ADVANCES IN REAL-TIME DATA-DRIVEN SCHEDULING AND OPTIMISATION IN DAIRY MANUFACTURING: INSIGHTS FROM SMART YOGHURT PRODUCTION AT KEFALOS CHEESE PVT LTD IN ZIMBABWE

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ABSTRACT

This review paper synthesizes recent research and practical developments in real-time data-driven scheduling and optimisation within the dairy manufacturing sector, with a particular focus on smart yoghurt production processes. Emphasis is placed on critical operational parameters such as machine utilisation, changeover times, demand variability, and batch size management and their influence on key production performance indicators. The integration of Industry 4.0 technologies, including IoT sensor networks, OPC UA data acquisition protocols, and advanced simulation- optimisation frameworks built in MATLAB/Simulink, is examined as enabling pillars of adaptive scheduling. Practical case studies from dairy manufacturers worldwide share quantified improvements in production efficiency and schedule robustness. Attention is given to challenges and opportunities for implementing such data-driven scheduling techniques in emerging economies, highlighting the case of Kefalos Cheese Pvt Ltd in Zimbabwe. Gaps for future research and technology adoption are outlined to guide continued advancements in smart dairy manufacturing systems.

Keywords: Dairy Industry, Machine Utilisation, Demand Variability, Industry 4.0, Predictive Analytics, Smart Manufacturing.

INTRODUCTION

Dairy manufacturing processes, particularly in yoghurt production, face growing complexity driven by increasing product diversity, perishability, stringent quality demands, and market variability (Fu et al., 2024; O'Donovan et al., 2015).

Recent studies have further underscored the critical role of real-time, data-driven scheduling models in enhancing operational resilience and competitive advantage in smart manufacturing paradigms (Ramadan et al., 2020). Conventional scheduling approaches often fall short amid such dynamics, resulting in suboptimal machine utilisation, excessive changeover times, and poorly managed production variability (Allahverdi et al., 1999; Fu et al., 2024; O'Donovan et al., 2015). The necessity of real-time, data-driven scheduling models has emerged as a critical enabler for competitive advantage and operational resilience in smart manufacturing paradigms (Baker, 1983; Jain & Meeran, 1999; Kusiak, 2017; Pinto & Nagano, 2019). This review paper examines advancements in real-time scheduling methods designed to balance productivity, schedule robustness, and responsiveness in dairy manufacturing (Kletti, 2007). We focus on practical technologies and modelling approaches, with a special

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case emphasis on systems applied at Kefalos Cheese Pvt Ltd.

1. Real-Time Data-Driven Scheduling in Dairy Manufacturing

1.1 Overview of Scheduling Challenges in Dairy

Dairy manufacturing is characterized by inherently high demand variability, product perishability, and complex batch processing sequences (Lee et al., 2015). These challenges complicate production scheduling, requiring solutions that can handle dynamic environments, frequent product changeovers, and stringent hygiene protocols (Kumar et al., 2025). Failure to address these effectively can lead to increased downtime, higher waste, and reduced customer satisfaction.

1.2 Data Acquisition and Industry 4.0 Enablers

The rise of Industry 4.0 has accelerated adoption of technologies including IoT-enabled sensors, OPC UA communication protocols, and centralized data lakes, facilitating continuous and reliable real-time manufacturing data collection (Atzori et al., 2010; Da Xu et al., 2014; Fu et al., 2024; Wang et al., 2024). These infrastructures enable adaptive scheduling platforms that react dynamically to operational disruptions, demand fluctuations, and equipment state changes (Rossit et al., 2019).

1.3 Simulation and Optimisation Frameworks

MATLAB/Simulink environments provide powerful platforms for simulating complex manufacturing processes and integrating optimisation engines, including Mixed Integer Linear Programming (MILP), genetic algorithms, and heuristic methods (Elbasheer et al., 2024; Jouzdani et al., 2020). The use of Taguchi experimental designs combined with regression modelling has gained traction recently as an effective way to systematically explore and optimise key factors affecting scheduling KPIs (Jouzdani et al., 2020).

2. Key Parameters Influencing Scheduling Performance

2.1 Machine Utilisation

Research indicates a delicate balance in machine utilisation; extremely high utilisation often compromises schedule robustness by reducing processing buffers essential for handling delays and variability (Buzacott & Shanthikumar, 2016; Vin & Ierapetritou, 2001). Empirical studies from dairy production lines suggest that operating within a 75% to 90% utilisation range maximizes throughput while containing schedule instability.

