

Article

Evaluating the Effectiveness of VFD Retrofit Under Operational and Manual Control Constraints in a Kenyan Petroleum Depot

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Abstract

Globally, downstream petroleum operations face increasing pressure to optimize energy use and reduce carbon emissions, with electrically driven pumping systems representing the dominant site-level electricity load. This study investigates why anticipated energy savings from a variable frequency drive (VFD) retrofit were not realized in a Kenyan petroleum depot. High-resolution PLC-SCADA data at 1 s intervals were analysed over a six-month period using a custom Pump-Arm Modelling framework, reconstructing pump operation and energy consumption as a function of loading arm demand, runtime, and control mode. Results show that, despite VFD installation, pump speeds remained effectively fixed, and energy consumption was governed by discrete loading arm demand rather than speed modulation. Eight months billing data confirmed that post-retrofit energy intensity increased, from an average of 0.493 to 0.555 kWh/m³, demonstrating that expected efficiency improvements were not achieved. Stratified analysis further showed that idle running due to manual overrides accounted for approximately 3% of total depot electricity consumption. To contextualize this performance gap, idealized affinity-law scaling was applied to observed partial-load intervals, revealing unrealized energy savings potential of approximately 92 MWh, equivalent to a depot-level savings potential of 28.4% ± 1.4%. The findings indicate that limited energy savings were attributable to open-loop control architecture, partial digital integration, and legacy equipment constraints rather than VFD hardware limitations, highlighting the need for demand-aware, closed-loop energy optimization in retrofitted petroleum depots.

Keywords: VFD retrofit; petroleum depot; Pump-Arm modelling; energy optimization; PLC-SCADA; Human-Machine Interaction

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1. Introduction

Rising industrial activity and expanding transportation networks are driving the increasing global energy demand while sustainability pressures intensify the need for efficient energy use. In industrial sectors, electricity-intensive operations represent a major portion of energy consumption, accounting for approximately 40% of global energy use [1]. Energy efficiency improvements yield both economic and environmental benefits [2]. In the downstream operations in the Oil and Gas sector, petroleum depots rely heavily on

electrically driven pumping systems for product storage, handling, and truck loading. These pumps can account for up to 80% of site-level electricity consumption during peak demand periods, with energy use highly sensitive to operational decisions during pump sequencing, loading patterns [3], the number of active loading arms, start-stop frequency, and manual interventions that bypass automated pumps control [4,5]. Additional factors that include legacy control logic, fragmented energy metering, sporadic truck arrivals, grid disturbances [6,7], and standby generator reliance [8] further influence energy performance in complex and unpredictable ways.

Variable Frequency Drives (VFDs) are widely adopted to improve pump energy efficiency by modulating speed according to demand. Although theoretically capable of significant savings in 5–50% [9] energy savings in variable-speed pump applications compared with fixed-speed operation, their practical impact can be limited by fixed-speed operation, manual overrides, incomplete control integration, and retrofits applied to ageing equipment without hydraulic or pump-motor upgrades [10,11]. Evidence on VFD performance in Kenyan and Sub-Saharan African petroleum depots remains scarce. Although a limited number of engineering reports and local case studies exist, there is a lack of operational research documenting actual energy performance in depot settings, particularly using operational data [12]. The broader literature on VFD applications in the African context indicates limited technical adoption, fragmented and largely market-oriented reports, as well as infrastructural and expertise gaps in this region [12].

Motivated by these realities, this research examines how operational decisions, control architecture, and human intervention influence energy outcomes following VFD retrofitting in a Kenyan petroleum depot operating under legacy constraints. Rather than evaluating VFD hardware in isolation, this study emphasizes the interaction between physical equipment, digital control systems, and operator actions, providing insight into why theoretical energy savings may not be fully realized and how efficiency improvements can be better aligned with real-world depot operations [10,11].

1.1. Objectives and Organization of This Study

The purpose of this study was to investigate the energy performance of pump–motor assemblies in a petroleum depot in Kenya following the retrofit of VFDs, motivated by monthly utility billing data indicating that expected reductions in energy intensity were not realized post-installation [13]. The analysis was based on data collected via installed utility energy metering, VFD-PLC-SCADA data logs, and on-site observations. Rather than assuming underperformance of the VFD technology, this study examined how operational conditions, control practices [14], and human interventions [15,16] influenced energy performance under real depot operating conditions.

Accordingly, this study pursued the following objectives.

1. Quantify pump-level energy use by decomposing total site energy into contributions associated with discrete loading demand, operational state, and manual overrides, enabling identification of key sources of inefficiency.
2. Assess the extent of demand-responsive operation following VFD retrofit by comparing observed pump behaviour with the theoretical energy-saving potential.
3. Examine the role of operational practices and data integration in shaping depot energy performance.

The remainder of this study is organized as follows: Section 2 describes the depot configuration, pumping system, and PLC-SCADA data acquisition; Section 3 presents the analytical framework for attributing pump energy to operational states; Section 4 reports the results and analyses operational and human factors affecting energy use; Section 5

discusses the findings, practical implications, and recommendations for retrofit strategies; and Section 6 concludes this study.

1.2. Problem Definition

In petroleum depot pumping operations, VFDs are expected to adjust pump operation to match loading requirements, theoretically yielding significant energy savings through reduced power draw at partial loads [9,17]. These benefits require continuous adjustment of pump speed, flow, and sequencing to match demand dynamically.

At the studied Kenyan petroleum depot, VFDs were retrofitted onto existing pump-motor assemblies as part of an energy efficiency initiative, aiming to align pump operation with stochastic loading demand arising from irregular truck arrivals and variable product dispatch schedules [18]. Observed energy performance, however, differed from expectations where total energy intensity remained unchanged, with some periods showing slight increases. These outcomes highlighted the need to investigate operational, human, and infrastructural factors influencing energy consumption. Critically, this gap underscores the limitations of applying standard VFD energy models in retrofit contexts with legacy equipment and partial digitalization [19,20,21]. The present study investigates this gap by reconstructing pump-level operation and energy performance, quantifying the effects of control logic, manual intervention, and demand variability, thus providing insights into why anticipated savings were not realized and how future retrofits can be more effective.

1.3. Rationale of the Study

Despite the increasing deployment of energy efficiency technologies in downstream petroleum facilities in the developing regions context [22], there are limited studies that explain why expected performance improvements are sometimes not realized after implementation [12]. In situ operational observations corroborated using historical audit and equipment performance documentation indicate that energy initiatives in such depots are evaluated at the aggregate facility level, typically using monthly or annual energy indicators, which obscures operational dynamics at the pump and loading levels where energy is actually consumed. Consequently, post-retrofit assessments do not explicitly distinguish whether observed performance outcomes arise from technology limitations [23], operational practices, or human decision-making interventions [15,24].

Further, existing studies indicate that most energy analyses in industrial facilities predominantly emphasize whole-facility benchmarking metrics, such as total electricity consumption or energy intensity, without resolving energy use at pump-levels or specific control actions [25]. Reported outcomes are therefore typically expressed as aggregate energy savings, with limited disaggregation by pump runtime, loading configuration, or operator intervention, which constrains diagnostic insight into the causes of post-retrofit underperformance [12,26]. Consequently, the interaction between pump operating modes, loading demand variability, and human control decisions remains largely unexamined in the existing literature.

