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Computational Model for Plant Modelling to Reduce Complexity with The Help of Fact Table and Its Multidimensional

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A B S T R A C T

Modern plant operations, whether in manufacturing or agriculture, face significant challenges due to complexity in workflows, diverse processes, and large datasets. The integration of technology has led to the generation of vast data that requires effective organization, analysis, and visualization for operational efficiency. Computational models, particularly those utilizing fact tables and multidimensional modelling, have emerged as essential tools for reducing complexity and improving decision-making. These models organize data into structured repositories, allowing plant operators to analyse production metrics, resource consumption, and operational costs from multiple perspectives. Through leveraging tools such as MATLAB Simulink, Python, and data visualization platforms, plant managers can enhance operational performance, optimize resource allocation, and predict trends. The future of plant modelling will see further integration of AI, machine learning, and IoT, driving more intelligent and connected plant management systems.

Keywords: Computational Models, Multidimensional Modelling, Data Analysis

1. Introduction

The complexity inherent in modern plant operations, whether in manufacturing or agriculture, often presents significant challenges to efficiency, decision-making, and optimization. The increasing integration of technology in these domains has led to the generation of vast amounts of data, spanning production metrics, resource utilization, environmental conditions, and equipment performance. The effective organization, analysis, and visualization of this data are critical for improving plant operations, minimizing costs, and enhancing productivity. Computational models, with their ability to simulate, analyse, and optimize systems, have emerged as vital tools in addressing these challenges. A computational model for plant modelling leverages structured data

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representation techniques to reduce operational complexity and enhance decision-making capabilities. Central to this approach is the use of a **fact table**, a key component in data warehousing that stores quantitative data, such as production outputs, resource consumption, and operational costs. By organizing data in a central repository, the fact table provides a unified view of plant performance, enabling efficient data analysis and facilitating actionable insights. The multidimensional nature of such models allows for the examination of plant operations from multiple perspectives, integrating dimensions such as time, equipment, product, and resource consumption. Multidimensional modelling, as an extension of the fact table approach, introduces structured dimensions that encapsulate attributes relevant to plant operations. These dimensions provide the ability to aggregate, slice, dice, and pivot data, offering both granular and high-level insights into plant performance. For example, the time dimension allows for trend analysis over specific periods, while the equipment dimension provides insights into machine efficiency and maintenance needs. By organizing data in this manner, computational models can reduce the cognitive and analytical burden on decision-makers, streamlining the process of identifying inefficiencies, forecasting trends, and implementing corrective actions.

In the context of manufacturing plants, these computational models are invaluable for analysing production bottlenecks, optimizing resource allocation, and minimizing downtime. For instance, a multidimensional model can identify how shifts in machine efficiency impact overall productivity or how resource consumption varies across production lines. Similarly, in agricultural plants, these models enable the monitoring of environmental variables such as soil quality, humidity, and temperature, which directly influence crop yields. By incorporating such data into a multidimensional framework, plant operators can predict yield outcomes, optimize resource usage, and mitigate potential risks. The strength of this approach lies in its ability to transform raw data into actionable intelligence. The fact table and multidimensional model provide a systematic method for organizing data, while advanced computational techniques enable complex simulations and analyses. Tools such as MATLAB Simulink, Python libraries, and data visualization platforms like Tableau and Power BI further enhance the utility of these models, providing interactive dashboards and predictive analytics. These tools empower plant managers to make data-driven decisions, improving overall operational efficiency and aligning with organizational goals. Furthermore, the adoption of computational models with multidimensional data analysis aligns with the broader trend toward Industry 4.0 and precision agriculture. As plants become more interconnected and data-driven, the need for robust models that can handle large datasets, integrate diverse data sources, and provide actionable insights becomes paramount. The integration of fact tables and multidimensional models ensures that these needs are met, offering a scalable and flexible solution for modern plant operations.

