

Empirical Load Profiling and Categorisation for a Hybrid Renewable Microgrid Serving an Integrated Farm in Nigeria

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Abstract

Off-grid hybrid renewable microgrids often serve farms that combine livestock and horticulture, yet published sizing studies rarely distinguish loads that cannot be interrupted without harming animals or crops from those that can. This paper presents an empirical load-profiling and criticality-categorisation study of an integrated farm in Minna, Nigeria, comprising a 400-cow dairy unit, a 25,000-bird layer poultry unit, a 10,000-bird broiler poultry unit, and a 5,000 m² greenhouse. Forty appliances, totalling 320.93 kW of installed capacity, were inventoried and disaggregated into hourly dispatch profiles for the Rainy, Harmattan, and Dry seasons. Each appliance was then classified into three biological-criticality tiers, Tier 1 (never shed), Tier 2 (shed only once battery state of charge falls low), and Tier 3 (fully deferrable), following a review process that checked functional consistency against species-specific thermal risk. The tiered profiles were expanded into three parallel, verified annual series covering all 8,760 hours of the year. Statistical analysis showed that the farm-level annual load factor reaches 0.628, giving a peak-to-average ratio of 1.59. Tier 1 alone showed a lower load factor of 0.446 and a higher peak-to-average ratio of 2.24, and was strongly correlated with the dairy milking schedule. The Tier 1 load duration curve remained above 24 kW for 58.1% of the year and never fell below 13.65 kW, a sustained base-load pattern with direct implications for battery-energy and diesel or biogas backup sizing. The novelty of this study lies in combining appliance-level disaggregation, three-season synthesis, and a physiologically justified three-tier criticality classification for a combined livestock-and-horticulture microgrid. The dataset and classification are recommended as a reusable, empirically grounded input for future research on microgrid sizing, reliability assessment, and demand-side management.

Keywords: Demand-side management, Empirical load profiling, Hybrid renewable energy, Load criticality, Microgrid.

1.0 Introduction

Nigeria, Africa's most populous nation, faces a severe energy crisis. The installed grid generation capacity is about 13,000 MW; however, only about 4,500 MW is typically generated, far below national demand [1]. As a result, a large share of the population still lacks reliable access to electricity [2]. Across Sub-Saharan Africa, off-grid and mini-grid hybrid renewable systems, rather than extension of the central grid, are increasingly closing this gap. Agricultural operations are central to the economic case for these systems, both as anchor loads and as productive users [3]. However, the demand side of these designs is often treated as a single aggregate curve. This hides an important fact: a farm's loads differ greatly in what happens if they are interrupted. A milk-refrigeration compressor failing for two hours spoils a tank of milk. An office light failing for two hours is merely inconvenient. Sizing and dispatching a hybrid system without this distinction carries two risks: the system is either expensively over-provisioned, by treating every load as critical, or unsafely under-provisioned, by treating every load as flexible.

Despite this, published techno-economic and load-profiling studies for African agricultural microgrids consistently treat demand as a single aggregate curve. They rarely disaggregate it to the appliance level, and they rarely tag each load by the biological consequence of an outage. This paper addresses that gap directly. It inventories, disaggregates, and classifies every electrical load on a representative integrated farm. It then characterises the resulting profile statistically, in enough depth to be useful to microgrid designers, reliability analysts, and demand-side-management researchers working on similar systems. The specific contribution is an empirically grounded, criticality-tiered, full-year hourly load dataset, together with a transparent, physiologically justified classification method. This paper does not present a dispatch, forecasting, or control algorithm; that work lies outside the present scope.

1.1 Contribution and Paper Organisation

The main contribution of this paper is an empirically grounded, criticality-tiered load dataset for an integrated dairy, layer-poultry, broiler-poultry, and greenhouse farm, a combination not previously profiled together in the literature, in which all 40 appliances are disaggregated into season-specific 24-hour profiles, assigned to a transparently reviewed three-tier biological-criticality structure, expanded into verified 8,760-hour annual profiles, and characterised statistically for battery and backup-generation sizing. The rest of the paper is organised as

follows. Section 2 reviews the relevant literature. Section 3 details the materials and methods. Section 4 presents and discusses the results, benchmarking the findings against comparable studies. Section 5 concludes.

2.0 Literature Review

This review was conducted systematically. Candidate literature was identified by keyword search, covering agricultural microgrid load profiling, demand-side management, load criticality and prioritisation, and hybrid renewable techno-economics. The search covered major publisher databases, including Elsevier ScienceDirect, IEEE Xplore, MDPI, and Springer. Results were screened for relevance to off-grid or weak-grid agricultural and microgrid energy systems, and organised into the sections below.

2.1 Load Profiling and Techno-Economics for Off-Grid Agricultural Systems

Techno-economic assessment of hybrid renewable systems in Nigeria has matured considerably. Odetoye et al. [4] carried out a multi-year, HOMER-based assessment of a zero-emission hybrid community microgrid. Adetoro et al. [5] validated an Enhanced Combined Dispatch strategy against the techno-economic and environmental performance of a hybrid system. Another study by Adetoro et al. [6] compared Artificial Bee Colony (ABC), Genetic Algorithm (GA), and Particle Swarm Optimisation (PSO) for sizing a hybrid solar, wind, biogas, battery, and diesel system for a real Nigerian dairy farm, Maizube Farm in Niger State, against an unreliable grid. This study reported a disaggregated 24-hour seasonal load table that is strikingly similar in structure to the one built here. It covers milking-parlour, milk-processing, milk-cooling, cow-shed, and feed-processing loads across the Dry, Rainy, and Harmattan seasons, although it does not classify these loads by criticality. Apart from this partial exception, none of these three studies disaggregates the demand side to the appliance level, none distinguishes loads by criticality, and all three treat the load as a single time series used as input to an optimisation.

A parallel body of literature has focused specifically on demand characterisation in rural African mini-grids. Wassie and Ahlgren [7] used 20 months of metered data from two Ethiopian mini-grid sites. They showed that customer load profiles differ significantly by sector, location, and time of day, and that productive-use loads shape the aggregate curve considerably. Farthing et al. [3] quantified agricultural productive-use-of-energy demand at 10 km resolution across Sub-Saharan Africa, covering irrigation, refrigeration, milling, and egg incubation. They showed that including this demand in microgrid design increases the required system size, but with only a modest levelised-cost penalty. Outside Africa, Pereira et al. [8] documented an implemented PV-plus-automation retrofit on a Portuguese livestock and crop farm, which cut grid energy draw by 83.2% with an 8-year payback. Al-Naemi and Al-Otloom [9] modelled a solar-powered, IoT-controlled greenhouse concept for the Gulf Cooperation Council region, with water-recycling integration, reporting a 340% return on investment at commercial scale. Rehman et al. [10] proposed a three-part integrated framework for a UAE case study, combining renewable-plus-battery supply, IoT-based precision-irrigation monitoring, and app-controlled precision robotics. This shows how the productive and control layers of a smart farm are increasingly designed together, rather than as separate additions. Within controlled-environment agriculture specifically, lighting is consistently reported as one of the most energy-intensive parts of greenhouse operation, whether a crop's daily light requirement is met through supplemental LEDs in a naturally-lit structure or through fully artificial photoperiod control [11]. This finding is directly relevant to the photoperiod-lighting loads of the present farm's livestock units and the cold-storage load of its greenhouse unit, described in Section 3.1 and Table 2. These studies confirm that agricultural loads are large, different in character from residential loads, and economically important. However, with the partial exception of the Maizube dairy-farm study by Adetoro et al. [6], they work at the level of aggregate demand categories or system-level economics, rather than individual appliances, and none classifies loads by the biological consequence of an outage.

