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THE IMPACT OF ARTIFICIAL INTELLIGENCE INTEGRATION ON ENERGY CONSUMPTION IN MEAT STORAGE FACILITIES

Amanda R. Ary[1*], Alison Spencer[2], Kenneth Nguyen[2], Alexander Woolf[2], Ifigenia Georgnaras[1], Mahesh N. Nair[1], Robert J. Delmore[1], John A. Scanga[1], John Ritten[1], Stephen W. Neel[2], and Keith E. Belk[1]

[1] Department of Animal Sciences, Colorado State University, Fort Collins, CO 80523, USA.

[2] Lineage, Novi, MI 48377, USA.

*Corresponding author email: amanda.ary@colostate.edu

I. INTRODUCTION

Freezing of food for preservation was practiced as early as 3,000 BC [1]. Freezing technology continues to play a crucial role in reducing food spoilage and waste in modern society, and allowing the transport of food globally, highlighting a need for continued advancement in freezing technology. The U.N. Food Waste Index Report (2024) estimated that, in 2022, about 955 million metric tons of waste were generated through household, food service, and retail distribution channels [2]. This accentuates the need to address the inefficiencies in energy usage within the frozen meat supply chain, particularly in cold storage facilities where advancements in technology can mitigate waste and reduce environmental impact. The International Institute of Refrigeration estimates 5 billion refrigeration systems operate globally that consume approximately 20% of electricity worldwide [3], indicating the scope and magnitude of such efforts. Through implementation of artificial intelligence (energy AI) monitoring and manipulation of temperature control in frozen storage facilities, the industry may benefit from reduced energy costs, optimized energy efficiency, and subsequently, reduced carbon footprint, leading to more sustainable cold storage practices. This present case study was conducted to examine how the implementation of energy AI affects power consumption in cold storage facilities.

II. MATERIALS AND METHODS

Power utilization (kW) data were collected from two large cold storage facilities, one located in Colorado, USA and the other in Illinois, USA. Before AI implementation, energy demand readings were collected through electricity meter readings. Following AI optimization, energy demand readings were collected using CrossnoKaye's ATLAS platform [4], a cloud-driven platform leveraging predictive modules and site-specific applications, designed to optimize ambient temperature regulation within facilities. Energy consumption readings were recorded at 15-minute intervals over a period of 94 days. Before statistical analysis, power usage metrics, initially recorded at 15-minute intervals, were aggregated into hourly averages (N = 73173). A statistical AOV model for evaluation of data included a two-way fixed effects factorial design with power usage as the dependent variable. Fixed effects included facility location (Colorado and Illinois) and AI software implementation status (before and after), along with the appropriate interaction. Hour was included as a random discrete covariate to account for potential temporal variations in power usage during the day. Estimated marginal means were computed for fixed and interaction effects within each facility and compared using Tukey-adjusted pairwise comparisons. Analyses were conducted in R (version 4.4.1) using the broom, car, and emmeans packages [5, 6, 7]. Significance level was set at $\alpha = 0.05$.

III. RESULTS AND DISCUSSION

Findings suggested a difference in power utilization when accounting for energy AI status ($P < 0.0001$). As expected, power utilization also differed by facility location ($P < 0.0001$). Additionally, the interaction between AI status and facility location was important, indicating that AI can have a differing impact among different independent facilities ($P < 0.0001$).

Table 1 – Means ± SE for energy utilization (kWh) by facilities in Colorado, USA and Illinois, USA before and after energy AI implementation.

	Energy AI Status		
Facility	Before	After	Tukey's *P*
Colorado, USA	671.5±0.815	443.9±0.822	<0.0001
Illinois, USA	1088.6±0.816	737.3±0.816	<0.0001

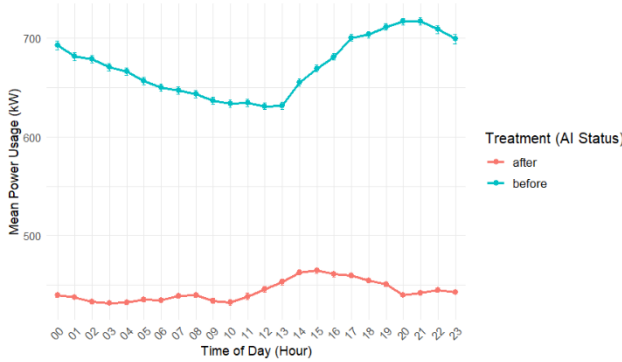


Figure 1. Power Usage (kWh) for Colorado, USA Facility

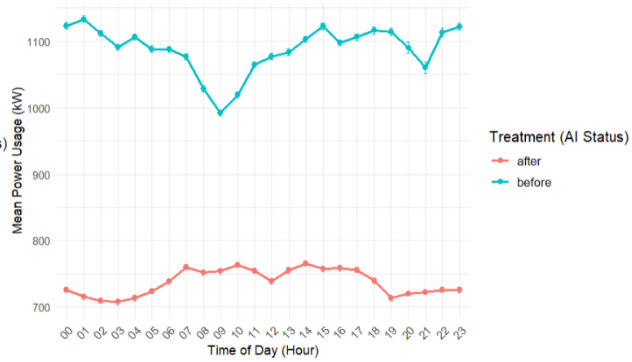


Figure 2. Power Usage (kWh) for Illinois, USA Facility

IV. CONCLUSION

This case study showed that implementation of AI-driven temperature control technology can result in reduced overall power utilization in a frozen meat storage facility. Findings validate the transformative potential of energy AI integration in cold storage facility management, with the potential to revolutionize energy consumption and efficiency. Through optimization, energy AI technology not only contributes to economic cost savings — where reductions in power usage averaged 289.5 kWh and translated to an estimated savings of US$208,714 per year (based on an average kWh rate of US$8.23 cents per kWh as reported by the U.S. Energy Information Administration for February 2025 [8]). Such reductions would undoubtedly reduce greenhouse gas emissions from a facility. This aligns with the broader environmental objectives of the supply chain and its consumers. Moreover, this study highlighted the role of technology in driving sustainable practices and provided a critical foundation for integrating advanced computational solutions to ensure peak performance in facility operations. Moving forward, further research is required to validate these findings in other facilities. Such efforts could inform policy development, industry standards, and drive innovations within the global cold chain.

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