1.1 Complexity in Modern Plant Operations

Modern plant operations, whether in manufacturing or agriculture, are characterized by intricate workflows, diverse processes, and extensive datasets. These complexities arise from multiple interdependent variables, including production metrics, resource utilization, equipment performance,

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and environmental factors. The growing reliance on advanced technologies in these domains has led to the exponential generation of data, which, while valuable, can overwhelm traditional data management approaches. Efficient organization, analysis, and visualization of this data are crucial for improving operational efficiency, optimizing resource allocation, and minimizing costs. Computational models have emerged as indispensable tools for addressing these challenges by enabling systematic analysis and optimization of plant processes. Computational models provide a framework for integrating data from diverse sources into a cohesive structure. By doing so, they help reduce the cognitive load on decision-makers, allowing for more accurate predictions and better-informed strategies. For instance, a manufacturing plant might utilize a computational model to identify production bottlenecks, while an agricultural operation could use it to monitor variables like soil health and crop yields. The overarching goal of these models is to streamline operations, enhance productivity, and ensure sustainability in increasingly complex environments.

1.2 Fact Tables as Central Repositories

At the core of computational models for plant operations is the fact table, a pivotal component in data warehousing that stores quantitative data. Fact tables act as centralized repositories for metrics such as production outputs, resource consumption, and operational costs. By consolidating this information, they provide a unified view of plant performance, which is essential for efficient data analysis and actionable decision-making. Fact tables are designed to capture and organize data in a structured format that supports multidimensional analysis. Each entry in a fact table is linked to specific dimensions, such as time, equipment, and product categories, enabling comprehensive insights into various aspects of plant operations. For example, a manufacturing plant might use a fact table to track daily production volumes, resource utilization rates, and machine downtime. Similarly, an agricultural plant could use it to monitor seasonal variations in crop yields, irrigation levels, and fertilizer usage. The primary advantage of using fact tables lies in their ability to simplify complex datasets. By organizing data in a consistent and accessible manner, they facilitate advanced analytics and predictive modeling. This, in turn, empowers plant managers to identify inefficiencies, forecast trends, and implement targeted interventions. Furthermore, fact tables can be seamlessly integrated with data visualization tools, such as Tableau and Power BI, to create interactive dashboards that enhance decision-making capabilities.

2. Review of Literature

Nägele et al. (2010) develop a mathematical model representing metabolite interconversions in the core carbohydrate metabolism of *Arabidopsis thaliana*, specifically focusing on diurnal dynamics of primary carbon metabolism in photosynthetically active leaves. The methodology involved organizing enzymatic processes into blocks of interconverting reactions, with the model using experimental data from wild-type *Arabidopsis* plants and a mutant lacking vacuolar invertase. Turnover rates for interconverting reactions were computed by simulating metabolite levels throughout the diurnal cycle. The findings showed that the wild-type model could predict higher sucrose levels when invertase activity was reduced, similar to the mutant. However, further modifications were required to accurately replicate hexoses and sugar phosphates, suggesting that the

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absence of invertase triggered changes in other enzymatic activities. This result indicated a decrease in photosynthesis and carbon export to sink organs, in line with the known function of vacuolar invertase in maintaining sink strength. The study demonstrated that mathematical modeling of complex metabolic networks could effectively analyze the role of individual enzyme activities in processes that are difficult to explain intuitively, highlighting the relevance of this approach for understanding metabolic regulation in plants.

Sipöcz, Tobiesen, and Assadi (2011) develop and validate an Artificial Neural Network (ANN) model for simulating the CO2 capture process, aiming to assess its utility for integration into standard heat and mass balance programs. The methodology involved using a multilayer feed-forward ANN to model the non-linear relationships between inputs and outputs of the CO2 capture process, with data gathered from CO2SIM, a process simulator for amine-based absorption plants. Two distinct techniques were employed for training the ANN, and a sensitivity analysis was conducted to determine the minimum number of input parameters required for an accurate model. The findings demonstrated that the ANN could recreate results from a rigorous process simulator in a fraction of the time, with a repeatability error rate of less than 0.2% in simulating the closed loop absorber/desorber plant. The study concluded that trained ANN models are effective in accurately simulating complex steady-state processes, offering significant time savings while maintaining high accuracy. The relevance of this study lies in its potential to optimize CO2 capture processes by enabling faster simulations and decision-making, contributing to more efficient plant operations and integration with existing process simulation tools.