In the studied Kenyan petroleum depot, the absence of a clear reduction in energy intensity following VFD retrofit created a practical and unresolved operational question for depot management. Without pump-level energy visibility and systematic analysis of operating states, it was not possible to determine whether the retrofit underperformed, whether operational conditions constrained its effectiveness, or whether manual interventions offset potential savings. This uncertainty reflects a broader challenge in many depots across Sub-Saharan Africa, where energy data may exist but are not structured or analysed in a way that supports diagnostic evaluation [14,27].

This study was therefore motivated by the need to move beyond aggregate energy indicators and provide an evidence-based explanation for post-retrofit energy performance in a real operational context. This study aims to bridge the gap between technology adoption and operational outcomes in a developing region's context, supporting more informed decisions on energy management, retrofit evaluation, and future optimization efforts by examining energy use at the level where control actions, loading demand, and operator decisions intersect [10].

1.4. Contributions and Novelty of the Study

This study advances the understanding of energy performance in petroleum depots in Kenya and Sub-Saharan Africa by examining pump-level operation under real-world conditions. It provides rare empirical evidence on the realized performance of VFD retrofits in a developing-region depot, highlighting how legacy constraints can limit theoretical energy savings. The principal contributions are as follows:

1. Pump-Arm Modelling framework—The study introduces a methodology that decomposes pump energy consumption by loading-arm demand and operational state, enabling attribution of energy use to discrete depot operating conditions and human interventions rather than relying solely on site-level averages.
2. Empirical evaluation of VFD retrofits—It demonstrates how operational practices, equipment constraints, and human interventions influence actual energy outcomes, providing concrete evidence from a Sub-Saharan African petroleum depot.
3. Operational and behavioural indicators—Develops and applies real-time metrics to quantify human-induced inefficiencies and uneven pump utilization typically hidden in conventional energy assessments.
4. Integration of Cyber-Physical-Human Systems (CPHSs) perspective [28]—The study combines high-resolution PLC-SCADA data, runtime logs, and manual override events to reveal interactions between physical equipment, digital control systems, and operator actions.
5. Actionable insights for depot management—It provides guidance for improving post-retrofit energy performance, emphasizing the need for pump-level energy disaggregation, closed-loop control, predictive integration, and alignment of operational procedures with available cyber capabilities.

Therefore, this work bridges the gap between theoretical VFD energy models and real-world depot operation by merging detailed empirical evidence, novel modelling, and actionable indicators, offering a practical framework for energy optimization under legacy and partial-digitalization constraints common in developing regions.

1.5. Limitations of Study

Although this study provides a detailed data-driven assessment of pump-motor assembly energy performance in a Kenyan petroleum depot, several limitations and boundary conditions are acknowledged.

1. The analysis was conducted in a single petroleum depot, reflecting a site-specific configuration of pumps, motors, loading arms, and control architecture. Although many of the operational characteristics examined are representative of depots in Sub-Saharan Africa, the quantitative results should be interpreted within this contextual scope.
2. The VFDs were retrofitted onto existing pump-motor assemblies that were originally designed for constant-speed operation. The pumps and motors are aged and not hydraulically or electrically re-matched at the time of retrofit. As a result, the installed VFDs operated within constrained speed ranges, and pumps continued to run at

rated speed regardless of loading demand. This legacy equipment constraint limited the extent to which theoretical affinity-law-based energy savings could be realized and must be considered when interpreting post-retrofit performance [19].

3. Although flow measurements were available at the depot loading points, they were not integrated into the PLC control loop or a unified analytics platform. The system was technically capable of such integration, but this was constrained by operational priorities that favoured uninterrupted pumping over energy optimization, limited assignment of energy management responsibilities, and gaps in technical expertise. As a result, the control system remained fragmented, with pump operation being governed by arm availability and static sequencing logic rather than closed-loop flow control. Consequently, energy analysis relied on runtime, arm-demand state, and operational mode, rather than continuous flow.
4. Energy metering was limited to aggregate and pump-level electrical measurements, while auxiliary systems and other depot loads were not individually disaggregated. The analysis therefore focused on pump–motor assembly energy consumption rather than total depot energy use.
5. Human interventions were inferred from PLC status bits and operational state transitions, rather than from direct observation or structured operator feedback. While this enabled objective and time-resolved identification of manual overrides, it did not capture the organizational or behavioural motivations underlying operator actions [24].
6. This study evaluated VFD performance under existing control logic and operational practices, without implementing alternative advanced control strategies such as flow-based control or model predictive control [29]. The results thus reflect realized operational performance rather than the maximum achievable efficiency under optimized system redesign.

2. Study Site and System Description

This study was conducted at a petroleum depot in Kenya, operating as a downstream distribution facility for refined petroleum products, including Automotive Gas Oil (AGO) and Motor Spirit Petroleum (MSP). The depot receives product from upstream supply and dispatches it to road tankers through a multi-arm truck loading system. Electrical energy consumption at the site is dominated by pumping operations associated with product transfer and loading, making pump performance the primary driver of site-level energy use. Loading demand varies discretely according to the number of active loading arms, which directly determines pump operation that includes pump selection, pump sequencing, and cumulative runtime. The main pumping and control equipment used in this study, together with their key technical specifications, are summarized in Table 1.

Table 1. Technical specifications of main pumping and control equipment.

Equipment	Component	Speed (rpm)	Max Flow (m ³ /h)	Head (m)	Power (kW)	Max Current (A)
MSP Pump (P01A/B)	Pump	1475	180	53.8	-	-
	Motor	1490	-	-	37.3	68.6
AGO Pump (P02A/B)	Pump	1475	180	53.8	-	-
	Motor	1490	-	-	37.3	68.6
Loading Arm	-	-	90	-	-	-
Flow meter	-	-	150	-	-	-

The pumps and motors, originally installed in the early 1990s for constant-speed operation, were retained without hydraulic redesign, resizing or replacement. To enable compatibility with this legacy equipment, the VFDs were configured to match the original

motor ratings and power requirements, and the protective settings were adjusted to ensure safe start-up and operation. Pump operation is governed by a PLC-VFD-SCADA architecture supporting automated pump sequencing, and manual operator overrides via a selector switch on the VFD panels. VFDs and PLCs communicate via Modbus TCP/IP. Each VFD provides localized energy data, but these measurements were not integrated for energy analytics. Operational data, including pump status, runtime, loading arm activation, override indicators, and energy consumption at the depot level, were logged through the control system. Although each loading arm has a flow meter with Modbus TCP/IP capability, they were not integrated into PLC for closed-loop pump control or energy analytics. The facility's electrical energy use was recorded via a single common energy meter, providing only site-level consumption data.

