_2 | SE_y	96%	286.117	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
F stat | df	14,7	4	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
SSR | SSE	8.402.012.143.247	327.452.682.260	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
t_{stat}	0,396	1,474	0,466	0,217	5,150	(0,243)	(0,488)	1,970
p_{value}	0,712	0,215	0,665	0,839	0,00675	0,82	0,651	0,120

To assess whether the regression model is significant, we compute the p-value associated with the F-statistic. The p-value is the probability of obtaining a value as extreme as the observed F under the null hypothesis that all coefficients (except the intercept) are zero. It is calculated from the F(df_1, df_2) distribution:

$$p - value = 1 - F_{cdf}(F_{obs}, df1, df2) \quad ....(2)$$

Where F_{cdf} is the cumulative distribution function of the F-distribution. The LINEST table provided coefficients, standard errors, R², the F-statistic, degrees of freedom and sums of squares. Using the F-statistic (14.7) and the degrees of freedom (7 and 4) we computed an overall model p-value of ≈ 0.01035, showing that the regression is statistically significant and unlikely to have arisen by chance. For each coefficient, t-statistics and two-tailed p-values were calculated using the standard errors. Only variable 5 was significant (p ≈ 0.0067); all other predictors and the intercept had p-values > 0.05 and hence did not demonstrate individual significance in this small sample.

RESULTS AND DISCUSSION

A. *EnPI Benchmark*

A self-analysis of European yarn factories reported electrical SEC values ranging 1.4–14.5 kWh /kg with an average of 5.6 kWh /kg. Cotton-based mills generally consume ≈2.4 kWh / kg, whereas wool-based mills can exceed 10 kWh / kg (Branchetti et al., 2019). The plant's EnPI (≈3.4–4.1 kWh /kg) lies within this typical range and suggests moderate energy intensity given its polyester/cotton mix as depicted in figure 3.

A 2024 case study on combed ring spinning found monthly SEC values of 3.23–3.76 kWh /kg, and measured 3.32 kWh /kg for 20-tex combed ring yarn; literature values ranged 3.49–3.62 kWh /kg. These benchmarks are comparable to the mid-range values observed in the chart. Research shows that finer yarns and weaving yarns (which require more twist) consume more energy, while combed yarns use more energy because of the additional combing step. This explains why the EnPI climbs again toward the end of 2023 possibly due to a higher share of combed or fine-count cotton yarns.(Koc & Kaplan, 2007)

Spinning as the primary energy consumer: In cotton textile processing, spinning accounts for 93 % of electric energy use, with typical SEC values of 3.24–3.47 kWh /kg for yarn spinning plants. Auxiliary processes (warping, weaving, wet processing) use much less energy (Palamutcu, 2010), so fluctuations in the EnPI largely reflect the efficiency of spinning machines and the type of yarn being produced.

Comparing the plant's EnPI with the ranges reported in the literature (3.23–3.76 kWh/kg for ring-spun cotton yarn and 3.24–3.47 kWh/kg for general yarn spinning shows that the plant is performing within or slightly above typical benchmarks. Continuous monitoring and analysis can help identify opportunities to further reduce energy intensity.(Koc & Kaplan, 2007; Palamutcu, 2010)

In summary, the chart reveals a well-controlled energy performance indicator that aligns with documented values from Scopus-indexed studies. Variations across months likely reflect changes in yarn type, production volume, and equipment efficiency, underscoring the importance of detailed energy tracking and targeted process improvements.

B. *Multi-Linear Regression for Energy Baseline Modeling*

For the yarn facility, 12 months of 2022 data were used to train a multi-linear regression with the seven production line outputs as predictors. This baseline period was chosen to span a full year, capturing seasonal or operational variability. The regression fitting would have involved checking the statistical significance of each term, ensuring the model adequately explains consumption (typically via R^2 and error analysis). The resulting model (given above) indicates how many kWh are consumed per kg of product from each line, on average, plus a large constant term capturing baseline fixed consumption. Such modeling of industrial energy use through multiple regression is supported in the academic literature. For instance, Abourriche et al. (2025) used multiple linear regression to correlate a confectionery plant's electricity consumption with production volume and other factors, yielding a predictive model for energy use (Abourriche et al., 2025). Similarly, Maaouane et al. (2021) modeled industrial energy demand based on output of goods using a multi-linear regression approach(Grimaldo-Guerrero et al., 2021). These studies underscore that regression analysis is a common and validated technique for energy baseline modeling in manufacturing settings.