Chuine et al. (2013) provide a concise review of mechanistic phenological models used in plant phenology, emphasizing their development, applications, and the differences between them. The methodology involved presenting a historical overview of plant phenology modelling, followed by an analysis of the various models discussed in the literature. The study also highlighted key distinctions among these models, including their complexity levels and the different response functions to temperature they utilize. Furthermore, the authors examined the methods used in constructing and parameterizing these models. The findings revealed that mechanistic plant phenological models have been successfully applied in areas such as predicting frost hardiness, modelling tree development, assessing tree species distribution, and reconstructing historical temperatures. The study's relevance lies in its comprehensive overview of the evolution of phenological modelling, its methodological diversity, and the significant real-world applications of these models, which provide valuable insights for understanding and predicting plant behaviour in response to climate change.

Wu and Cournède (2014) aimed to develop a comprehensive sensitivity analysis (SA) methodology for complex mechanistic models that describe multi-physical processes. The study emphasized the importance of considering the interactions between model modules and the relevance of parameters for effective model diagnostics. Their methodology involved analyzing model nonlinearity, ranking the importance of modules, screening parameters for each module, and assessing intra- and inter-module interactions, all within a sequential framework. A key aspect of the methodology was the

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reduction of model parameters through systematic screening, which was illustrated through a case study of the Nitrogen Economy Model in plant architecture (NEMA). The findings demonstrated that the proposed SA approach effectively identified the most influential parameters, reducing the number of parameters from 83 to 17, significantly improving the parameterization of the NEMA model. This reduction highlighted the methodology's ability to enhance the understanding of the model's evolution and module interactions while also optimizing computational efficiency. The relevance of this study lies in its contribution to improving model diagnostics and enhancing the accuracy of complex mechanistic models in plant development.

Boudon et al. (2015) develop a conceptual and modeling framework to integrate the understanding of morphogenesis in plant biology, particularly focusing on the genetic control of shape and size during cell development. The methodology involved creating a 3D virtual tissue model, which simulates plant tissue growth by manipulating the mechanical properties of the cell wall and turgor pressure. The model explored how local and non-local forces, driven by turgor pressure, influence growth at the cellular level. The findings revealed that different scenarios of growth lead to similar shape changes, but they yield distinct mechanical and geometric predictions, which can be tested experimentally. The model also demonstrated how minimal gene activity could explain the complex shape changes during organ expansion, using flower formation as an example. The relevance of this study lies in its potential to enhance the understanding of morphogenetic processes in plants, providing a framework for investigating genetic control mechanisms and the physical forces that influence plant development, with implications for both basic biology and applied fields such as plant breeding and genetic engineering.

Larsen et al. (2016) address the challenges in landscape-scale modeling of coupled ecological-geophysical systems, particularly in the context of interdisciplinary communication and model integration. The authors introduced the "Appropriate-Complexity Method" (ACME), which combines pattern-oriented modeling in ecology and exploratory modeling in geophysics to create process-oriented models. The methodology involved systematically evaluating model attributes, using operational decision trees, iterative adjustments based on pattern-oriented evaluations, and leveraging appropriate datasets to formulate predictions. The findings emphasized that ACME aids in balancing model complexity by considering computational detail, validation potential, interpretability, tractability, and generality. The approach helps modelers determine the right level of complexity for answering research questions and enables scenario testing for broader applications. The study is highly relevant as it offers a practical framework for developing landscape models in restoration programs, particularly in the face of climate change and environmental management. By promoting interdisciplinary collaboration, the research provides a robust method for refining models across scales, enhancing the accuracy and applicability of ecological and geophysical modeling.