2.2 Demand-Side Management (DSM) and Load Criticality Classification

As a smart-grid concept, DSM was consolidated in the foundational review by Gelazanskas and Gamage [12], which catalogued shiftable-load scheduling and peak-shaving techniques and proposed real-time-pricing-based user-side control. More recent systematic reviews have since scaled up this literature considerably. Bakare et al. [13] conducted a review of demand-side management's technical, economic, and regulatory challenges across residential, commercial, industrial, and agricultural sectors. Panda et al. [14] reviewed demand-side management specifically in the context of deregulated electricity-market design, bidding strategies, and distributed-generation integration. A companion review by Panda et al. [15] examined residential DSM models, optimisation techniques, and future perspectives. Nebey [16] catalogued recent DSM advances spanning fuzzy-logic, evolutionary, and reinforcement-learning control strategies. Across these reviews, DSM is consistently organised around a small set of canonical strategies, such as peak clipping, valley filling, load shifting, and strategic conservation, applied at the level of a whole customer or a whole appliance category rather than through a graded, within-farm criticality hierarchy.

Within this literature, a smaller stream addresses load prioritisation specifically for reliability-constrained rural microgrids. Rajbhandari *et al.* [17] formulated a day-ahead energy-allocation technique that gives higher-priority loads more hours of service than lower-priority ones, showing measurable gains in served-energy hours and state-of-charge management. Elazab *et al.* [18] surveyed the wider space of demand-response programme designs and their mathematical formulations. Closest to this study is Gelchu *et al.* [19], who classified an Ethiopian rural mini-grid's load into four categories: household, community, productive-use-with-night-load, and productive-use-without-night-load. They showed, through PSO sizing, that category-specific DSM reduces the levelised energy cost by up to 45.8% for the household category and 20.7% for the productive-use category, relative to a no-DSM baseline. This category-level framework is methodologically close to, but coarser than, the appliance-level tiering developed here. This work, and similar priority- or category-based DSM studies, typically define priority in generic operational or sectoral terms, such as household versus community versus productive use, rather than through a domain-specific, physiologically grounded rule set applied within a single farm.

2.3 Summary of Related Studies

Table 1 summarises the studies discussed above to allow a direct comparison of location, load-data resolution, and criticality treatment. The table draws out a pattern that recurs across the literature: case studies with a specific location and system tend to work with aggregate, rather than appliance-level, load data, while the studies that do classify loads by priority use generic, non-biological criteria rather than a species- or system-specific rule set.

Table 1: Summary of related studies on agricultural load profiling and demand-side management

Reference	Location and System	Load Data Resolution	Criticality Classification	Key Finding
[3]	Sub-Saharan Africa; regional productive-use mapping	10 km grid, aggregate by sector	None	Productive-use demand raises system size, with only a modest cost penalty
[4]	Nigeria; zero-emission hybrid community microgrid	Aggregate, multi-year	None	Multi-year HOMER-based techno-economic assessment
[5]	Nigeria; hybrid microgrid with Enhanced Combined Dispatch	Aggregate, daily and hourly	None	Validated a rule-based dispatch strategy against techno-economic performance
[6]	Nigeria, Maizube Farm; dairy farm HRES	Appliance-level, seasonal, 24-hour	None	Meta-heuristic sizing comparison; closest comparator to this study
[7]	Ethiopia; PV mini-grid, two sites	Metered, 20 months, customer-level	None	Load shape differs by sector, location, and time of day
[8]	Portugal; livestock and crop farm PV retrofit	Aggregate, implemented system	None	83.2% cut in grid draw, 8-year payback
[9]	Qatar; solar-IoT greenhouse concept	Aggregate, modelled	None	340% return on investment, 5-year payback
[10]	UAE; renewable, IoT, and robotics framework	Conceptual, framework-level	None	Combines supply, monitoring, and robotics layers
[11]	Global; greenhouse lighting review	Not applicable (review)	None	Lighting is a dominant share of greenhouse energy use
[12]	Global; smart-grid DSM review	Not applicable (review)	Generic strategies	Sets out a foundational DSM taxonomy
[13]	Global; DSM for smart grids	Not applicable (review)	Generic, sector-based	Reviews technical, economic, and regulatory DSM issues

Reference	Location and System	Load Data Resolution	Criticality Classification	Key Finding
[14]	Global; DSM and market design	Not applicable (review)	Generic, market-based	Reviews DSM within deregulated market design
[16]	Global; DSM for optimal energy use	Not applicable (review)	Generic, AI-based	Surveys recent DSM control strategies
[17]	Rural microgrids; load prioritisation	Day-ahead scheduling	Binary priority list	Priority-based allocation improves served-energy hours
[18]	Global; DSM strategy survey	Not applicable (review)	Generic strategies	Surveys demand-response programme designs
[19]	Ethiopia; rural mini-grid DSM sizing	Aggregate, four load categories	Category-based	DSM cuts cost by up to 45.8%, depending on category

As Table 1 shows, no earlier study combines appliance-level resolution, multi-season synthesis, and a multi-tier criticality classification within a single integrated farm. Most either work at an aggregate level, as in the HRES sizing and techno-economic studies, or apply a generic priority scheme, as in the DSM reviews and the category-based study by Gelchu et al. [19]. This gap motivates the present study.

2.4 Synthesis: Trends and Research Gap

Two trends emerge across this literature. First, techno-economic and load-profiling studies of African agricultural and rural microgrids, including the closely comparable Nigerian dairy-farm case [6], consistently operate at the aggregate sectoral or farm-unit level, rather than the individual-appliance, hourly, season-resolved level, even where the underlying data collection was itself appliance-based. Second, DSM is maturing from simple load-shedding towards structured, priority- or category-based frameworks, as shown by the priority list of Rajbhandari et al. [17] and the four-category classification of Gelchu et al. [19]. Broader reviews [12, 16, 18] confirm that this is now a mainstream direction in the field. However, these frameworks are consistently grounded in generic operational or sectoral criteria, such as household versus community versus productive use, or high versus low priority, rather than in domain-specific, biologically justified criteria. Even the most closely related agricultural techno-economic studies [5, 6] treat the load as an undifferentiated aggregate, rather than tagging individual appliances by criticality.