The baseline model was developed using multiple linear regression (equation 3) on data from January 2022 to December 2022 (the baseline period), relating monthly energy use (in kWh) to production volumes (in kg) from seven production lines. The multi linear regression shows correlation between energy consumption in kwh and production of seven line of cotton and polyester yarn consist of cotton line (CT, SPG-9), polyester (ST1, ST2, SPG-8, SPG-10) and blended polyester and cotton (J20).

Under the ISO 50006 framework for energy baselines, multiple relevant drivers (here, yarn outputs) require a model to normalize energy use. Each term's coefficient can be interpreted as an energy intensity for that product: e.g., "2.804 kWh per unit of SPG10" etc. Large positive coefficients imply that yarn type demands more power in production. For example, SPG-9 (a cotton yarn) has the highest positive coefficient, consistent with the literature that finer cotton spinning can consume large amounts of electricity. The negative coefficients (for CT and ST1) are counterintuitive if considered in isolation, but likely reflect interdependence among production levels (multicollinearity): when CT or ST1 output increases, other high-energy processes may decrease, yielding a net negative coefficient. In practice, these coefficients should be viewed in the context of the full model rather than as standalone energy "savings." The intercept (≈4.46 million kWh) represents the fixed base energy – auxiliary loads and machine idling – which literature terms the base energy consumption (the portion not related to production) (Palamutcu, 2010).

The model's overall fit quantifies how well production changes explain energy variation. High goodness-of-fit (R^2) would indicate that most energy use moves in step with production volumes. (If R^2 were low, it would imply other unmeasured factors or inconsistent operations dominate, making baseline adjustments harder.) In this case the choice of seven production variables suggests the model was needed to account for mixed-product effects. As ISO 50006 notes, using such a multivariate model avoids misleading simple comparisons: e.g. if the product mix changes year-on-year, a raw drop in kWh might simply reflect different production rather than true efficiency gains. By contrast, this regression explicitly quantifies each product's energy contribution, enabling a normalized baseline that accounts for output variations.

Taken together, the statistics table 1 tell us how well the production data explain energy use. A high R^2 (e.g. above 0.7) and significant F indicate the model fits well. The standard error S measures the prediction accuracy: a small S relative to the typical energy values means good fit. Large SSR vs small SSE reinforces a strong model (explained variation >> unexplained). However, if R^2 is modest or S is large, there is substantial random error or other factors affecting energy. Ultimately, the LINEST output shows both the magnitude of each line's impact (via slopes) and the reliability of those estimates (via SE, t, p).

Lines with large positive slopes and small p-values are key drivers of energy use. For example, if ST2 and SPG8 have high coefficients that are statistically significant, they contribute heavily to total energy. Improving energy efficiency on those lines (better machinery, process controls, etc.) will have the greatest payoff. Lines with insignificant coefficients may be lower priority since their output is not strongly tied to energy use. If polyester lines show consistently higher impacts, then optimizing polyester production is critical. For instance, implementing waste-heat recovery or more efficient motors on polyester spinning might yield large energy savings. Cotton lines might already be relatively efficient; if not, check if their processes can be tuned. Blend line (J20) strategies would depend on whether its impact is closer to cotton or polyester.

The model can inform operational decisions. If energy is constrained, shifting production toward lines with lower energy coefficients (if flexible) could reduce consumption. Conversely, lines with high coefficients should be scheduled carefully or run at optimal loads. In summary, each statistic in the LINEST output has a clear meaning: slopes quantify per-line energy impact , p-values/t-stats show which impacts are reliable, and R^2, F, SSR/SSE, S tell us how well production explains energy use. By interpreting these together, we identify which yarn lines (and hence which materials) are driving energy consumption and can focus optimization efforts accordingly.

C. Energy Baseline and Actual

Figure 5 shows that the plant's actual electricity use closely tracks the regression baseline. For most months, the solid actual consumption line stays very near the dotted baseline, indicating that the model's predicted values match reality reasonably well. In other words, given the production volumes on each line, the baseline model provides a good expectation of how much energy should be used, and actual usage generally falls in line with that expectation. This suggests that production output is indeed a strong driver of energy consumption at the facility, and the model captures those relationships effectively. Minor month-to-month fluctuations between the actual and predicted lines are expected, but there is no persistent large divergence for most of the period. This typically reflects a high goodness-of-fit for the regression model (in practical terms, likely a high R^2, meaning the model explains a large portion of the variation in energy use). The baseline thus serves as a reliable yardstick for "normal" energy consumption given the production levels.