Evers et al. (2019) aimed to explore the productivity benefits of plant species mixtures over monocultures, focusing on the role of complementarity in resource acquisition. The researchers utilized functional–structural plant (FSP) modelling to understand how individual plants in species mixtures interact to optimize resource capture across both time and space. The methodology involved simulating plant growth dynamics and interactions, particularly how competition avoidance and adaptive strategies contribute to resource acquisition, such as nitrogen uptake and photosynthesis. The findings revealed that plant species mixes benefit from enhanced resource acquisition due to complementary growth responses, ultimately improving community performance. The study highlighted the potential of FSP models to accelerate research in mixed-species plant systems, suggesting that such models can support sustainable agricultural practices by maximizing yields with optimized resource inputs. This research is relevant for advancing agricultural productivity and sustainability, offering insights into how species mixtures can be utilized to improve crop yields while maintaining resource efficiency.

Ridha, E., Nolting, L., & Praktiknjo, A. (2020) aimed to investigate the connection between the purpose of energy system models and their complexity. They manually clustered 145 models based on their overall purpose and underlying research questions and further validated the results by employing various clustering methods. The study categorized model complexity into four dimensions: temporal, spatial, mathematical, and modelling content complexity. Statistical analysis through confidence intervals revealed four major clusters—unit commitment, electrical grids, policy assessment, and future energy systems—each with distinct complexity profiles. The researchers found that high complexity in one dimension was often balanced by lower complexity in others, suggesting that modellers prioritize certain features depending on the model's purpose. The findings provide valuable insights into managing model complexity in energy system modelling, offering a foundational framework for future research in this field. This research is highly relevant to both the scientific community and policymakers or industry professionals who rely on these models for decision-making.

Gil et al. (2021) address the challenges of integrating expert models to quantify the responses of complex systems, such as the interactions between droughts, water reserves, and agricultural productivity. The methodology involved analysing the difficulties faced by modellers in integrating diverse models and data sources across various disciplines, particularly the semantic, spatiotemporal, and execution mismatches that hinder effective model integration. These mismatches, which currently require manual resolution, often take years to address. The findings highlighted the critical need for improved methods to resolve these incompatibilities and streamline the use of expert models in addressing complex societal and environmental issues. The study emphasized that despite the promise of expert models to predict the impacts of various interventions, the practical challenges of model integration and data conversion still pose significant barriers. This research is highly relevant as it underscores the importance of developing more efficient methodologies for combining models and data, facilitating more effective decision-making for environmental management and agricultural planning in the face of changing conditions.

Siala et al. (2022) aimed to explore the effects of various factors on power market models used for decarbonization pathways in Europe until 2050. The methodology involved conducting experimental inter- and intramodal comparisons using five different power market models, considering variables such as model type (optimization vs. simulation), planning horizon (intertemporal vs. myopic), temporal resolution (8760 vs. 384 hours), and geographical resolution (28 nations vs. 12 mega-regions). The findings revealed a basic relationship between model type and capacity increase, with high carbon costs showing minimal influence from the planning horizon. Myopic models produced significantly different results compared to intertemporal models in low carbon pricing scenarios. Additionally, reducing temporal and geographical resolutions promoted wind power generation through storage, overcoming transmission barriers. The study concluded that, to reduce computational complexity, it may be essential to use simulation rather than optimization, shorten the planning horizon, and lower temporal and geographical resolutions. The relevance of the study lies in its provision of valuable insights for modellers working on decarbonization strategies, offering guidance on minimizing discrepancies in results while balancing model complexity and accuracy.

Multidimensional Modelling for Comprehensive Insights

Multidimensional modelling extends the capabilities of fact tables by introducing structured dimensions that encapsulate attributes relevant to plant operations. These dimensions enable users to view data from multiple perspectives, offering both granular and high-level insights. Key dimensions typically include time, equipment, product, resource consumption, and environmental variables. The time dimension, for instance, allows for trend analysis over specific periods, such as daily, weekly, or monthly production cycles. This helps identify patterns, such as seasonal variations or recurring bottlenecks. The equipment dimension provides insights into machine performance, maintenance schedules, and efficiency rates, enabling proactive maintenance and reduced downtime. The product dimension helps analyze production outputs, quality metrics, and batch-specific variations, ensuring adherence to standards and customer requirements. Through enabling data aggregation, slicing, dicing, and pivoting, multidimensional models make it easier to extract meaningful insights from complex datasets. For example, a plant manager can use these models to compare resource consumption across different production lines or evaluate the impact of environmental conditions on crop yields. This level of analytical flexibility is invaluable for optimizing operations, reducing waste, and achieving sustainability goals.