The corresponding gap, which this paper addresses, is twofold. First, published agricultural load-profiling and techno-economic studies operate at the aggregate sectoral or farm-unit level, rather than the individual-appliance, hourly, season-resolved level. Second, published DSM criticality frameworks, whether rule-based [17] or category-based [19], are generically prioritised or sector-labelled, rather than built from a three-tier, species- and system-specific biological-risk rule set spanning dairy cattle, layer poultry, broiler poultry, and horticulture within a single integrated farm. Almost no published work builds a criticality classification from species-specific biological risk across multiple livestock types and horticulture at once, and propagates it through to a full annual hourly dataset. This is the specific gap that the classification in Section 3.3 addresses.

3.0 Methodology

3.1 Study Location Description

The study location is an integrated farm in Minna, Niger State, Nigeria, at 9.4338°N, 6.3756°E. The farm has four units: a 400-cow dairy unit, covering animal housing, milk harvesting, refrigeration, processing, and feed preparation; a 25,000-bird layer poultry unit, covering lighting, water supply, sanitation, and an on-site feed mill; a 10,000-bird broiler poultry unit, covering brooder controls, lighting, feed and water delivery, and ventilation and cooling; and a 5,000 m² greenhouse unit, covering irrigation and fertigation, cold storage, and office and storage services. These four units host 40 distinct appliances, with a combined installed capacity of 320.93 kW.

3.2 Load Inventory and Seasonal Load Profiling

For each appliance, the equipment quantity, rated power, and hourly on/off operating schedule were recorded independently for the three climatic seasons that structure the Nigerian annual cycle: Rainy (May to November, 214 days), Harmattan (December to January, 62 days), and Dry (February to April, 89 days). The daily energy drawn by an appliance during a given season follows directly from its quantity, its rated power, and the number of hours it operates that day:

$$E_i = N_i \times P_i \times t_i \quad (1)$$

where E_i is the daily energy drawn by appliance i in a given season, in kWh/day; N_i is the quantity of that appliance; P_i is its rated power, in kW; and t_i is the number of hours it operates that day. Summing across appliances within a farm unit, and across units, gives the 24-hour farm-level dispatch table for each season, structured identically to the disaggregated dispatch used by Adetoro *et al.* [5] and, at the appliance level, by the Maizube dairy-farm study [6], so that direct benchmarking is possible, as shown in Section 4.8. Table 2 lists all 40 appliances, grouped by farm unit, with their quantity, rated power, and seasonal operating hours and daily energy.

Table 2: Daily energy demand of the studied farm, broken down by appliance and season

S/ N	Appliance	Qt y	Rate d kW	Rain h/d	Rain kWh/d	Har m. h/d	Harm. kWh/d	Dry h/d	Dry kWh/d
A. Dairy Unit (400 cows)									
1	Ventilation fans	18	0.5	12	108	6	54	18	162
2	Halogen lamps	35	0.4	10	140	10	140	8	112
3	Service water pump	1	3	1	3	1	3	1.5	4.5
4	Milking machines	13	5	2	130	2	130	2	130
5	Vacuum compressor	1	2.5	2	5	2	5	2	5
6	Wash-water heater	1	4.5	1	4.5	1	4.5	1	4.5
7	Wash-down pump	1	5	2	10	2	10	2	10
8	Parlour fans	10	0.5	2	10	0	0	2	10
9	Bulk-tank compressor I	1	12	20	240	20	240	22	264
10	Bulk-tank compressor II	1	6	21	126	20	120	22	132
11	Homogeniser	1	30	3	90	3	90	3	90
12	Pasteurisers	20	1.5	6	180	6	180	6	180
13	Cream separator	3	3	3	27	3	27	3	27
14	Process water heater	2	4.5	3	27	2	18	3	27
15	Process water pump	1	5	1	5	2	10	2	10
16	Bucket elevator	1	5	3	15	3	15	3	15
17	Grinder / mill	2	5	3	30	3	30	3	30
18	Feed mixer	1	10	2	20	2	20	3	30
19	Miscellaneous (office, workshop, tools)	8	1	7	56	6	48	8	64
	Sub-total, Dairy unit (400 cows)		242		1226.5		1144.5		1307
B. Layer Poultry Unit (25,000 birds)									
1	Energy-saver bulbs	127	0.1	7	88.9	7	88.9	7	88.9
2	Submersible water pump	1	1.13	12	13.56	12	13.56	12	13.56
3	Pressure pump	1	5.5	2	11	2	11	2	11
4	Hammer mill	1	16.5	0.8	12.38	0.8	12.38	0.8	12.38
5	Screw conveyor	1	11	0.8	8.25	0.8	8.25	0.8	8.25
6	Mixer motor	1	5.5	0.5	2.75	0.5	2.75	0.5	2.75
7	Offloading motor	1	5.5	0.5	2.75	0.5	2.75	0.5	2.75
	Sub-total, Layer poultry unit (25,000 birds)		57.83		139.59		139.59		139.59
C. Broiler Poultry Unit (10,000 birds)									
1	Control panel, sensors & brooder controls	1	0.05	24	1.2	24	1.2	24	1.2
2	LED house lighting	1	0.4	4	1.6	4	1.6	4	1.6
3	Feed auger / pan feeder	1	1.2	0.5	0.6	0.5	0.6	0.5	0.6
4	Drinker water pump	1	0.7	0.5	0.35	0.5	0.35	0.5	0.35
5	Minimum-ventilation exhaust fans	2	0.25	8.5	4.25	8.5	4.25	8.5	4.25
6	Circulation fans	2	0.65	2.5	3.25	0	0	2.5	3.25
7	Tunnel / heat-stress fans	2	0.5	0	0	0	0	5	5

8	Evaporative cooling-pad pump	1	0.5	1.5	0.75	0.5	0.25	3.5	1.75
	Sub-total, Broiler poultry unit (10,000 birds)		5.65		12		8.25		18
D. Greenhouse Unit (5,000 m²)									
1	Submersible / irrigation pump	1	1.1	1.2	1.32	4	4.4	5	5.5
2	Fertigation pump	1	1.85	0.5	0.93	1	1.85	1	1.85
3	Cold-storage compressor	1	8.8	18	158.4	12	105.6	20	176
4	Office / storage air-conditioner	1	1.1	3	3.3	0	0	6	6.6
5	Halogen lamps (external / security)	4	0.4	8	12.8	8	12.8	8	12.8
6	Office / storage fans	2	0.5	8	8	0	0	4	4
	Sub-total, Greenhouse unit (5,000 m²)		15.45		184.74		124.65		206.75
	Farm Total - All Units		320.9		1562.83		1416.99		1671.34
			3						

3.3 Load Criticality Classification

Each appliance was assigned to exactly one of three tiers, defined in Table 3. The initial appliance-to-tier matrix was checked for two forms of internal consistency. First, functionally identical loads across different farm units, such as photoperiod lighting for dairy and layer housing, were assigned the same tier. Second, each assignment was checked against the physiological thermal risk specific to the species involved, under Minna's climate, rather than being read off the nameplate function alone. This review revised six of the forty initial assignments. The broiler drinker-water pump was raised from Tier 2 to Tier 1, to match the dairy and layer drinking-water pumps, since broilers have proportionally less thermal buffer than either species, owing to their higher metabolic rate relative to body mass. The dairy and layer photoperiod lighting circuits and the greenhouse cold-storage compressor were relaxed from Tier 1 to Tier 2, since a brief interruption does not measurably disrupt a cumulative daily photoperiod or compromise cold-chain integrity for produce, in contrast to raw milk, which spoils quickly without continuous refrigeration. The broiler tunnel and heat-stress ventilation fans and the evaporative cooling-pad pump were raised from Tier 3 to Tier 2, since these loads are needed precisely during heat events, which is exactly the condition under which they would otherwise be shed, making them unsafe to classify as fully deferrable. The revised matrix keeps all 40 appliances, distributed as 10 Tier 1, 25 Tier 2, and 5 Tier 3 loads, with no appliance duplicated or omitted.

