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**Quantificação Do Risco Em Investimentos Na Indústria De Transformação:
Uma Abordagem Estocástica**

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QUANTIFICAÇÃO DO RISCO EM INVESTIMENTOS NA INDÚSTRIA DE TRANSFORMAÇÃO: UMA ABORDAGEM ESTOCÁSTICA

Rafael Vieira da Silva

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Orientador: Enzo Morosini Frazzon

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Resumo

A quantificação do risco em investimentos na indústria de transformação constitui um desafio analítico relevante, em função da elevada intensidade de capital, dos longos horizontes temporais e da incerteza associada à evolução conjunta de variáveis econômicas fundamentais. Custos, preços, demanda e demais fatores que afetam o desempenho econômico de projetos industriais apresentam dinâmicas estocásticas e interdependentes, cuja representação inadequada pode comprometer a consistência das análises de viabilidade e das decisões de alocação de capital.

Esta dissertação propõe uma abordagem metodológica voltada ao suporte à quantificação do risco em investimentos produtivos, fundamentada na projeção estocástica multivariada de longo prazo de séries temporais econômicas. Ressalta-se que o método proposto não calcula diretamente medidas de risco, seu objetivo central é gerar representações probabilísticas coerentes dos insumos necessários para a aplicação consistente dessas métricas em análises posteriores de risco.

O trabalho estrutura-se em três eixos complementares: (i) uma revisão sistemática da literatura sobre análise de viabilidade econômica e quantificação do risco na indústria de transformação, com ênfase em abordagens baseadas na geração de cenários; (ii) a proposição de um modelo conceitual para a análise de investimentos industriais, integrando a representação do processo produtivo, a projeção estocástica das variáveis econômicas e a obtenção de distribuições probabilísticas de indicadores financeiros; e (iii) o desenvolvimento e a validação de um modelo computacional híbrido para projeção probabilística multivariada de longo prazo.

O modelo proposto, denominado CMP-LSTM, combina a estimação de distribuições marginais por meio de redes Long Short-Term Memory (LSTM) com a modelagem da dependência multivariada via cópulas do tipo R-vine, permitindo a geração de cenários estocásticos coerentes em horizontes de longo prazo. A partir desses cenários, torna-se possível derivar distribuições de indicadores financeiros, como fluxos de caixa e métricas de viabilidade econômica, que servem de base para a quantificação do risco associada a decisões de investimento.

A abordagem é avaliada por meio de aplicações em dados reais de cadeias produtivas da indústria de transformação, sendo comparada a métodos tradicionais, como o modelo VARMA combinado com simulação de Monte Carlo. Os resultados indicam desempenho superior do método proposto em métricas probabilísticas univariadas e multivariadas, como CRPS, WIS, Energy Score e Variogram Score, especialmente em horizontes de cinco e dez anos. Além da melhoria na calibração marginal, o modelo demonstra capacidade consistente de preservar a estrutura de dependência entre variáveis econômicas, aspecto

fundamental para a geração de cenários realistas e para análises robustas de risco em investimentos produtivos sob incerteza

Palavras-chave: Risco em Investimentos, Abordagem Estocástica, Inteligência Artificial, Séries Temporais Multivariadas, Long Short-Term Memory (LSTM), Copulas.

Abstract

The quantification of risk in investments in the manufacturing industry constitutes a relevant analytical challenge due to high capital intensity, long time horizons, and the uncertainty associated with the joint evolution of fundamental economic variables. Costs, prices, demand, and other factors affecting the economic performance of industrial projects exhibit stochastic and interdependent dynamics, whose inadequate representation may compromise the consistency of feasibility analyses and capital allocation decisions.

This dissertation proposes a methodological approach aimed at supporting risk quantification in productive investments, grounded in long-term multivariate stochastic forecasting of economic time series. It is important to emphasize that the proposed method does not directly compute risk measures; rather, its primary objective is to generate coherent probabilistic representations of the inputs required for the consistent application of such metrics in subsequent risk analyses.