The general depot layout is as shown in Figure 1 below:

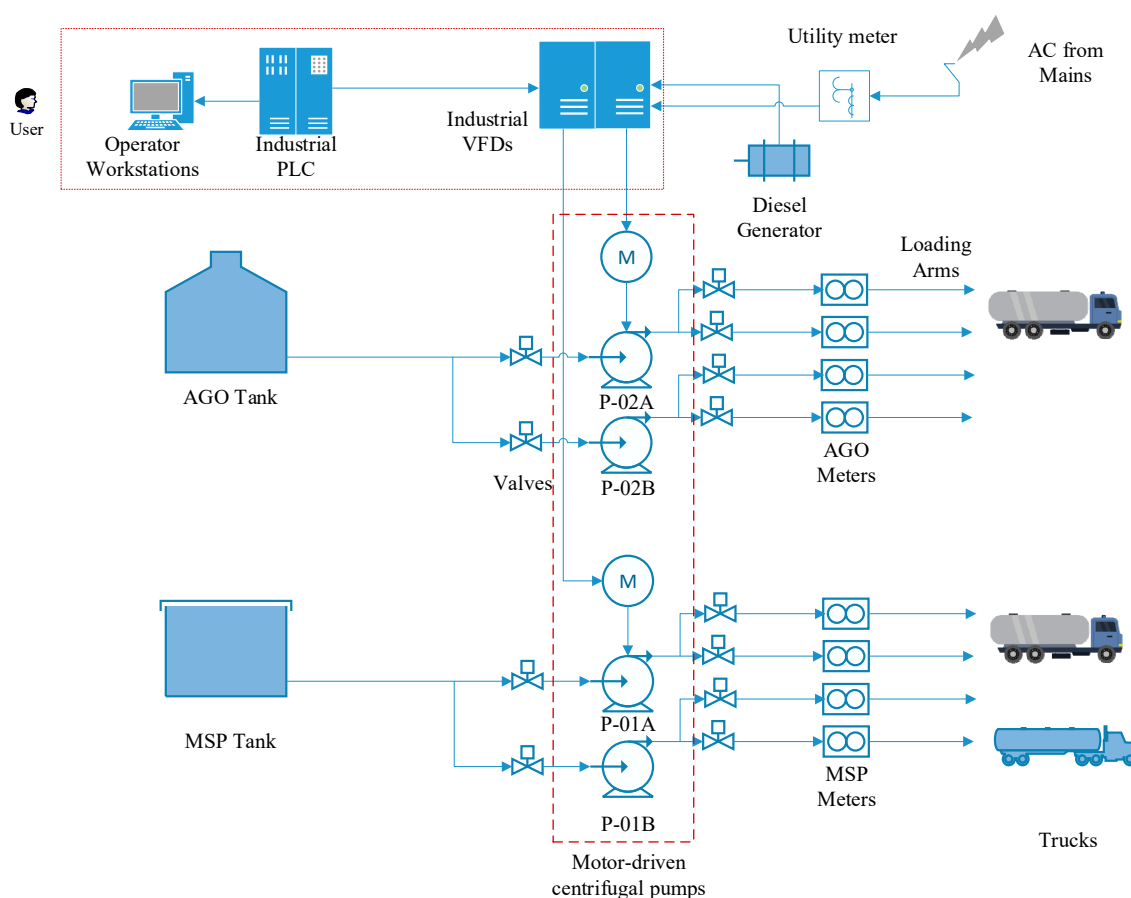


Figure 1. Truck loading system layout for two products at depot.

3. Methodology

To investigate why the anticipated energy savings from the VFD retrofit were not realized in practice, the methodology focuses on reconstructing how pumps were actually operated under real depot conditions. Rather than assuming ideal variable-speed behaviour, the analysis examined realized pump operation as governed by loading demand, control logic, and operator interventions. This approach enabled direct attribution of energy consumption to operational states observed before and after VFD installation. The methodology was based on high-resolution operational data acquired from the depot VFD-PLC-SCADA system and applied a stratified analysis that links pump runtime, loading-arm demand, and control mode to energy use. By structuring depot operation into discrete, observable states, the method allowed consistent comparison between expected VFD performance and measured energy outcomes under practical operating conditions.

3.1. Pump-Arm Modelling Framework and Energy Attribution Model

To analyse pump-level energy performance under real operating conditions and limited instrumentation, a Pump-Arm Modelling framework was developed. Within this framework, a pump-level energy attribution model was formulated to disaggregate total depot pumping energy according to discrete loading demand and operational state. The framework reflects the inherently discontinuous nature of truck-loading operations in petroleum depots, where pumps are activated in discrete combinations in response to loading-arm availability rather than continuous flow modulation [30].

At each time step t , depot operation was represented by a discrete system state vector capturing loading arm demand and pump operational states as recorded by the PLC:

$$S(t) = \{A(t), R_i(t), u_i(t), F_i(t)\}$$

where $A(t) \in \{0, 1, 2, \dots, k\}$ denotes the number of active loading arms, $R_i(t) \in \{0, 1\}$ represents the run status of pump $i \in \{1, \dots, N_p\}$, $u_i(t) \in \{0, 1\}$ indicates control mode (1 = PLC auto, 0 = manual operation), and $F_i(t) \in \{0, 1\}$ denotes pump fault/trip status (1 = fault/trip, 0 = healthy).

Operational data were collected at a temporal resolution of $\Delta t = 1$ s for each pump assembly $i \in \{1, \dots, N_p\}$, i.e., P01A/B and P02A/B. Pump speed was observed to remain effectively constant at nearly 1500 rpm throughout the monitoring period. Consequently, pump speed was treated as fixed, and energy variation was attributed to runtime, pump combination, and operational state rather than speed modulation.

The pump-level energy attribution model quantifies electrical energy at time t as

$$E_{\text{pumps}}(t) = \sum_{i=1}^{N_p} \sum_{k=0}^K P_{i,k}(t) T_{i,k}(t) [1_{\text{auto}}(i, t) + 1_{\text{manual}}(i, t)] \quad (1)$$

with indicator functions:

$$1_{\text{auto}}(i, t) = u_i(t) (1 - F_i(t)), \quad 1_{\text{manual}}(i, t) = (1 - u_i(t)) (1 - F_i(t))$$

where:

- $T_{i,k}(t)$ is the runtime of pump i while serving k arms;
- $P_{i,k}(t)$ is the estimated pump power for pump i while serving k arms derived from pump operating state and runtime proxies and calibrated against motor nameplate ratings to provide realistic pump-level energy attribution under each arm-demand state.

This state-based formulation enables explicit quantification of energy contributions from PLC-controlled operation and manual overrides. The pump-arm energy model therefore provides a rigorous, operationally grounded method for analysing pump energy consumption, operational patterns, and human-induced inefficiencies in a real-world petroleum depot environment [31,32].

3.2. Data Stratification and Extraction Methodology

Pump runtime was segmented by the number of simultaneously active loading arms to represent discrete operating modes. Based on the pump sizing and technical specifications summarized in Table 1, a single pump is rated to supply up to two loading arms at nominal flow. Under one-arm demand, a pump would ideally operate at approximately 50% of rated speed, while two-arm demand corresponds to full-speed operation. For three-arm demand, two pumps are expected to operate in parallel at approximately 75% of rated speed to share the load, and at four-arm demand both pumps operate in parallel at rated speed. Energy-saving opportunities therefore arise under low- and medium-demand conditions, where variable-speed operation would allow a single pump to operate

at reduced speed during one-arm loading and parallel pumps to operate below rated speed during three-arm demand.

Based on the Pump-Arm Modelling framework introduced in Section 3.1, the measured operational data were stratified to isolate the contributions of arm demand, individual pump runtime, manual overrides, and ideal power supply demand. This stratification enabled a comparison of pump energy use before and after VFD installation, while maintaining consistency with the available instrumentation and existing PLC-VFD control architecture at the depot.