Table 3: Definition of the three load categories

Category	Rationale
Tier 1, Critical	Animal welfare, food safety, or biological survival directly at risk if interrupted
Tier 2, Semi-Critical	Operationally important but tolerant of short interruption
Tier 3, Deferrable	Non-essential or time-flexible; shiftable to off-peak periods

3.4 Annual Hourly Electricity Demand

Because the source data specify one representative 24-hour profile per season, rather than a continuous year, each tier's annual hourly series was synthesised by mapping every calendar day of a non-leap reference year to its season, January and December to Harmattan, February to April to Dry, and May to November to Rainy, and repeating that season's 24-hour profile for every day of the season. This calendar mapping reproduces the exact 214/62/89-day season lengths specified for the site and yields three parallel, appliance-consistent 8,760-hour series, one per criticality tier, directly usable as time-indexed inputs to subsequent sizing and dispatch simulations.

3.5 Statistical Characterisation Methods

Beyond descriptive totals, several statistics were computed to characterise the demand data for sizing and control purposes. The Load Factor was computed for the farm total and each tier, both per season, using the 24-hour representative profile, and annually, using the full 8,760-hour series:

$$LF = \frac{P_{avg}}{P_{peak}} \quad (2)$$

Here, the numerator is the average demand of the series in question and the denominator is its peak demand. A Load Factor close to 1 indicates a flat, well-utilised demand, while a value close to 0 indicates a peaky, poorly utilised one. The annual Peak-to-Average Ratio was computed for the same series, as the reciprocal of the Load Factor:

$$PAR = \frac{P_{peak}}{P_{avg}} = \frac{1}{LF} \quad (3)$$

The Coefficient of Variation was computed twice: an intra-seasonal value describing the diurnal variability within each season's 24-hour profile, and an inter-seasonal value describing the variability of the three seasonal means relative to one another:

$$CV = \frac{\sigma}{\mu} \quad (4)$$

where σ is the standard deviation and μ is the mean of the series in question. To examine what drives the shape of the Tier 1 (critical) demand curve, an hourly indicator series was built for the dairy milking equipment (the milking machines and vacuum compressor, rows A4 and A5 in Table 2) and for the broiler drinker-water pump (row C4 in Table 2). Each was correlated against the aggregate Tier 1 hourly demand curve for each season, using the Pearson correlation coefficient:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\left[\sum (x_i - \bar{x})^2 \times \sum (y_i - \bar{y})^2 \right]}} \quad (5)$$

where x_i and y_i are paired hourly observations of the two series being compared, and $\bar{x}$ and $\bar{y}$ are their respective means. Finally, the annual load duration curve was constructed by sorting each tier's 8,760 hourly values in descending order, and the number and percentage of hours in the year during which Tier 1 demand equals or exceeds a series of thresholds (14, 20, 24, 30, 40, 50, and 60 kW) was tabulated, since these thresholds bound the sustained base load that the battery and backup generation must be sized to serve without interruption.

3.6 Verification Procedure

Two independent checks were applied to the underlying dataset before any statistic was computed on it. First, at the appliance level, every one of the 40 loads was confirmed to carry its full rated demand in exactly one tier and zero demand in the other two, so that summing the three tiers reproduces the original installed capacity, seasonal daily energy, and all 72 seasonal hourly columns of the source dispatch table exactly. Second, at the annual-profile level, the sum of each tier's 8,760 hourly values was checked against the independently computed expected annual energy, which is the seasonal daily energy multiplied by the season length, summed over the three seasons. All three tiers matched to within numerical rounding, less than 0.01 kWh.

4.0 Results and Discussion

4.1 Installed Capacity and Energy Composition by Load Classification

Of the 320.93 kW total installed capacity, 99.88 kW (31%) is Tier 1, 200.60 kW (63%) is Tier 2, and 20.45 kW (6%) is Tier 3, as shown in Figure 1. Annual energy is dominated by Tier 2, at 310,311 kWh/yr (54%), followed by Tier 1, at 234,336 kWh/yr (41%), and Tier 3, at 26,401 kWh/yr (5%), for a farm total of 571,048 kWh/yr. Tier 2's installed-capacity share (63%) is considerably higher than its energy share (54%), because it includes high-rated processing and feed-milling machinery, such as pasteurisers, the homogeniser, and hammer mills, that runs intermittently rather than continuously.

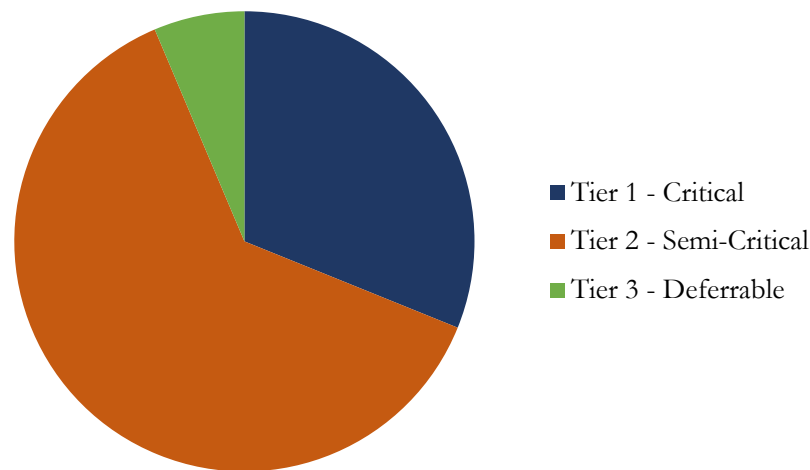


Figure 1: Installed capacity share by load categories

4.2 Daily and Seasonal Demand Patterns

Farm-level demand follows a clear double-hump daily pattern in all three seasons. It rises sharply from an overnight base load of 23 to 38 kW to a mid-morning peak, driven by milk processing and feed milling, dips in the early afternoon, and rises again towards evening milking and cooling loads, as shown in Figure 2. Peak demand is highest in the Dry season, at 103.82 kW, and lowest in the Harmattan season, at 95.45 kW. This is consistent with the higher cooling and water-pumping duty as ambient temperatures rise towards the Dry season.