The study is structured around three complementary pillars: (i) a systematic literature review on economic feasibility analysis and risk quantification in the manufacturing industry, with emphasis on scenario-generation-based approaches; (ii) the proposal of a conceptual framework for industrial investment analysis, integrating the representation of the production process, stochastic forecasting of economic variables, and the derivation of probabilistic distributions of financial indicators; and (iii) the development and validation of a hybrid computational model for long-term multivariate probabilistic forecasting.

The proposed model, named CMP-LSTM, combines the estimation of marginal distributions using Long Short-Term Memory (LSTM) networks with multivariate dependence modeling through R-vine copulas, enabling the generation of coherent stochastic scenarios over long-term horizons. From these scenarios, it becomes possible to derive distributions of financial indicators, such as cash flows and economic feasibility metrics, which serve as a basis for risk quantification in investment decision-making.

The approach is evaluated through applications to real data from manufacturing supply chains and is compared with traditional methods, such as the VARMA model combined with Monte Carlo simulation. The results indicate superior performance of the proposed method in univariate and multivariate probabilistic metrics, such as CRPS, WIS, Energy Score, and Variogram Score, particularly at five- and ten-year horizons. In addition to improved marginal calibration, the model demonstrates a consistent ability to preserve the dependence structure among economic variables, a fundamental aspect for generating realistic scenarios and conducting robust risk analyses in productive investments under uncertainty.

Keywords: Investment Risk, Stochastic Approach, Artificial Intelligence, Supply Chain, Multivariate Time Series, Long Short-Term Memory (LSTM), Copulas.

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Lista de abreviaturas e siglas

ANNs	Redes Neurais Artificiais
BIM	Building Information Modelling
EMH	Hipótese do Mercado Eficiente
FCF	Fluxo de Caixa de Financiamento
FCI	Fluxo de Caixa de Investimento
FCO	Fluxo de Caixa Operacional
IA	Inteligência Artificial
MCDM	Decisão Multicritério
NDEA	Análise Envoltória de Dados de Rede
P&D	Pesquisa e Desenvolvimento
RFs	Florestas Aleatórias
RL	Aprendizagem por Reforço
SBF	Sociedade Brasileira de Física
SCRM	Gerenciamento de Risco na Cadeia de Suprimentos
SVM	Máquinas de Vetores de Suporte
VPL	Valor Presente Líquido

Lista de símbolos

ϵ_t	Ruído branco
$N(0, \sigma^2)$	Distribuição normal com média zero e variância σ^2
X_t	Valor do ruído no instante t
X_{t-1}	Valor do ruído no instante $t - 1$
FCO_t	Fluxo de Caixa Operacional no tempo t
FCI_t	Fluxo de Caixa de Investimento no tempo t
FCF_t	Fluxo de Caixa de Financiamento no tempo t
VPL	Valor Presente Líquido
PRP	Probabilidade de Retorno Positivo
Y_t	Valor da série temporal no tempo t
T_t	Componente de tendência da série temporal
S_t	Componente de sazonalidade da série temporal
Φ	Matriz de coeficientes do modelo VAR
Θ	Matriz de coeficientes do modelo VAR na forma matricial
λ	Parâmetro de suavização na decomposição de séries temporais

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1 Introdução

Nesse capítulo é apresentada a contextualização, justificativa do tema, objetivos e delimitação do trabalho. Fundamentam-se os principais elementos que tratam da motivação do trabalho a seguir e as abordagens tomadas para a realização da pesquisa.