3.2.1. Stratification by Pump and Arm Demand

For each pump i , operational time was segmented according to the number of simultaneously active loading arms k . The cumulative energy contribution of pump i under arm state k over the observation period was computed as

$$E_{i,k} = \bar{P}_{i,k} T_{i,k} \quad (2)$$

where $\bar{P}_{i,k}$ is estimated power using PLC-SCADA runtime and operational signals, capturing energy associated with each pump-arm combination under both automatic and manual control under arm state k . This stratification reflected the physical loading logic of the depot, where increasing arm demand resulted in higher flow requirements and, for $k > 2$, parallel pump operation. Given that flow measurements available at the station level were not integrated into the PLC-VFD control loop, arm demand thus served as operational proxy for loading conditions.

3.2.2. Manual Override and Human Intervention Stratification

Manual operation was identified using the PLC auto-mode status bit, where $u_i(t) = 0$ indicated manual control while the PLC-VFD system remained healthy ($F_i(t) = 0$). The energy associated with human intervention for pump i was quantified as follows:

$$E_i^{\text{manual}} = \sum_{k=0}^K E_{i,k} \mathbb{1}\{u_i = 0, F_i(t) = 0, R_i(t) \neq 0\} \quad (3)$$

Human-induced deviations are explicitly accounted for via $u_i(t)$ during active loading ($k > 0$), which reduces demand-responsiveness and increases energy beyond automatic operation, and during idle periods ($k = 0$), representing pure idle energy waste.

3.2.3. Pre- and Post-VFD Installation Comparison

Overall depot energy consumption using monthly utility billing records were reviewed to establish broader pre- and post-VFD energy trends. Although pre-VFD operation was at fixed speed and aggregate energy use was influenced by runtime and throughput, pump-level stratification was only possible for the post-VFD period due to the availability of high-resolution PLC-SCADA data. Post-VFD, stratified energy metrics were computed across discrete arm-demand states and individual pumps, allowing direct assessment of how VFD-enabled variable-speed capability and manual interventions affected energy use. To minimize the influence of grid disturbances or planned downtime, periods with recorded supply interruptions, identified via time-stamped mains-loss bits in the PLC-SCADA data, or anomalous operating conditions were excluded from comparative analyses. Through examining energy across equivalent (i, k) combinations, the analysis isolated operational and control factors from changes in overall depot throughput, highlighting gaps between theoretical energy savings and observed performance.

3.2.4. Scope and Measurement Boundaries

Given the depot was equipped with a single common electricity meter supplying pumps, auxiliaries, lighting, and standby systems, load-segregated electrical metering at the individual pump or motor level was not available. Consequently, direct measurement of per-pump electrical energy consumption, hydraulic efficiency, motor efficiency, or combined wire-to-product efficiency could not be performed.

As highlighted in Section 2, the VFD retrofit altered only the drive and control layer of the pumping system, with pumps, motors, piping, and hydraulic configuration remaining unchanged before and after the VFD retrofit. As a result, intrinsic pump and motor efficiencies were assumed constant across pre- and post-retrofit conditions, and the analysis did not attempt to infer component-level efficiency variations in the absence of dedicated instrumentation. Operational data were obtained from the PLC-VFD system and included pump run status, sequencing, and loading-arm activity. With flow measurements at the loading arms not integrated into the PLC-VFD control loop, the analysis focused on runtime-based operating patterns and discrete demand states as observable proxies for energy-use behaviour.

The measurement boundaries defined above informed the analytical approach adopted in this study, which emphasizes how pump operation, sequencing, and control practices interact with VFD capability under real depot operating conditions, rather than attempting component-level efficiency estimation beyond the limits of the available data.

3.3. Statistical Analysis and Operational Performance Indicators

Statistical analysis was conducted to quantify the effects of VFD deployment, operational loading, and human intervention on pump/motor assembly energy consumption. All analyses were performed on stratified pump–arm energy data derived from the Pump–Arm Modelling framework.

3.3.1. Behavioural Energy Deviation Index (BEDI)

The impact of manual operation was quantified using the Behavioural Energy Deviation Index (BEDI), defined for each pump i as follows:

$$\text{BEDI}_i = \frac{E_i^{\text{manual}}}{E_i} \quad (4)$$

where E_i^{manual} represented energy consumed while pump i operated in manual mode under a healthy PLC-VFD state, and E_i was the total energy consumed by the pump over the same period. BEDI provided a normalized measure of human-induced deviation from automated control logic and enabled direct comparison across pumps and operating periods. This indicator was vital to enable assessing the individual pump and system-wide implications on energy. Elevated BEDI values indicate prolonged or frequent manual overrides, which bypass coordinated PLC-VFD sequencing and enforce fixed-speed operation during loading. This behaviour reduces load sharing, increases aggregate runtime unnecessarily, and constrains the system's ability to modulate speeds in response to demand. This reduces overall pumping system efficiency even when individual pumps are mechanically healthy.

3.3.2. Idle Energy Waste Indicator

To capture inefficiencies associated with pumps running without active loading demand, an Idle Energy Waste Indicator was defined as

$$\text{EWI}_{i,0} = \frac{E_{i,0}}{E_i} \quad (5)$$

where $E_{i,0}$ represented the energy consumed by pump i during periods with zero active loading arms ($k = 0$). Elevated values of $EWI_{i,0}$ indicated persistent operation during idle conditions, reflecting either control misalignment or operational practices inconsistent with demand-responsive control.

3.3.3. Runtime Imbalance Coefficient (RIC)

Runtime imbalance between pumps operating in parallel or rotational configurations was quantified using the runtime imbalance coefficient (RIC), defined for a pump pair (i, j) as follows:

$$RIC_{i,j} = \frac{|T_i - T_j|}{T_i + T_j} \quad (6)$$

where T_i and T_j denote the total operating time of pumps i and j , respectively, over the analysis period.

By construction, $0 \leq RIC_{i,j} \leq 1$, where $RIC_{i,j} = 0$ indicates perfectly balanced operation and values approaching unity indicate severe runtime imbalance. This metric was used to assess whether VFD deployment and arm-based demand allocation resulted in more equitable pump utilization or exacerbated uneven loading [33].

3.3.4. Statistical Testing and Residual Diagnostics

Comparative analyses between pre- and post-VFD periods were evaluated using paired statistical tests applied at the pump–arm level. Residual diagnostics were conducted to assess normality, independence, and homoscedasticity using standard statistical tests. Where assumptions were violated, non-parametric alternatives or robust estimators were employed to ensure statistical validity [34].

3.3.5. Uncertainty and Sensitivity Analysis

Uncertainty in energy estimates arises from measurement resolution, runtime discretization, and operational state classification. To assess robustness, a sensitivity analysis was performed by perturbing key inputs, i.e., runtime allocation and arm-state classification, within plausible bounds $\pm 5\%$ for modelled unrealized savings and idle running losses, and $\pm 1\%$ for measured total energy consumption. The $\pm 1\%$ bound reflects the accuracy class of electrical metering, while the wider $\pm 5\%$ bound reflects uncertainties associated with arm-state stratification and operational logging deviations. The effect of these perturbations on key indicators, e.g., the Behavioural Energy Drift Index, was modest. BEDI varied by $\pm 0.5\%$ absolute, confirming that the main findings are robust to reasonable uncertainty in operational measurements [35].