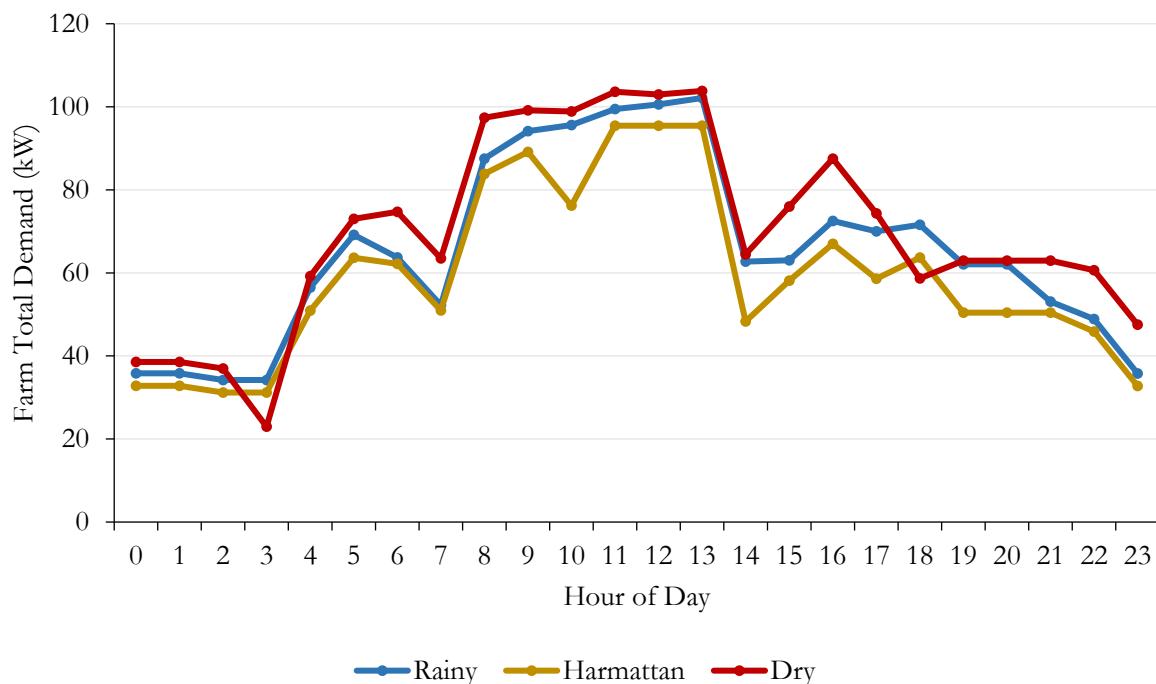


Figure 2: Daily farm-level demand for the Rainy, Harmattan, and Dry seasons

4.3 Load Factor and Peak-to-Average Ratio

Table 4 and Figure 3 report the load factor by season and tier. The farm-total load factor is consistently the highest of the four series, ranging from 0.619 to 0.671 across seasons, with an annual value of 0.628. This reflects the load-diversification benefit of aggregating many appliances with different operating schedules. Tier 1 has a lower load factor than both the farm total and Tier 2 in every season, ranging from 0.413 to 0.498, with an annual value of 0.446, and correspondingly a higher annual peak-to-average ratio, at 2.24. In other words, Tier 1 is proportionally peakier than the farm aggregate, despite being the tier that can least afford an unmet-demand event. Tier 3 has the lowest absolute load factor of any series, ranging from 0.217 to 0.275, with an annual value of 0.232 and a peak-to-average ratio of 4.31. This is consistent with its make-up of intermittently scheduled irrigation, fertigation, and workshop loads.

Table 4: Load factor and peak-to-average ratio by season and criticality

Series	Rainy LF	Harmattan LF	Dry LF	Annual LF	Annual PAR
Farm Total	0.638	0.619	0.671	0.628	1.59
Tier 1, Critical	0.453	0.413	0.498	0.446	2.24
Tier 2, Semi-Critical	0.516	0.510	0.520	0.507	1.97
Tier 3, Deferrable	0.217	0.220	0.275	0.232	4.31

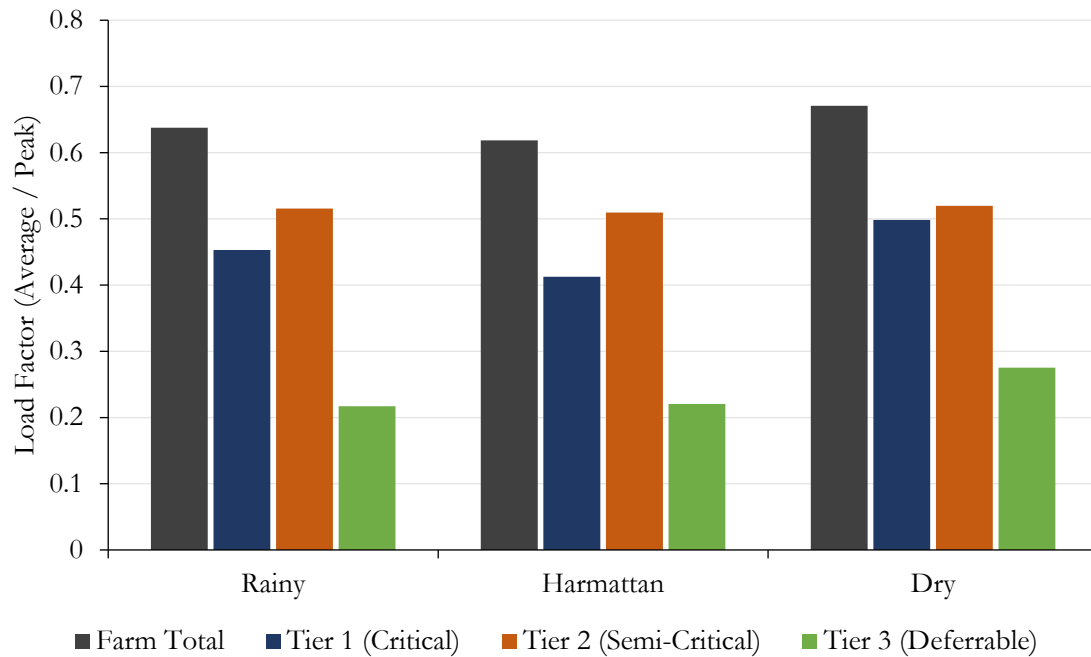


Figure 3: Seasonal load factor for farm-total demand and each load category

4.4 Coefficient of Variation: Intra- and Inter-Seasonal Variability

Table 5 reports the coefficient of variation of each series' 24-hour diurnal shape (intra-seasonal) and of the three seasonal means relative to one another (inter-seasonal). The intra-seasonal coefficient of variation rises steadily from the farm total (0.33 to 0.35), through Tier 1 (0.41 to 0.53) and Tier 2 (0.51 to 0.55), to Tier 3 (1.21 to 1.48). Tier 3's coefficient of variation exceeds 1.0 in every season, confirming that its loads are used in short, sharply defined bursts rather than sustained operation, which is exactly the profile a deferrable, schedulable tier should have. The inter-seasonal coefficient of variation, which shows how much the seasonal average itself shifts across the year, is comparatively small for every series, ranging from 0.05 to 0.11. This means that, while the diurnal shape within a season is quite variable, the overall seasonal magnitude of demand is relatively stable. Tier 3 (0.112) and Tier 1 (0.093) show the most seasonal sensitivity, and Tier 2 (0.050) the least.