1.1 Contextualização

A indústria de transformação caracteriza-se por operar em um ambiente intensivo em capital, no qual decisões de investimento envolvem elevados volumes de recursos financeiros, longos horizontes temporais e significativa irreversibilidade (Pindyck, 1991; Hildebrandt; Knoke, 2011; Mombello; Olsina; Pringles, 2025). Projetos industriais, como a implantação de novas plantas, a ampliação de capacidades produtivas ou a adoção de novos processos tecnológicos, demandam escolhas cujos efeitos se estendem por anos ou décadas, limitando a possibilidade de reversão ou ajuste após sua implementação. Nesse contexto, a qualidade das decisões iniciais assume papel central para a viabilidade econômica e financeira dos empreendimentos (Khuong Ninh; Hermes; Lanjouw, 2004).

Essas decisões são tomadas sob condições de incerteza inerentes ao ambiente econômico em que a indústria de transformação está inserida. Variáveis como preços de insumos, custos operacionais, demanda por produtos, taxas de câmbio e condições macroeconômicas evoluem de forma incerta ao longo do tempo, afetando diretamente os fluxos de caixa esperados e, conseqüentemente, o retorno dos investimentos (Pindyck, 1991). Assim, o risco associado a investimentos produtivos não se restringe a eventos operacionais pontuais, mas está fortemente relacionado à dinâmica estocástica dessas variáveis econômicas ao longo do horizonte de análise (Conning, 2020).

Diferentemente de abordagens voltadas ao risco operacional ou à gestão de riscos logísticos, o risco em investimentos produtivos refere-se à incerteza quanto aos resultados econômicos futuros decorrentes de decisões estratégicas de alocação de capital (Mombello; Olsina; Pringles, 2026). Nesse sentido, a avaliação de investimentos na indústria de transformação exige métodos capazes de lidar explicitamente com a incerteza temporal, incorporando não apenas valores esperados, mas também a variabilidade e a estrutura de dependência entre as variáveis que influenciam o desempenho econômico dos projetos (Aalto; Kuosa; Stucki, 2025).

Um dos principais desafios nesse processo consiste na projeção de variáveis econômicas relevantes ao longo de horizontes de médio e longo prazo (Conning, 2020). Além de estimar tendências, torna-se necessário capturar adequadamente a incerteza associada a

essas projeções, bem como as relações de dependência entre diferentes séries temporais, uma vez que custos, preços e retornos frequentemente evoluem de forma correlacionada (Pindyck, 1991; Khuong Ninh; Hermes; Lanjouw, 2004). Ignorar tais dependências pode levar à geração de cenários inconsistentes e, conseqüentemente, a avaliações distorcidas do risco envolvido (Aalto; Kuosa; Stucki, 2025).

Dessa forma, a análise de risco em investimentos produtivos demanda a geração de cenários estocásticos coerentes, capazes de representar simultaneamente a dinâmica individual das variáveis econômicas e suas inter-relações. Esses cenários constituem a base para a quantificação do risco, permitindo avaliar a distribuição de possíveis resultados econômicos e fornecer subsídios mais robustos para o processo decisório. É nesse contexto que se insere a presente dissertação, ao propor uma abordagem voltada à quantificação do risco em investimentos na indústria de transformação, fundamentada na modelagem estocástica de séries temporais e na geração de cenários multivariados de longo prazo.

1.2 Objetivos

A apresentação a seguir destaca o objetivo geral da pesquisa e apresenta os objetivos específicos, que serviram como guia para o projeto.

1.2.1 Objetivo Geral:

Desenvolver uma abordagem metodológica para a projeção estocástica multivariada de longo prazo de séries temporais econômicas, incorporando incertezas e dependências relevantes à análise de risco em investimentos na indústria de transformação.

1.2.2 Objetivos Específicos:

- Sistematizar e analisar a literatura sobre quantificação do risco em investimentos produtivos, com ênfase em abordagens baseadas na geração de cenários e na modelagem estocástica de variáveis econômicas relevantes.
- Propor e estruturar um modelo conceitual para a quantificação do risco em investimentos na indústria de transformação, definindo seus principais componentes, fluxos e relações para a geração de cenários estocásticos de longo prazo.
- Desenvolver, aplicar e avaliar um modelo computacional para a geração de cenários estocásticos multivariados de longo prazo, analisando sua capacidade de representar incertezas e dependências relevantes para a quantificação do risco em investimentos produtivos.