4. Results and Analysis

The Pump-Arm Modelling framework was applied to high-resolution PLC-SCADA data to reconstruct pump operation under real depot conditions. Analysis revealed that pump activity was governed by discrete arm-demand states rather than variable-speed modulation, with VFDs operating near rated speed during the observation period. Stratification of runtime and energy across demand states highlighted deviations from theoretical energy-saving expectations, driven by manual overrides, sequencing logic, and operational practices. These results quantify the interaction between operational decisions, control execution, and realized energy performance at the pump level.

4.1. Pump Runtime Distribution and Operational Imbalance

Across the depot, low- and medium-demand states (1-arm and 3-arm, respectively) accounted for over 62% of total pump runtime (Table 2), highlighting periods where VFD modulation could have reduced energy consumption. The corresponding runtime distribution across operating modes is illustrated in Figure 2.

Table 2. Pump runtime (hours) distribution.

Product	Pump	1-Arm Demand	3-Arm Demand	2-Arm Demand	Total Runtime
MSP	P01A	272.28	563.28	418.4	1253.96
	P01B	276.3	563.64	433.3	1273.24
AGO	P02A	151.8	305.7	362.58	820.08
	P02B	199.14	413.46	433.53	1046.13
Total		899.52	1846.08	1647.81	4393.41

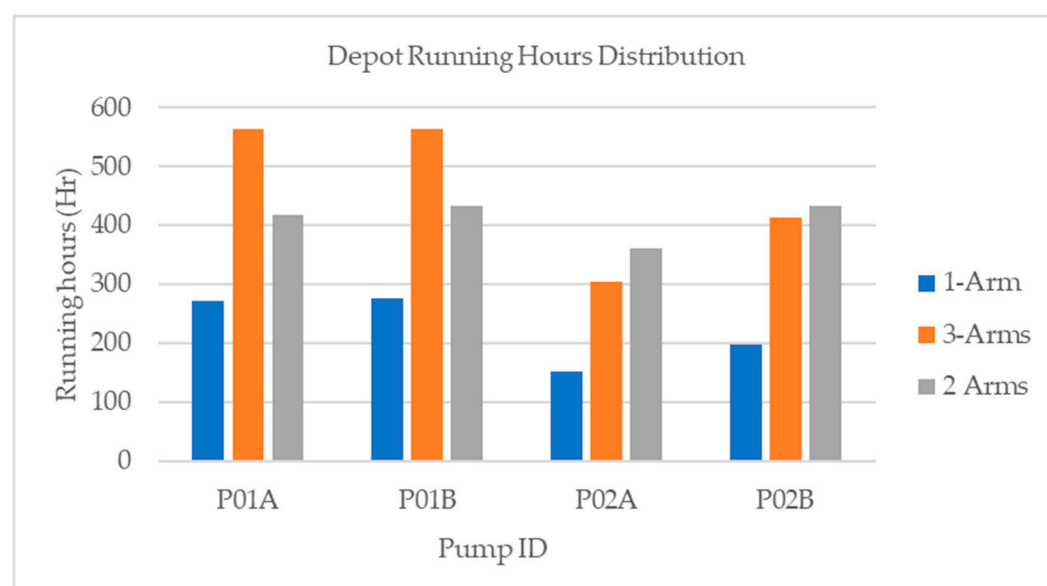


Figure 2. Depot running hours distribution.

Because electrical energy was metered only at the site level, per-pump energy consumption was estimated by mapping runtime to energy using affinity-law-based power scaling ($P \propto n^3$), with operating speeds of 50%, 75%, and 100% for 1-arm, 3-arm (when two pumps run in parallel), and 2-arm demand, respectively. Shaft power estimates were further corrected for motor ($\eta_{\text{motor}} = 0.91$) and pump ($\eta_{\text{pump}} = 0.85$) efficiencies to approximate actual electrical energy consumption, with these values informed by manufacturer pump and motor performance curves from original equipment documentation retained at the depot. Mode-specific electrical energy was calculated as the product of runtime and efficiency-corrected power. Table 3 presents runtime alongside estimated electrical energy for all pumps across operating modes, enabling runtime-weighted, per-pump comparisons.

Table 3. Pump runtime and estimated electrical energy by operating mode.

Product	Arm Mode (Number of Active Loading Arms)	Duration (hours)	Estimated Energy (kWh)
P01A	1	272.28	1630
	3	563.28	11,360

	2	418.4	20,000
P01B	1	276.3	1652
	3	563.64	11,368
	2	433.3	20,720
P02A	1	151.8	908
	3	305.7	6162
	2	362.58	17,330
P02B	1	199.14	1193
	3	413.46	8330
	2	433.53	20,730

Analysis of pump pairs revealed significant operational imbalance in AGO pumps, P02B operated 226 h longer than P02A over the 6-month observation period, resulting in a runtime imbalance coefficient (RIC) of 0.121 and an effective ageing ratio [36] of 1.28. This imbalance arose from operators' manual pump sequencing practices and operational priorities, combined with ergonomic factors, as P02B is located closer to operator desks, making it faster and more convenient for manual selection. The legacy control logic also lacked automated runtime balancing. In contrast, MSP pumps (P01A/B) showed near-balanced operation ($\text{RIC} \approx 0.026$, runtime ratio ≈ 1.05), indicating evenly distributed duty allocation. The observed runtime imbalance in AGO pumps implies uneven mechanical wear, which could accelerate maintenance requirements and reduce service life for the overused unit (P02B), while underutilized units may experience lower lubrication and seal degradation, creating a long-term maintenance and reliability concern for the depot.

In Figure 3, electrical energy consumption was estimated per pump by mapping mode-specific runtime to energy using affinity-law-based power scaling, corrected for motor and pump efficiencies. The distribution highlights the contribution of individual pumps under 1-arm, 3-arm, and 2-arm operating modes per pump. Estimated electrical energy distributions shows that pump full-speed operation (2-arm mode) dominates energy consumption even when runtime is comparable or shorter, highlighting the nonlinear relationship between pump runtime and electrical energy use under fixed-speed operation.