Table 5: Coefficient of variation, intra-seasonal and inter-seasonal, by load category

Series	Intra-CV Rainy	Intra-CV Harmattan	Intra-CV Dry	Inter-Seasonal CV
Farm Total	0.334	0.349	0.328	0.067
Tier 1, Critical	0.494	0.526	0.406	0.093
Tier 2, Semi-Critical	0.507	0.552	0.512	0.050
Tier 3, Deferrable	1.400	1.477	1.208	0.112

4.5 Correlation Between Tier 1 Demand and Operational Schedules

The Pearson correlation between the aggregate Tier 1 hourly demand curve and the dairy milking-equipment activity indicator (milking machines and vacuum compressor) is strong and highly significant in every season: $r = 0.917$ ($p = 3.2 \times 10^{-10}$) in the Rainy season, $r = 0.946$ ($p = 2.9 \times 10^{-12}$) in Harmattan, and $r = 0.920$ ($p = 2.1 \times 10^{-10}$) in the Dry season.

in the Dry season. Figure 4 shows why: the two Tier 1 peaks each day occur exactly during the two daily milking windows, when the milking machines and the vacuum compressor switch on. In contrast, the broiler drinker-water pump's operating schedule is weakly and non-significantly correlated with the Tier 1 aggregate, with r between -0.10 and -0.04 and p above 0.6 in every season. This shows that, unlike milking, broiler drinking-water demand does not coincide with the farm's overall critical-load peaks, and instead contributes a comparatively flat, distributed load across the day.

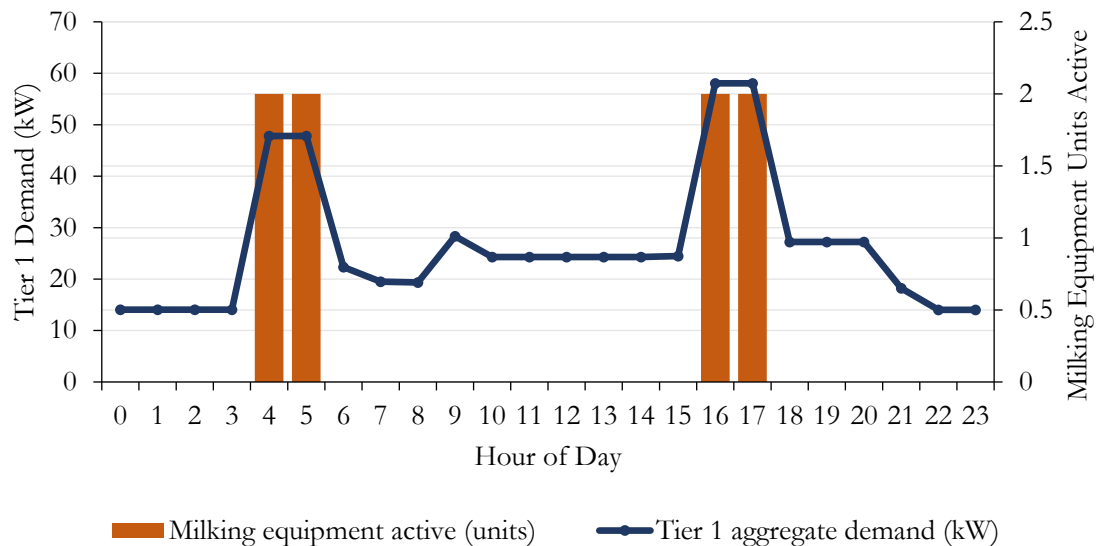


Figure 4: Tier 1 aggregate demand overlaid with the dairy milking-equipment operating schedule

4.6 Annual Load Duration Curve and Reliability Implications

Sorting all 8,760 hourly Tier 1 and farm-total values in descending order, as shown in Figure 5, gives the load duration curves used for sizing and reliability assessment. The farm-total curve falls from a peak of 103.82 kW to a base of roughly 23 kW across the year, with an annual mean of 65.19 kW and a median of 62.97 kW. The Tier 1 curve, which is the natural basis for a Loss-of-Power-Supply-Probability reliability metric defined on Tier 1 loads only, ranges from a maximum of 59.93 kW to a minimum of 13.65 kW, with an annual mean of 26.75 kW and a median of 24.31 kW, and it never falls to zero at any hour of the year. Table 6 gives the duration-curve threshold breakdown: Tier 1 demand equals or exceeds 14 kW for 95.8% of the year, 20 kW for 64.0% of the year, 24 kW for 58.1% of the year, 30 kW for 17.7% of the year, and 50 kW for 7.6% of the year, and it never reaches 60 kW.

Table 6: Tier 1 annual load duration curve: hours per year at or above threshold demand

Threshold (kW)	Hours $\geq$ Threshold	% of Year
14	8,388	95.8%
20	5,610	64.0%
24	5,086	58.1%
30	1,549	17.7%
40	1,460	16.7%
50	668	7.6%
60	0	0.0%