1.3 Estrutura do Documento

Esta dissertação está organizada em oito capítulos, estruturados de forma a conduzir o leitor desde a fundamentação teórica e metodológica até a apresentação dos resultados e conclusões do trabalho.

O Capítulo 2 apresenta o referencial teórico que fundamenta a pesquisa. São abordados os principais conceitos relacionados ao gerenciamento de risco em contextos produtivos, ao processo de decisão em investimentos e à utilização de métodos quantitativos e computacionais para a análise de incertezas econômicas. Esse capítulo tem como objetivo estabelecer o enquadramento conceitual necessário para o desenvolvimento do modelo proposto, alinhando os temas discutidos ao escopo da indústria de transformação.

O Capítulo 3 descreve os métodos e técnicas de pesquisa adotados, detalhando as etapas do estudo e a lógica metodológica que conduz ao atendimento do objetivo geral e dos objetivos específicos da dissertação. Nesse capítulo são apresentadas as fases da pesquisa e a forma como elas se articulam, desde a revisão da literatura até o desenvolvimento e a aplicação do modelo metodológico proposto.

O Capítulo 4 apresenta o artigo “Economic Feasibility Analysis in the Manufacturing Industry – A Literature Review”, no qual é realizada uma revisão sistematizada da literatura sobre análise de viabilidade econômica na indústria de transformação. Além do levantamento de metadados, o artigo concentra-se em identificar abordagens, métodos e lacunas relevantes, contribuindo para a compreensão do estado da arte no escopo do trabalho.

O Capítulo 5 é dedicado ao artigo “Risk Quantification in Manufacturing Industry Investments: A Stochastic Approach with Artificial Intelligence”, que propõe um modelo conceitual para a quantificação do risco em investimentos na indústria de transformação. Nesse artigo, são apresentados os principais componentes do modelo e discutidas as ferramentas metodológicas que o compõem, com base em uma revisão narrativa da literatura.

O Capítulo 6 apresenta o artigo “Joint Modeling of LSTM Marginals and R-vine Copulas for Long-term Probabilistic Forecasting of Multivariate Time Series”, no qual a parcela do modelo conceitual relacionada à projeção de séries temporais é aprofundada e reformulada. Nesse capítulo, é desenvolvido e aplicado um modelo metodológico para a projeção estocástica multivariada de longo prazo, cuja eficácia é demonstrada por meio de aplicações em dados reais de cadeias produtivas.

O Capítulo 7 apresenta e discute os principais resultados obtidos ao longo do desenvolvimento do trabalho, destacando as contribuições metodológicas alcançadas. Por fim, o Capítulo 8 reúne as conclusões da dissertação, abordando as principais contribuições, limitações e possibilidades de extensão da pesquisa.

2 Referencial Teórico

2.1 Risco e Incerteza em Investimentos Produtivos

A formalização do conceito de risco em economia está associada à distinção clássica proposta por Knight (1921) entre risco e incerteza. Segundo esse autor, o risco refere-se a situações nas quais os resultados futuros podem ser descritos por distribuições de probabilidade conhecidas ou estimáveis, enquanto a incerteza corresponde a contextos em que tais distribuições são desconhecidas ou não podem ser inferidas de forma objetiva. Essa distinção é central para análises quantitativas, uma vez que apenas o risco, no sentido knightiano, admite tratamento analítico por meio de modelos probabilísticos.