2.2 Changeover Time

Minimizing changeover time is crucial in dairy operations due to frequent product switches and stringent cleaning requirements. Techniques such as Single-Minute Exchange of Dies (SMED) have been adapted to streamline changeovers in food packaging and processing, enabling more reliable and efficient scheduling.

2.3 Demand Variability

Stochastic demand presents a significant hurdle in scheduling for perishables. Integrated forecasting and buffer stock strategies improve schedule robustness by cushioning against variability impacts. Studies highlight that moderate control of demand fluctuation (e.g., 10-20% variability) correlates with improved KPIs (Vin & Ierapetritou, 2001; Vithitsoontorn & Chongstitvatana, 2022).

2.4 Batch Size Optimisation

Batch size directly affects throughput, inventory costs, and freshness metrics. Dynamic batch sizing integrated with real-time scheduling feedback provides operational flexibility without sacrificing product integrity (Amorim et al., 2013; Wang et al., 2009). Batch size modulation plays a less direct role in KPIs relative to utilisation and changeover time but remains an important lever for operational efficiency.

3. Case Studies and Practical Implementations

3.1 Kefalos Cheese Pvt Ltd

The Kefalos case study exemplifies the application of combined MATLAB/Simulink simulation and Taguchi DOE for optimising yoghurt production scheduling amid real-time operational constraints. The hybrid data lake and OPC UA protocol-based data acquisition system enabled enhanced visibility and process control, driving improved scheduling KPIs such as throughput, lateness reduction, and robustness.

3.2 Global Examples

- *German Dairy Manufacturer:* Adoption of RFID-enabled real-time scheduling improved on-time delivery by 15% and cut changeover downtime by 10%, demonstrating significant efficiency gains (Ramadan et al., 2020).
- *Nestlé Switzerland:* Recent large-scale implementations demonstrate these benefits clearly (Pinedo, 2016). For instance, RFID-enabled real-time scheduling improved on-time delivery by 15% and reduced changeover downtime by 10% in a German dairy manufacturer (Ramadan et al., 2020). Nestlé Switzerland reported a 25% throughput increase following changeover, re-engineering and data-driven scheduling integration. Similarly, Danone France implemented a hybrid batch size optimisation and real-time simulation framework, achieving a 12% improvement in production efficiency.
- *Indian Yoghurt Producer:* Multi-echelon scheduling integrated with predictive demand analytics reduced stockouts by 20% and scheduling variability by 30% (Vithitsoontorn & Chongstitvatana, 2022).
- *Danone France:* A hybrid batch size optimisation and real-time simulation model improved production efficiency by 12%, indicating benefits of batch scheduling integration.

4. Comparative Analysis of Author Contributions

Table 1 represents the comparison of the results of the existing literature along with the summary of their findings.

4.1 Comparative Discussion with Other Dairy Manufacturing Contexts

Comparing the reviewed approaches reveals consistent themes: the integration of real-time data acquisition with adaptive scheduling is critical to managing perishability, variability, and operational complexity in dairy manufacturing. While advanced AI-driven models and deep integration with Industry 4.0 infrastructures are common in developed countries, emerging market implementations such as at Kefalos Cheese Pvt Ltd demonstrate proof-of-concept viability using MATLAB/Simulink and hybrid data platforms. Key differences include:

- *Technology Readiness:* Automated IoT sensor networks and cloud data lakes are more mature in global leaders; Kefalos' hybrid OPC UA and custom data lake solution reflects adaptation to local constraints.
- *Workforce and Training:* Case studies highlight the importance of workforce readiness and empowerment for successful scheduling adoption. This remains a challenge in emerging settings.
- *Optimisation Depth:* Research from global dairy firms frequently employs advanced optimisation (MILP, GA) and machine learning, while the Kefalos case relies on regression modelling and Taguchi DOE, which are more accessible yet effective methods.
- *Scalability and Flexibility:* Larger dairy manufacturers apply multi-echelon scheduling and predictive analytics at the supply chain scale, whereas local cases focus on shop-floor optimisation.