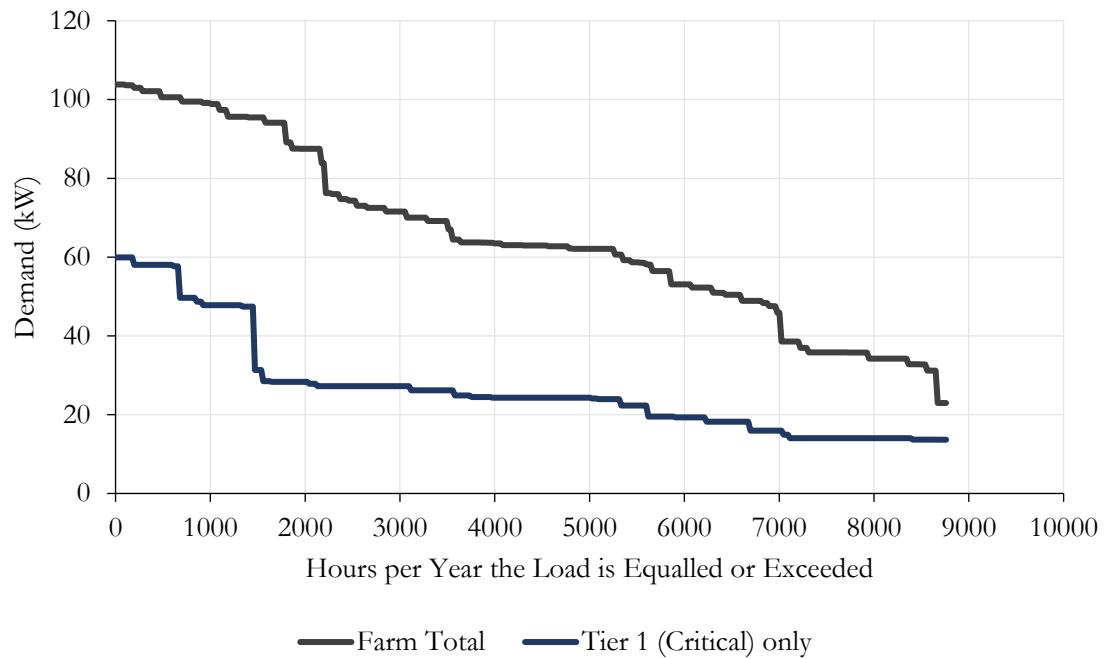


Figure 5: Annual load duration curve for farm-total and critical demand

These figures constrain battery and backup sizing in two distinct ways. First, because Tier 1 demand never falls below 13.65 kW, any storage-and-backup design must guarantee at least this continuous floor with zero tolerance for shortfall, at every hour of the year. This is the true, non-negotiable base load that the battery bank and diesel or biogas backup must never simultaneously fail to cover. Second, because Tier 1 demand exceeds 24 kW for 58.1% of the year (5,086 hours) but exceeds 30 kW for only 17.7% of the year (1,549 hours), the incremental storage or generation capacity needed to cover the band between 24 kW and 30 kW must be available for roughly three times as many hours as the capacity needed to cover the band above 30 kW. This means that battery energy (kWh) sizing is disproportionately sensitive to correctly serving the broad mid-range of the curve, while diesel or biogas backup power (kW) sizing is disproportionately sensitive to the comparatively rare upper tail above 40 to 50 kW. Any sizing approach that accounts for this full duration curve, rather than sizing to the peak alone, should therefore be able to reduce oversizing materially, compared with a peak-based rule of thumb.

4.7 Tier Composition of Daily Demand and Seasonal Energy

Decomposing a representative Rainy-season day by tier, as shown in Figure 6, shows that Tier 1 demand is not flat: it steps up sharply during the morning and evening milking windows and falls back to a housing and refrigeration base load between milkings, exactly matching the correlation result in Section 4.5. Tier 2 dominates the mid-morning and midday hours, when processing and milling equipment runs, while Tier 3 contributes a comparatively small, sharply peaked share throughout the day, consistent with its intra-seasonal coefficient of variation above 1.2 (Section 4.4). Table 7 and Figure 7 summarise daily and annual energy by tier and season.

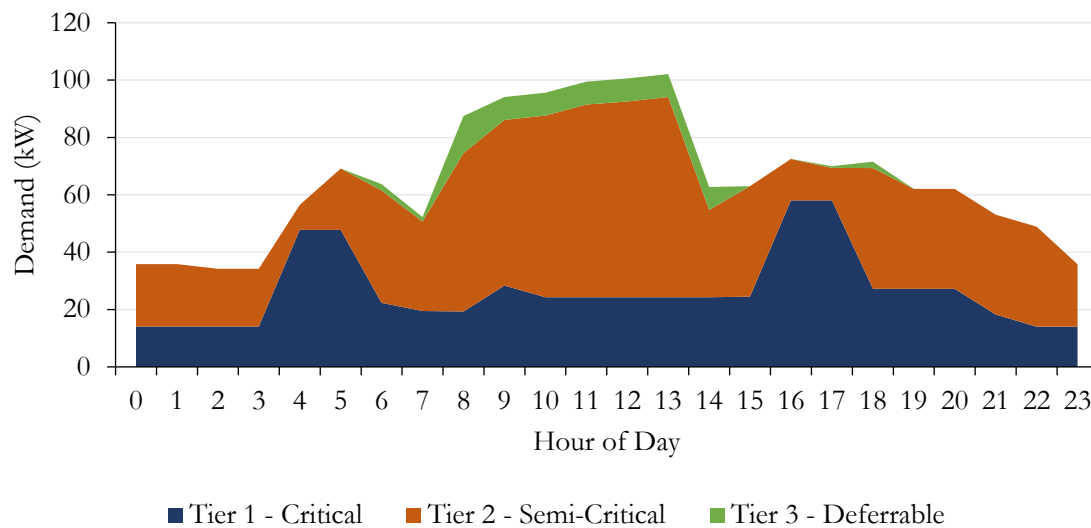


Figure 6: Stacked tier composition of farm demand on a representative Rainy-season day

Table 7: Daily and annual energy demand by load category and season

Tier	Rainy (kWh/day)	Harmattan (kWh/day)	Dry (kWh/day)	Annual (kWh/yr)
Tier 1, Critical	631.4	571.4	716.9	234,335.9
Tier 2, Semi-Critical	863.7	776.9	868.6	310,311.0
Tier 3, Deferrable	67.7	68.8	85.9	26,400.6
Farm Total	1,562.8	1,417.0	1,671.3	571,047.5

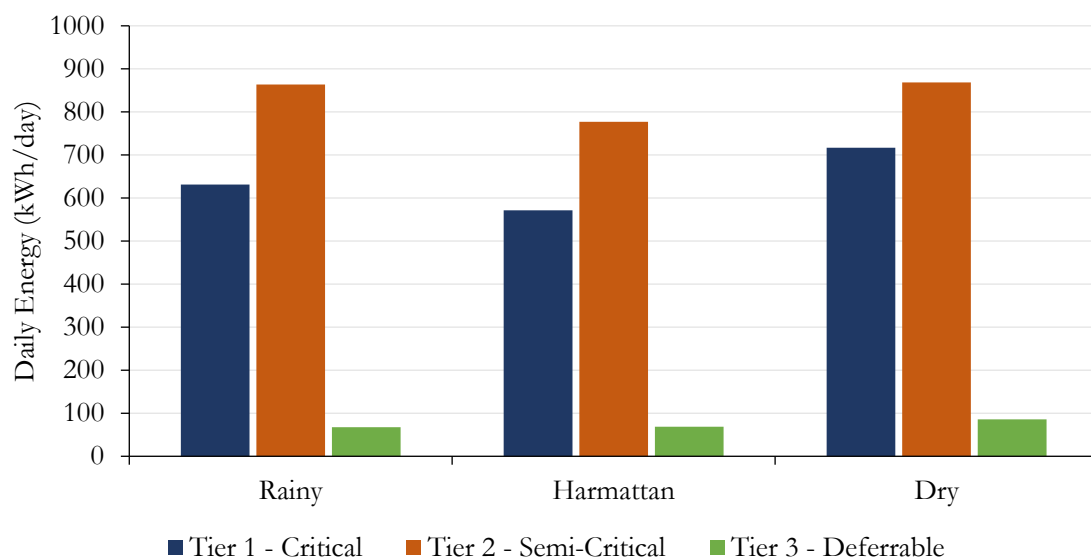


Figure 7: Seasonal daily energy demand by load category

4.8 Comparison with Existing Agricultural Load Profiles

The most direct published comparator for this study is the Maizube Farms case in Sabon Dagah, Niger State, a 400-cow-scale dairy operation roughly 26 km from Minna, on the same regional grid, and sized using an analogous disaggregated seasonal load table [6]. Table 8 places the two farms side by side. Despite Maizube's single-enterprise (dairy-only) scope, compared with the present farm's four enterprises (dairy, layer, broiler, and greenhouse), its peak demand (83 kW) is of the same order as this farm's (95.5 to 103.8 kW), while its load factor (0.49) is markedly lower than the present farm's annual value of 0.628. This is consistent with the diversification benefit of aggregating multiple, temporally offset farm enterprises under one microgrid, rather than sizing each enterprise's supply separately.