Sob essa perspectiva, o risco pode ser representado como uma variável aleatória, cuja distribuição sintetiza o conjunto de resultados possíveis associados a uma decisão econômica (Ma; Li; Qin, 2024). Em investimentos produtivos, essa variável está associada a fluxos econômicos futuros, como custos, receitas ou retornos, cuja realização depende de processos subjacentes. A análise do risco, portanto, não se restringe a medidas pontuais, como valores esperados, mas requer a caracterização completa das distribuições envolvidas, incorporando dispersão, assimetria e dependências estatísticas relevantes, conforme amplamente discutido na literatura econômica sobre decisões sob incerteza (Alexander; Chen; Ward, 2021).

Essa concepção de risco aplica-se ao risco econômico-financeiro, entendido como a incerteza mensurável associada aos resultados monetários futuros decorrentes de decisões de investimento. Esse tipo de risco, tratado no sentido knightiano, admitindo representação por distribuições de probabilidade. A análise econômica de investimentos pressupõe, portanto, que os resultados financeiros futuros possam ser descritos como realizações de variáveis aleatórias, cuja distribuição reflete a incerteza inerente ao ambiente econômico (Aalto; Kuosa; Stucki, 2025; Mohammadivojdan; Merzifonluoglu; Geunes, 2022).

Dessa forma, a análise quantitativa do risco econômico-financeiro está intrinsecamente relacionada à capacidade de representar, de forma consistente, os possíveis estados futuros das variáveis econômicas relevantes (Khuong Ninh; Hermes; Lanjouw, 2004). Abordagens baseadas em projeções estocásticas e geração de cenários desempenham papel central, ao fornecer representações probabilísticas dos resultados futuros e de suas interdependências. Tais cenários não constituem, por si só, uma avaliação do risco, mas sim insumos fundamentais para análises posteriores, nas quais a distribuição dos resultados projetados pode ser utilizada para mensurar a exposição ao risco associada a decisões de investimento (Alexander; Chen; Ward, 2021).

É reconhecido na literatura sobre investimentos produtivos a existência de dife-

rentes níveis de incerteza associados a sistemas produtivos (Hildebrandt; Knoke, 2011; Mombello; Olsina; Pringles, 2025). Sendo o risco operacional relacionado ao desempenho e à variabilidade do sistema durante sua operação, enquanto incertezas de natureza técnica referem-se à viabilidade teórica e tecnológica do processo produtivo, incluindo sua adequação às restrições físicas, técnicas e de engenharia. Essas incertezas antecedem a análise econômica, na medida em que delimitam o conjunto de alternativas tecnicamente admissíveis sobre as quais o risco econômico-financeiro pode ser definido (Alexander; Chen; Ward, 2021).

2.2 Medidas Quantitativas de Risco

As medidas quantitativas de risco utilizadas na análise econômica de investimentos não constituem entidades autônomas, mas funções aplicadas a distribuições de probabilidade que descrevem resultados econômicos futuros (Wang; Ziegel, 2021). Assim, a mensuração do risco depende fundamentalmente da qualidade e da coerência das representações probabilísticas, sendo as medidas propriamente ditas etapas posteriores de síntese estatística. Sob essa perspectiva, a discussão das principais métricas de risco deve ser compreendida a partir dos requisitos informacionais que elas impõem às distribuições e aos cenários estocásticos utilizados na análise (Udugama *et al.*, 2018; Addy *et al.*, 2024).

As medidas clássicas de dispersão, como a variância e a volatilidade, baseiam-se na caracterização global da distribuição em torno de seu valor esperado. Essas métricas pressupõem que a incerteza relevante possa ser adequadamente resumida pela magnitude média dos desvios, tratando flutuações positivas e negativas de forma simétrica. Tal abordagem é consistente apenas quando a distribuição apresenta comportamento aproximadamente regular e quando eventos extremos não desempenham papel dominante. Em contextos econômicos mais complexos, essas medidas revelam limitações evidentes, pois ignoram assimetrias, caudas pesadas e interações entre variáveis que afetam a forma da distribuição conjunta dos resultados (Addy *et al.*, 2024).