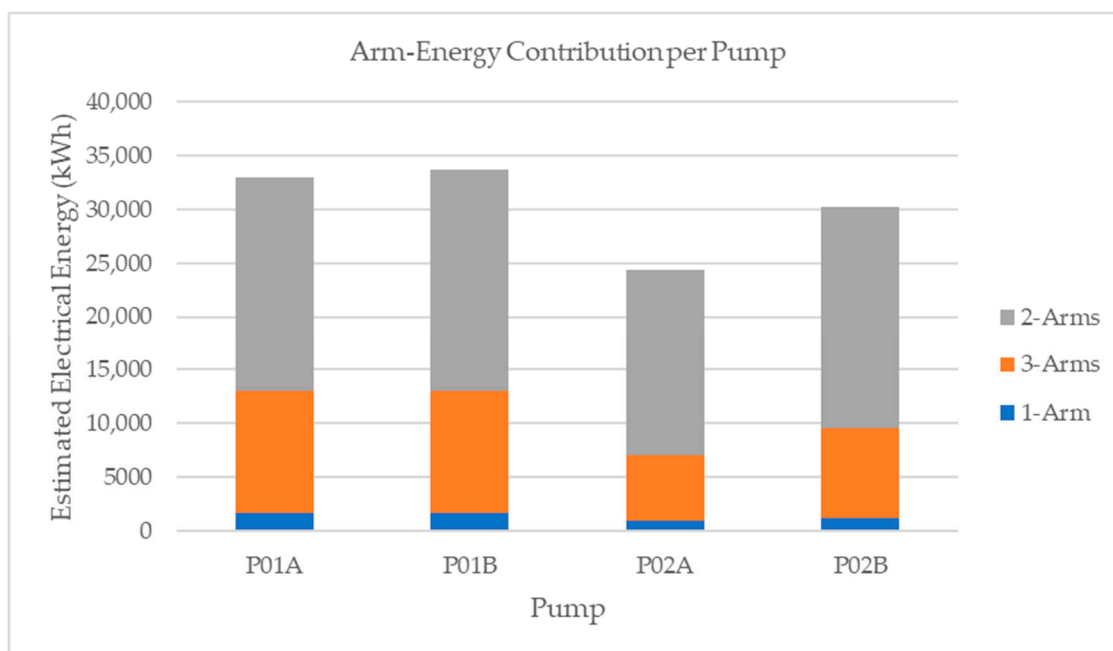


Figure 3. Runtime-weighted electrical energy distribution per pump across different loading-arm demand states (1-arm, 2-arm, and 3-arm) under VFD operation.

4.2. Manual Overrides and Human-Induced Inefficiencies

Manual operation was identified when the PLC–VFD system was healthy, but pumps were operated outside automatic control. Across the depot, a measurable fraction of pump runtime occurred under manual operation, redistributing workload and often locking pumps into fixed patterns insensitive to arm demand. The cumulative energy associated with human intervention was quantified via the Behavioural Energy Deviation Index, which aggregated to approximately 3% of total pump energy consumption (Table 4). The distribution of BEDI contributions across individual pumps is shown in Figure 4.

Table 4. Pump demand vs duration and corresponding excess energy consumption during manual overrides.

Product	Arm Demand	Duration (hours)	Energy Waste (kWh)
P01A	0	17	849.77
	1	39.7	1736.41
	3	47.8	2090.69
P01B	0	3.9	194.95
	1	1.6	69.98
	3	5.25	229.63
P02A	0	32.1	1604.57
	1	19.8	866.02
	3	51.6	2256.89
P02B	0	0.3	15.00
	1	1.9	83.10
	3	0.82	35.87
Total			10,032.87

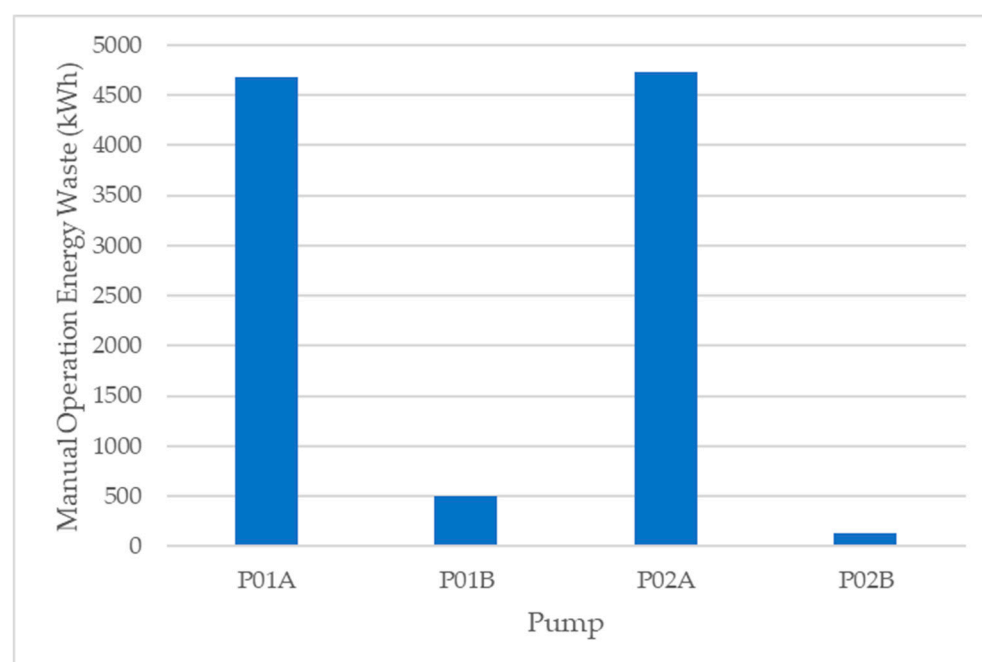


Figure 4. BEDI contribution per pump, showing proportion of energy attributed to manual operation.

4.3. Comparison Between Pre- and Post-VFD Operation

Comparison of pre- and post-VFD operation indicates that the retrofit did not yield measurable reductions in pump energy consumption. At the depot level, energy use remained correlated with pump runtime and loading arm demand, while speed modulation was absent due to static control logic and legacy system constraints. As shown in Table 5, average energy intensity (kWh/m³) increased slightly in the post-VFD period, underscoring that hardware deployment alone, without aligned control strategies and operational practices, is insufficient to realize theoretical energy savings. As highlighted in Section 2, the VFD was retrofitted into legacy equipment designed for constant-speed operation, without hydraulic redesign, resizing or replacement. Pump assemblies continued to run at full speed operation regardless of the VFD existence. This behaviour is consistent with PLC-VFD logs, which show minimal speed variation (~1497–1503 rpm) even under low demand conditions, as illustrated in Figure 5 for 1-arm loading scenario.

Table 5. Pre- vs post-VFD energy intensity (kWh/m³) for each month in the observation period.

Month	Energy Intensity (kWh/m ³)	
	Pre-VFD Installation	Post-VFD Installation
January	0.462	-
February	0.511	-
March	0.506	-
April	0.491	-
July	-	0.557
August	-	0.542
September	-	0.524
October	-	0.597
Average	0.493	0.555