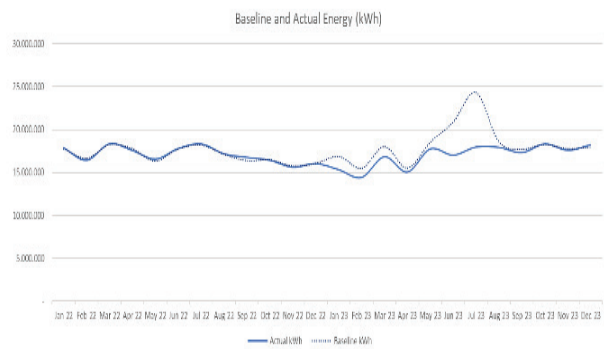

Figure 5. Energy baseline and actual chart

The time-series chart juxtaposes baseline consumption (the model-based reference) against actual usage. Typically, one would use the 2022 data to calibrate the model and then project a "2023 baseline" by plugging actual 2023 production into the regression. Comparing that baseline prediction to the measured 2023 energy reveals performance. If the actual energy curve lies below the baseline curve, the plant has consumed less energy than expected for its production level – indicating energy savings or efficiency improvement. Conversely, actual values above baseline suggest worse-than-expected performance.

D. Performance and Savings

Quantitatively, energy savings can be expressed as the difference between baseline and actual, or as a percentage change. For example, the ISO 50006 guidance describes an "EnPI difference" metric (*BSI Standards Publication Energy Management Systems-Measuring Energy Performance Using Energy Baselines (EnB) and Energy Performance Indicators (EnPI)-General Principles and Guidance*, 2015):

Energy savings (difference) = Baseline EnPI – Actual EnPI……………………….……… (4)

Energy savings (%) = [(Baseline – Actual) / Baseline]×100……………………..………….(5)

In our context, using the regression, one would compute the expected kWh for 2023 at 2022 baseline conditions and compare to actual kWh in 2023. A persistent gap as shows in figure 6 (baseline higher than actual) signifies cumulative savings.

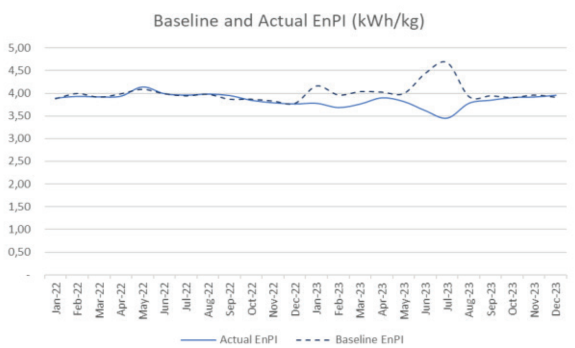

Figure 6. Baseline and Actual EnPI

This approach is analogous to M&V practices in industry: regression models are often used to isolate savings by holding production constant. Without such normalization, attributing energy changes to efficiency versus production shifts would be unreliable. As Amundson et al. emphasize, one must "distinguish the effects of improvements from changes in production" using models, or evaluations will be questioned (Amundson et al., n.d.). The cumulative savings during the year 2023 period shows energy savings improvement equal to 18 GWh or 7,48% compared to baseline.

CONCLUSION

As a conclusion, we have several key insights for energy efficiency focus and verification. First, the model validates which yarn processes drive energy use. Managers can focus conservation efforts on the highest-intensity products (e.g. those with large positive coefficients) and on reducing the base load. Second, the baseline comparison provides a transparent benchmark. By plotting actual vs. baseline, the company can see seasonal or operational deviations. For instance, if an efficiency measure was implemented in spring 2023, the chart would show actual consumption dipping below baseline afterwards, quantifying saved kWh. Over long periods, one can track whether efficiency targets (like a percent reduction) are met. Third, normalizing energy to production (often expressed as kWh per unit yarn) can be computed from the model. Declining energy-per-unit year-over-year (even if production grows) is a clear sign of improved performance. As Cerdancova et al. observed in a similar textile case study, energy use typically "shows a close connection" to output; this regression lets one factor out that link and examine efficiency gains beyond production-driven changes (Cerdancova et al., 2021).

In summary, the regression-based baseline model explains the bulk of year-to-year energy variation through changes in product mix and volume. It enables a fair comparison of "apples-to-apples" energy use, so that actual vs. baseline differences legitimately reflect operational performance. When the actual 2023 curve deviates downward from the baseline line, the manufacturer has demonstrated saved energy. This methodology – grounded in best practices for industrial energy monitoring – ensures that energy savings claims are defensible and tied to technical causes (Amundson et al., n.d.).

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- **Glossary/Nomenclature/Abbreviations**

EnPI	Energy Performance Indicator
MLR	Multiple Linear Regression
SEC	Specific Energy Consumption
SE	Standard Error
SSR	Regression Sum of Squares
SSE	Error Sum of Squares
M&V	Measurement and Verification

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