Medidas baseadas em quantis, como o Value-at-Risk (VaR), introduzem uma mudança conceitual ao deslocar o foco da dispersão global para regiões específicas da distribuição. O VaR sintetiza o risco por meio de um quantil associado a um nível de confiança, sendo, portanto, diretamente dependente da forma da distribuição de perdas. Embora amplamente utilizado, o VaR fornece informação apenas sobre um ponto da distribuição, não capturando o comportamento dos resultados além desse limiar. Essa característica torna sua interpretação sensível à especificação das caudas e às dependências entre variáveis, especialmente em sistemas econômicos multivariados (Inui; Kijima, 2005; Abad; Benito; López, 2014).

O Expected Shortfall (ES) emerge como uma extensão natural dessa abordagem

ao incorporar explicitamente a severidade média das perdas que excedem o VaR. Ao depender da média condicional na cauda da distribuição, o ES exige uma representação mais completa do comportamento extremo dos resultados. Essa dependência reforça o papel central da modelagem probabilística adequada, uma vez que erros na especificação das marginais ou das dependências podem comprometer significativamente a estimação dessa medida, sobretudo em cenários caracterizados por não normalidade e correlações não lineares (Inui; Kijima, 2005).

De forma geral, todas as medidas quantitativas de risco discutidas na literatura compartilham uma característica fundamental: sua validade analítica está condicionada à correta representação das distribuições de probabilidade e das estruturas de dependência entre variáveis econômicas. Em investimentos produtivos, nos quais múltiplos fatores de custo e retorno evoluem de maneira estocástica e interdependente, a quantificação do risco não pode ser dissociada da geração de cenários probabilísticos coerentes que preservem essas propriedades estatísticas (Udugama *et al.*, 2018).

Nesse sentido, este trabalho não se propõe a calcular diretamente medidas de risco como variância, Value-at-Risk ou Expected Shortfall. Seu objetivo é fornecer, por meio da projeção estocástica multivariada, os insumos probabilísticos necessários para que tais medidas possam ser aplicadas de forma consistente em análises posteriores de investimentos. A ênfase recai, portanto, na construção de representações probabilísticas adequadas dos resultados econômicos futuros, reconhecendo que a mensuração do risco é uma consequência direta dessa etapa e não um fim em si mesma.

2.3 Projeção Estocástica de Séries Temporais

As variáveis econômicas relevantes para a análise de investimentos produtivos são, em sua maioria, observadas na forma de séries temporais, refletindo a evolução dinâmica de custos, preços, receitas ou indicadores de desempenho ao longo do tempo (Kong *et al.*, 2025). Essas séries são caracterizadas por estruturas complexas, que incluem não estacionariedade, regimes distintos, volatilidade variável e relações não lineares entre observações passadas e futuras (Sachs, 2020). Em horizontes de longo prazo, tais características tornam-se ainda mais pronunciadas, ampliando a incerteza associada às trajetórias futuras e limitando a adequação de abordagens puramente determinísticas (Amato *et al.*, 2025).

A projeção de séries temporais econômicas sob incerteza exige, portanto, métodos capazes de representar não apenas trajetórias médias esperadas, mas o conjunto de caminhos possíveis que as variáveis podem assumir ao longo do tempo (Eggen *et al.*, 2025). Métodos probabilísticos atendem a essa necessidade ao tratar as observações futuras como realizações de processos estocásticos, permitindo a geração de cenários consistentes com a dinâmica histórica das séries. Em contextos de longo prazo, a relevância desses métodos

é ampliada, uma vez que pequenos desvios acumulados podem resultar em distribuições amplas e assimétricas de resultados econômicos (Amato *et al.*, 2025).