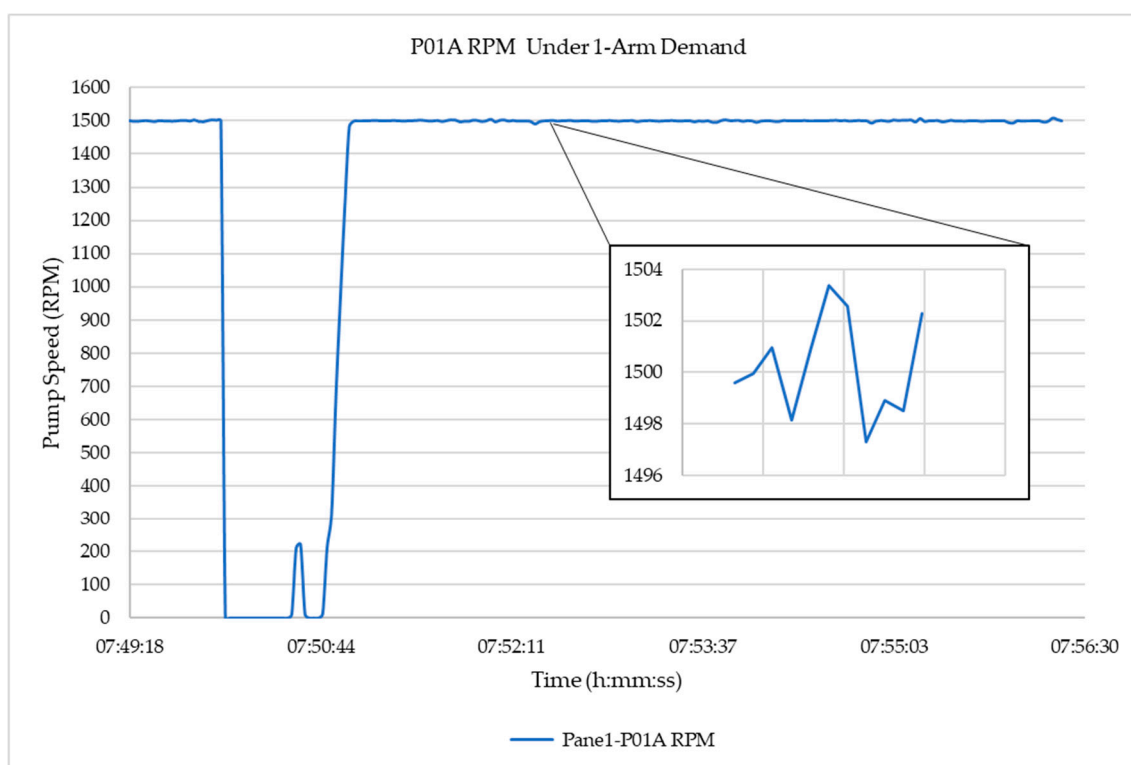


Figure 5. Trend of pump speeds under 1-arm loading post-VFD, highlighting constant operation.

These findings highlight that meaningful VFD-based energy optimization in depot pumping systems would be expected only under closed-loop control architectures, in which real-time flow demand is fed back to the VFD for dynamic speed modulation and coordinated pump sequencing to support partial-load operation. In the absence of such mechanisms, VFDs operate effectively as soft starters and their theoretical energy savings remain unrealized.

4.4. Cyber and Data Integration Limitations in VFD-Based Pump Operation

Although operational data were available within the depot systems, the VFD retrofit was implemented in the absence of closed-loop integration between measurements and pump control [17]. The PLC logic did not reference real-time flow or energy variables, and VFD-native signals, including current, power, torque, and frequency, were not utilized for automated energy-aware control or supervisory decision-making [33]. As a result, pump operation remained governed by loading arm availability and fixed sequencing logic rather than by demand-responsive control [37]. Under these conditions, energy performance could only be evaluated retrospectively using the Pump–Arm Modelling framework. Partial instrumentation and siloed data streams therefore constrained the realization of demand-aligned operation and limited the practical energy benefits achievable from the VFD retrofit.

4.5. Energy Saving Potential of Depot VFD Technology

Applying idealized affinity-law cubic-power relationships [13] to the runtime-weighted pump energy model described in Section 4.1, the ideal energy savings were computed when pumps ran at 50% of the rated speed during 1-arm demand and at 75% speed during 3-arm demand. At constant full speed operation during low- and medium-load operating intervals, pumps consumed approximately 137,243 kWh, whereas demand-modulated operation under ideal affinity-law conditions would have required an estimated 44,551 kWh. This difference corresponds to 92,692 kWh of unrealized energy savings attributable to the absence of effective speed modulation, assuming that pump characteristic curve shape remains approximately constant over the operating range and that efficiency variation across moderate speed reductions is limited.

When idle-running losses (≈ 2664 kWh under zero-arm demand conditions) are included, the total potential energy savings over the observation period is estimated at approximately 28.4% of measured depot electricity consumption, with an uncertainty of $\pm 1.4\%$ reflecting modelling assumptions and measurement limitations [35].

5. Discussion

This study investigated why the VFD retrofit failed to deliver the expected energy savings at a Kenyan petroleum depot, highlighting the gap between theoretical equipment capability and actual operational performance under real-world loading, control logic, and human interventions.

5.1. Why Anticipated VFD Energy Savings Were Not Realized

The results presented in Section 4, specifically the mode-stratified pump runtime and energy estimates summarized in Table 3, the quantified behavioural energy deviation in Table 4, and the post-retrofit energy intensity trends in Table 5 indicate that the limited post-retrofit energy improvement arose from several constraints rather than from deficiencies in the VFD hardware [38]. VFD energy savings are realized when system-level compatibility between pump hydraulics, control architecture, and operating philosophy are considered. In the studied depot, the pumping system was originally designed in the early 1990s for constant-speed operation, with pumps sized to meet peak loading

conditions and controlled through discrete on/off sequencing depending on the number of active arms. The VFD retrofit implemented in 2024 did not consider hydraulic resizing, redesign of the pump duty point, or integration of loading arms flow feedback into closed-loop speed control. As a result, the VFDs operated within a rigid logic, governed by the number of active loading arms and manual operator interventions rather than continuous demand modulation to realize affinity-law-based energy savings [13]. Although manual interventions contributed to an observed 3% increase in energy consumption during the study period, their cumulative impact is likely to be more significant over longer operational period.

Under these conditions, the VFDs operated at rated speed, effectively behaving as constant-speed drives while introducing additional electrical losses associated with power electronics and additional cooling needs for VFDs. Consequently, the expected affinity-law-based energy reductions were not realized [13], and the energy consumption billing was comparable to (or in some operating states higher than) pre-retrofit constant-speed operation. This outcome shows a technology–system mismatch that did not exploit the variable-speed operation inherent VFDs to reduce pumping energy under varied operational demand.

5.2. Impact of Open-Loop Control and Partial Digitalization

A central factor limiting post-retrofit performance was the open-loop operation despite the availability of relevant data streams [38]. Flow metering installed at loading arms and the VFDs' capability of reporting energy data were not exploited for operational intelligence. These signals were not integrated into PLC logic for pump selection, sequencing, or speed reference modulation. As a result, pump operation remained event-driven rather than demand-responsive [39]. Loading arm activation functioned as a binary enable condition, and pump-level energy consumption was not explicitly monitored [4]. Reliance on a common feeder-level power meter further restricted visibility into the energy consequences of specific pump–arm operating states.

The reconstructed pump–arm energy profiles indicate that this lack of closed-loop integration allowed suboptimal patterns to persist post-VFD installation. Without disaggregated energy feedback or adaptive control logic, neither automated systems nor operators were equipped to distinguish efficient from inefficient operating states [27].

5.3. Human Intervention as a System-Level State

Although manual overrides contributed approximately 3% energy deviation from total consumption, this study interprets operator intervention not as an isolated behavioural phenomenon but as an observable system operating state. Manual operation was captured through PLC control signals and reflected in measurable energy outcomes [24]. Elevated BEDI values coincided with increased energy waste in P01A and P02A, and runtime imbalance in P02A/B, indicating that manual operation typically bypassed demand-responsive sequencing rather than compensating for control faults. These interventions occurred within an operational environment characterized by limited demand visibility, absence of predictive control, grid reliability concerns, and legacy equipment constraints. Manual control therefore emerges as a rational operational response to system uncertainty, rather than as a behavioural anomaly [15].