Table 8: Comparison of this study's farm with the Maizube dairy-farm case study

Metric	This Farm (4 Enterprises)	Maizube Dairy Farm [6] (Dairy Only)
Peak demand (kW)	95.5 – 103.8 (seasonal)	83.0
Mean / average demand (kW)	65.2 (annual)	41.0
Load factor	0.628 (annual)	0.49
Annual energy (kWh/yr)	571,048	$\approx 358,700$ ($982.86 \text{ kWh/day} \times 365$)
Criticality classification	3-tier, physiologically derived (this study)	None, aggregate load only

A second benchmark concerns the potential economic value of criticality- or category-based demand-side management, independent of any specific dispatch algorithm. Gelchu *et al.* [19] found that applying DSM to an Ethiopian mini-grid's household load category alone cut the levelised energy cost by 45.8% for a 100%-renewable configuration and 47.6% for a hybrid configuration, relative to a no-DSM baseline, while their lowest-impact productive-use category still achieved a 13 to 20.7% reduction. Only when demand-side management was applied across every load category at once did the reduction reach 58 to 58.7%. The present study's Tier 1, Tier 2, and Tier 3 split (31%, 63%, and 6% of installed capacity) is structurally similar to the distinction drawn by Gelchu *et al.* [19] between high-impact and shiftable load categories, and suggests that a comparable order of cost benefit could plausibly be realised once a specific dispatch or control strategy is built on top of this categorisation, and its impact is measured directly against a no-DSM baseline for this farm, rather than inferred by analogy alone.

Finally, on the economic side, two implemented smart-farm retrofits provide useful order-of-magnitude context for any future cost-benefit analysis built on the present profile. Pereira *et al.* [8] reported an 83.2% reduction in grid energy draw and an 8-year payback for a PV-plus-automation retrofit on a Portuguese farm, while Al-Naemi and Al-Otoom [9] modelled a 340% return on investment and a 5-year payback for a commercial-scale solar greenhouse concept in the Gulf region. Neither study, however, reports appliance-level load factor or a criticality-tiered capacity breakdown directly comparable to Table 4 and Figure 1 of this paper. So, with the exception of the Maizube dairy-farm comparison above, a precise, data-to-data benchmark of this study's tier-level statistics against the wider literature remains an opportunity for future work, as more appliance-disaggregated, criticality-labelled agricultural datasets become available.

4.9 Implications for Microgrid Sizing and Demand-Side Management

Three empirical findings from this study carry general implications for how a microgrid serving this type of farm should be sized and managed, independent of the specific dispatch or control strategy eventually chosen. First, the substantial gap between peak and average demand, at both the farm and Tier 1 level, means that sizing generation and storage against the peak alone would leave a system oversized for most operating hours. The farm's annual load factor is 0.628 (peak-to-average ratio of 1.59), while Tier 1's is markedly lower, at 0.446 (peak-to-average ratio of 2.24), as shown in Section 4.3. The appliance-level, time-resolved profile developed here allows any subsequent component-sizing exercise to size against the full annual duration curve, as shown in Section 4.6, rather than a single peak figure, and to recognise that Tier 1 in particular carries a peakier, less-utilised demand shape than the farm aggregate alone would suggest.

Second, the categorisation review documented in Section 3.3 shows that criticality assignment cannot be read off nameplate function alone. It requires species- and system-specific physiological reasoning, and in three of the six revised cases (the two photoperiod-lighting relaxations and the heat-stress-fan elevation), the correct tier depends on environmental or operational context that a static, once-and-for-all classification cannot fully capture. This motivates a natural extension for any future demand-side-management scheme built on this categorisation: rather than a fixed tier label, the tunnel and heat-stress ventilation load in particular is a strong candidate for a state-dependent criticality rule, critical only when ambient temperature exceeds a defined threshold, and ordinary Tier 2 otherwise.

Third, because Tier 1 demand never falls below 13.65 kW and is sustained above 24 kW for 58.1% of the year, as shown in Section 4.6, any reliability metric defined on Tier 1 loads only, such as a Loss-of-Power-Supply-Probability calculated on critical demand, will be driven mainly by the system's ability to cover sustained, multi-hour critical demand, rather than by its ability to cover brief demand spikes. This has a direct bearing on dispatch-strategy choice in general: strategies that react only to the current system state are structurally less able to protect a multi-hour deficit, before it begins eroding battery state of charge, than strategies that can anticipate demand ahead of time, precisely because the Tier 1 base load documented here is sustained rather than spiky. Together, these findings show that the empirical load structure of this specific farm carries real, quantifiable consequences

for whatever sizing and control strategy is eventually chosen to serve it. A system sized and dispatched on aggregate or peak demand alone would either fail to protect the sustained Tier 1 base load during multi-day low-resource periods, or would be oversized well beyond what the diversified, appliance-level demand structure actually requires.

5.0 Conclusion

This paper has presented an empirical load-profiling and criticality-categorisation study for an integrated dairy, layer-poultry, broiler-poultry, and greenhouse microgrid in Minna, Nigeria. Its novelty lies in combining three elements not previously brought together in the literature: first, disaggregated, appliance-level hourly load profiling across four simultaneously operating agricultural sub-sectors; second, season-specific synthesis, for the Rainy, Harmattan, and Dry seasons, into a verified 8,760-hour annual dataset; and third, a physiologically justified, explicitly reviewed three-tier biological-criticality classification spanning dairy cattle, layer birds, broiler birds, and horticultural produce. Statistical characterisation (load factor, peak-to-average ratio, coefficient of variation, and schedule-correlation analysis) moves the profiling exercise beyond descriptive reporting to quantities directly usable in component sizing and reliability assessment. It demonstrates concretely why the sustained, low-load-factor Tier 1 base load documented here places real, quantifiable demands on whatever generation, storage, and control strategy is eventually chosen to serve it.

This dataset and categorisation are intended as a reusable empirical foundation for microgrid sizing, reliability assessment, and demand-side-management studies on this farm, or on comparable integrated livestock-and-horticulture systems. The categorisation review in Section 3.3, and the state-dependence noted for the heat-stress-fan tier in Section 4.9, further suggest that criticality classification itself, moving from a fixed label towards a context- or condition-dependent one, is a worthwhile direction for continued refinement.

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