2.4 Dependência Multivariada e Geração de Cenários

A geração de cenários estocásticos para análise de investimentos produtivos envolve, necessariamente, a representação conjunta de múltiplas variáveis econômicas que evoluem de forma interdependente ao longo do tempo (Sachs, 2020). Custos de insumos, preços de produtos, taxas de câmbio e outros fatores relevantes compartilham fontes comuns de incerteza e respondem de maneira correlacionada a choques econômicos, regulatórios ou tecnológicos (Kong *et al.*, 2025). Dessa forma, a caracterização isolada de cada variável é insuficiente para descrever o espaço de resultados economicamente possíveis, sendo indispensável a consideração explícita das relações de dependência entre elas.

Do ponto de vista probabilístico, a dependência multivariada refere-se à estrutura de associação que conecta variáveis aleatórias além de suas distribuições marginais (Kong *et al.*, 2025). Essa estrutura determina como realizações simultâneas das variáveis se organizam ao longo de toda a distribuição conjunta, influenciando tanto o comportamento médio quanto a ocorrência conjunta de eventos extremos (Platanioti; McCoy; Stephens, 2005). Em análises de investimentos, tais eventos são particularmente relevantes, pois perdas ou ganhos significativos tendem a emergir da combinação desfavorável ou favorável de múltiplos fatores, e não de variações isoladas (Sachs, 2020).

A ausência de uma representação adequada da dependência multivariada compromete a coerência estatística dos cenários gerados. Mesmo quando as distribuições marginais individuais são corretamente especificadas, a combinação arbitrária dessas marginais pode resultar em trajetórias conjuntas incompatíveis com o comportamento histórico ou com a lógica econômica do sistema produtivo analisado (Toubeau *et al.*, 2018; Salinas *et al.*, 2019). Esse problema é agravado em horizontes de longo prazo, nos quais erros na estrutura de dependência se acumulam ao longo do tempo, distorcendo a distribuição conjunta dos resultados projetados (Shuetrim; Thompson, 2003).

Além disso, a dependência entre variáveis econômicas não se manifesta de forma uniforme ao longo de toda a distribuição (Patton, 2012). Regiões específicas, como extremos superiores ou inferiores, podem apresentar padrões de associação distintos daqueles observados em regiões centrais. Essa heterogeneidade implica que a avaliação do risco associado a investimentos produtivos requer representações capazes de preservar relações de co-movimento em diferentes estados do sistema, especialmente sob condições adversas que impactam simultaneamente múltiplas dimensões do desempenho econômico (Toubeau *et al.*, 2018).

2.5 Métodos Computacionais e Aprendizado de Máquina

A projeção estocástica de séries temporais em ambientes multivariados e de longo prazo impõe desafios computacionais que excedem a capacidade de abordagens analíticas tradicionais (Song *et al.*, 2024). A presença de não linearidades, dependências temporais complexas e elevada dimensionalidade dificulta a especificação explícita de modelos paramétricos capazes de representar, de forma simultânea, a dinâmica das variáveis e a incerteza associada às suas trajetórias futuras (Kong *et al.*, 2025). Nesse contexto, métodos computacionais baseados em aprendizado de máquina emergem como ferramentas para aproximar relações funcionais complexas a partir de dados observados (Yu *et al.*, 2025).

Eles podem ser compreendido como um conjunto de métodos estatísticos e computacionais destinados à estimação de funções desconhecidas que relacionam entradas e saídas, sem a necessidade de especificação explícita de uma forma funcional paramétrica (Kong *et al.*, 2025). Em aplicações com séries temporais econômicas, desde que devidamente treinados e validados, esses métodos permitem capturar padrões dinâmicos, dependências de longo alcance e regimes distintos de comportamento (Houssein *et al.*, 2025). Seu uso, portanto, deve ser entendido como uma estratégia de aproximação funcional orientada por dados, e não como um mecanismo autônomo de tomada de decisão (Song *et al.*, 2024).