5.4. Implications for Retrofit Strategies in Developing-Region Depots

Although derived from a single depot, these findings of this Kenyan depot case reflect structural characteristics common to downstream petroleum facilities in developing regions, where VFD retrofits are implemented as standalone efficiency measures. Expectations of energy savings in such projects are often shaped by theoretical affinity-law

models developed for fully instrumented, digitally integrated, and demand-responsive systems. When applied to ageing infrastructure without corresponding upgrades to sensing, control logic, and data analytics, these expectations are unlikely to be realized [40,41]. The results of this study indicate that effective energy optimization under retrofit-constrained conditions is dependent on system integration rather than on VFD hardware capability alone. Based on the reconstructed pump–arm energy profiles and observed control configurations, the following design and control requirements emerge.

1. Pump-level energy disaggregation is essential. Reliance on feeder-level power measurement obscures energy-performance differences between individual pumps and operating states, limiting both diagnostic insight and control refinement. VFD-native electrical measurements that include active power, current, and operating frequency should be exposed to supervisory systems and used for pump-level performance assessment [27].
2. Demand information must be integrated into control logic. Treating loading arms solely as binary enable signals decouples pump operation from actual demand, leading to unnecessary parallel operation and idle energy consumption. Even discrete demand indicators can support improved sequencing decisions [33].
3. Open-loop sequencing should be augmented by supervisory optimization. In retrofit environments where hydraulic redesign is impractical, hybrid supervisory approaches such as MPC operating over discrete demand states and bounded speed references offer a feasible pathway for aligning pump operation with loading requirements [42].
4. Operational procedures must align with cyber and data capabilities. Manual intervention, as quantified through BEDI, reflects structural uncertainty rather than anomalous behaviour. Integrating operational states into supervisory monitoring can reduce reliance on overrides while improving transparency and consistency [43].

In the absence of these elements, VFD retrofits may deliver only marginal energy gains while obscuring persistent inefficiencies rooted in system architecture, control structure, and data underutilization rather than in component-level efficiency.

5.5. Toward a Cyber-Physical-Human System Perspective

The pump–arm level and quantification of energy deviations associated with control and intervention states demonstrates the need to view depot energy systems as Cyber-Physical-Human Systems (CPHSs) [28]. Energy performance emerges from the interaction of physical equipment, digital control infrastructure, human decision-making, and other factors rather than from any single layer in isolation.

From this perspective, pump energy consumption can be interpreted as the outcome of a multiplicative efficiency structure, in which physical efficiency, control effectiveness, operational compliance, institutional policies and culture, and other external factors jointly determine realized performance [44]. Even when component-level efficiency is high, deficiencies in one layer can substantially erode system-level gains. Rather than relying solely on affinity-law projections, the proposed modelling and stratification framework enables explicit comparison between theoretical energy expectations and realized outcomes at pump-level under real depot conditions. This approach is relevant for incremental modernization pathways, where staged upgrades must deliver measurable benefits despite legacy constraints.

5.6. Limitations and Directions for Future Work

This study is subject to several limitations. Pump-level energy estimation relied on operational reconstruction due to the use of a common feeder-level power meter and real-

time flow feedback unavailability for closed-loop control analysis [33]. The findings therefore reflect observed operational behaviour rather than optimized control performance.

Future work will evaluate hybrid MPC-based supervisory control strategies layered over the existing PLC-VFD architecture. MPC would operate as a higher-level optimization layer generating adaptive pump speed and dispatch setpoints based on forecast loading demand, operational constraints, and historical energy-performance data. Real-time measurements (pump status, VFD speed reference, electrical power, and loading-arm demand state) would then be streamed from PLCs to the supervisory controller, which would compute optimal speed references or pump enable recommendations over a receding horizon. These setpoints would then be transmitted back to the PLC, which would retain responsibility for safety interlocks, permissives, and sequencing enforcement before passing validated speed commands to the VFD [43,45]. When combined with CPHS-aware dashboard indicators such as BEDI, idle energy waste and RIC, the supervisory MPC layer could also incorporate behavioural disturbance modelling, thus improving applicability under manual overrides and operational deviations in a real depot environment [46].

6. Conclusions

This study investigated the energy performance of a VFD retrofit in a Kenyan petroleum depot by reconstructing actual pump operation under real loading conditions using 1 s resolution PLC-SCADA data. A Pump-Arm Modelling framework was developed to stratify pump runtime and energy consumption patterns by discrete loading demand states, control mode, and operational context. This approach enabled direct comparison between expected demand-aligned pump operation and observed field behaviour.

The results demonstrate that, despite the presence of VFD hardware, pump operation remained dominated by fixed-speed running. Loading demand varied discretely with the number of active loading arms, and pump speed references remained locked at rated pump speed values throughout the monitoring period. As a consequence, energy consumption was strongly correlated with runtime and parallel pump operation rather than with speed modulation. Monthly utility billing data further confirmed that post-retrofit energy intensity did not reduce and was, on average, higher than pre-VFD values, indicating that the anticipated energy savings were not realized in practice.

Stratified analysis revealed additional operational inefficiencies, including uneven runtime distribution between duty-standby pump pairs for AGO product, and over 62% of runtime operation under low and moderate demand states. Runtime imbalance coefficients showed divergent ageing trajectories within pump pairs, with one pump operating up to 12% longer than its counterpart, translating to 28% ageing ratio over the observation period. Manual overrides contributed measurably to energy deviation, with a Behavioural Energy Deviation Index (BEDI) of approximately 0.03 but were shown to be secondary to systemic inefficiencies arising from full-speed operation during partial-load conditions.

Idealized affinity-law scaling was applied to observed partial-load intervals, and this study quantified an unrealized energy savings potential of approximately 92.7 MWh over the six-month period. When combined with idle running losses, the total depot-level energy savings potential was estimated at $28.4\% \pm 1.4\%$ of depot-wide measured electricity consumption. This gap between theoretical and realized performance was traced not to VFD hardware limitations, but to open-loop control architecture, partial digitalization, and legacy system constraints that prevented demand-responsive operation.

Overall, the findings demonstrate that VFD retrofits implemented as standalone upgrades on legacy pumping systems are unlikely to deliver meaningful energy reductions without redesign, concurrent upgrades of associated legacy equipment, integration of demand measurements, pump-level energy visibility, and control intelligence. The Pump-Arm Modelling framework introduced in this study provides a practical and reproducible

method for evaluating real-world energy performance in such retrofit environments, where discrete demand, human intervention, and inherited control logic dominate system behaviour.

These insights are relevant for downstream petroleum depots in developing regions, where incremental modernization pathways are common. Effective energy optimization in such contexts requires moving beyond component-level efficiency assumptions toward integrated cyber-physical-human system (CPHS) design, in which physical equipment, digital control infrastructure, operational decision-making, and institutional and macro-level efficiency modifiers are treated as coupled determinants of energy performance.

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Abbreviations

The following abbreviations are used in this manuscript:

AGO	Automotive Gas Oil
BEDI	Behavioural Energy Deviation Index
CPHS	Cyber-Physical-Human System
EWI	Energy Waste Index
MPC	Model Predictive Control
MSP	Motor Spirit Petrol
PLC	Programmable Logic Controller
RIC	Runtime Imbalance Coefficient
SCADA	Supervisory Control and Data Acquisition
VFD	Variable Frequency Drive

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