Applications in Manufacturing and Agriculture

The application of computational models in manufacturing plants is transformative. These models enable the identification of production bottlenecks, optimization of resource allocation, and minimization of downtime. For instance, a multidimensional model can analyze how shifts in machine efficiency impact overall productivity or how variations in resource consumption affect production costs. Such insights are critical for achieving lean manufacturing goals and maintaining a competitive edge. In agricultural plants, computational models play an equally vital role. They facilitate the monitoring of environmental variables such as soil quality, humidity, and temperature, which are crucial for optimizing crop yields. Through integrating this data into a multidimensional framework, plant operators can predict yield outcomes, optimize resource usage, and mitigate potential risks. For example, a farmer could use a computational model to determine the optimal irrigation schedule based on real-time weather data and soil moisture levels. The strength of these models lies in their ability to transform raw data into actionable intelligence. By providing a

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systematic method for organizing and analyzing data, computational models enable plant managers to make data-driven decisions that enhance operational efficiency and align with organizational goals.

Tools and Future Trends

- ✓ **Tools Enhancing Computational Models:** The utility of computational models is greatly amplified by the availability of advanced tools and technologies. MATLAB Simulink, for instance, provides a robust platform for simulating dynamic systems and testing various operational scenarios. Python libraries, such as Pandas and NumPy, enable efficient data manipulation and analysis, while visualization tools like Tableau and Power BI offer interactive dashboards that present insights in an accessible and actionable format. These tools not only facilitate real-time decision-making but also empower plant managers to simulate potential changes before implementing them, reducing risks and costs associated with trial-and-error approaches. Additionally, emerging technologies such as cloud computing and edge analytics further enhance the capabilities of computational models. Cloud platforms provide scalable storage and computational power, allowing plants to manage and analyze large datasets with ease. Edge analytics, on the other hand, enables real-time data processing at the source, reducing latency and ensuring faster response times. These advancements are particularly valuable for operations that require immediate insights, such as monitoring equipment health or responding to environmental changes in agricultural settings.
- ✓ **Future Trends in Plant Modeling:** The future of plant modeling lies in the integration of artificial intelligence (AI) and machine learning (ML) into computational models. These technologies can analyze historical data to identify patterns, predict future outcomes, and recommend optimal strategies. For example, AI algorithms can predict equipment failures based on sensor data, enabling predictive maintenance and minimizing downtime. Similarly, ML models can optimize resource allocation by analyzing past production trends and environmental conditions. Another promising trend is the adoption of IoT (Internet of Things) and blockchain technologies. IoT devices provide real-time data from equipment and environmental sensors, enhancing the accuracy and relevance of computational models. Blockchain, with its secure and transparent data storage capabilities, ensures data integrity and facilitates collaboration among multiple stakeholders. Together, these technologies create an interconnected ecosystem that supports efficient and sustainable plant operations. As plants transition towards Industry 4.0 and precision agriculture, the demand for computational models that can handle complex datasets and integrate diverse data sources will continue to grow. The adoption of fact tables and multidimensional modeling techniques ensures that these needs are met, providing a scalable and flexible foundation for modern plant management.

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Conclusion

Computational models, especially those utilizing fact tables and multidimensional frameworks, play a crucial role in optimizing plant operations across both manufacturing and agricultural sectors. By organizing vast amounts of data into structured formats, these models provide valuable insights into production efficiency, resource management, and environmental factors. The integration of advanced tools and emerging technologies such as AI, IoT, and cloud computing further enhances the capabilities of these models, offering predictive analytics and real-time decision-making. As industries continue to evolve toward smarter and more data-driven operations, the adoption of computational models will be essential for improving productivity, reducing costs, and ensuring sustainability. The future of plant management lies in leveraging these models to achieve operational excellence and alignment with broader Industry 4.0 and precision agriculture trends.

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