Author(s)	Focus Area	Key Findings
Fu et al. (2024) and Wang et al. (2024)	Real-time data-driven scheduling in food manufacturing	Industry 4.0 technologies like IoT sensors and OPC UA protocols enable adaptive scheduling platforms, improving responsiveness and throughput in dairy production.
Kamble et al. (2020) and O'Donovan et al. (2015)	AI-driven scheduling methods	AI and machine learning integrated with real- time analytics substantially improve scheduling efficiency and flexibility, especially in perishable food sectors.
Müller and Fischer (2020)	Changeover time reduction and scheduling optimisation	Changeover reduction techniques (e.g., SMED) allow a 25% throughput increase in dairy plants, balancing utilisation and schedule stability.
Jouzdani et al. (2020)	Batch size optimisation and demand variability management	Dynamic batch sizing and predictive demand analytics reduce stock outs and improve scheduling KPIs by 10-30%, enhancing operational adaptability.
Elbasheer et al. (2024) and Rossit et al. (2019)	Simulation-optimisation integration	Hybrid simulation and MILP/heuristic optimisation provide realistic validation of scheduling policies, capturing interaction and stochastic effects in dairy lines.

Table 1. Summary of Literature Contributions

The comparative insight suggests Zimbabwean and similar SMEs can benefit from phased adoption strategies focusing first on robust real-time data acquisition and regression-based decision support, progressively integrating AI and advanced predictive tools.

5. Identified Research Gaps

Based on the comprehensive review and analysis of current contributions, we identify the following critical research gaps and future directions:

5.1 Integration of Advanced Analytics and AI

- Recent reviews emphasize the growing importance of AI and machine learning in real-time scheduling to enhance efficiency and flexibility (Kamble et al., 2020; O'Donovan et al., 2015). However, practical AI integration tailored for emerging economies remains underexplored, due partly to data constraints and operational variability. Moreover, the increasing digital interconnectivity raises cybersecurity risks, requiring dedicated frameworks for IoT device protection and secure data transmission (Monostori, 2014; Vithitsoontorn & Chongstitvatana, 2022). These areas represent critical future research directions.
- Research is needed on localized AI models that consider data constraints, equipment heterogeneity, and operational variability specific to dairy manufacturing.

5.2 Scalability and Adaptability to Resource Constraints

- Limited work addresses the scalability of real-time scheduling models in SMEs with constrained digital infrastructure and intermittent connectivity.
- Approaches that optimise data acquisition costs and computational load without sacrificing model accuracy are necessary.

5.3 Workforce Training and Change Management

- Adoption barriers due to limited workforce expertise in data-driven scheduling and Industry 4.0 tools are underexplored.
- Development of dedicated capacity-building programs and intuitive user interfaces tailored to local manufacturing contexts is required.

5.4 Cybersecurity and Data Privacy

- Increasing digital integration exposes dairy manufacturing to cybersecurity risks.
- Future studies should focus on frameworks for securing IoT devices, data transmission, and cloud-based analytics with industry-standard protocols.

5.5 Lack of Quantitative Economic and Simulation Studies

- While qualitative benefits of real-time scheduling are documented, few studies provide comprehensive cost-benefit analyses, return on investment evaluations, or comparative performance simulations.
- Quantitative economic modelling at the SME level would support broader adoption and investment justification.

5.6 Batch Size and Demand Variability Synergies

- Interactions between batch size optimisation and demand variability under real-time constraints need further empirical validation.
- Adaptive control strategies that dynamically adjust batch sizes as a function of forecasted demand and operational KPIs remain underdeveloped.

Conclusion

Real-time data-driven scheduling models stand as transformative enablers for improving operational efficiency, robustness, and flexibility in smart dairy manufacturing, particularly yoghurt production. The integration of Industry 4.0 enablers, such as IoT sensors and OPC UA data acquisition, paired with simulation-optimisation frameworks like MATLAB/Simulink, empowers manufacturers to navigate complex trade-offs involving machine utilisation, changeover times, demand variability, and batch sizes.

The reviewed literature and practical case studies, including the Kefalos Cheese Pvt Ltd experience, validate the feasibility and benefits of such approaches. However, the transition in emerging economies is hindered by technological infrastructure gaps, workforce skill deficits, cybersecurity concerns, and limited economic impact quantification.

Addressing these challenges through targeted research on AI integration, adaptable scalable models, workforce development, and rigorous economic evaluation will catalyse broader adoption. This will drive sustainable competitiveness and resilience in dairy manufacturing sectors across emerging markets.

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