Entre os modelos de aprendizado de máquina aplicáveis à modelagem temporal, as redes neurais recorrentes ocupam posição de destaque por sua capacidade de incorporar dependências sequenciais. Ao contrário de modelos estáticos, essas arquiteturas processam informações de forma recursiva ao longo do tempo, permitindo que estados passados influenciem as projeções futuras (Yu *et al.*, 2025). Essa característica é particularmente relevante para séries econômicas, nas quais a dinâmica presente é condicionada por trajetórias históricas que podem se estender por múltiplos períodos (Houssein *et al.*, 2025).

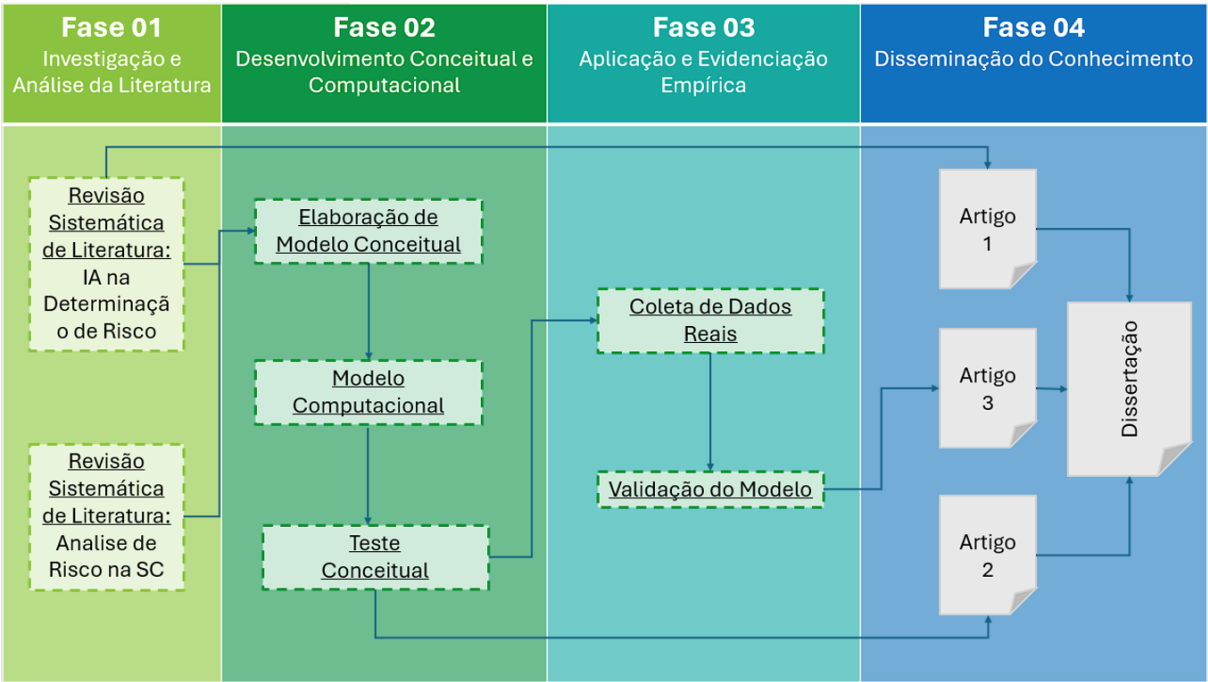
3 Métodos e Técnicas de Pesquisa

3.1 Procedimentos Metodológicos

Para alcançar os objetivos definidos nesta pesquisa, foi adotada uma abordagem metodológica estruturada e sequencial, organizada em quatro fases principais, compostas por subetapas interdependentes. Essa estrutura reflete o desenvolvimento progressivo do trabalho, desde a investigação teórica até a aplicação empírica e a disseminação dos resultados, conforme ilustrado na Figura 3.1 e compilado na Tabela 3.1. Cada fase está associada aos objetivos específicos apresentados na Seção 1.2 e aos produtos científicos correspondentes.

A organização do estudo em fases permite explicitar o caráter iterativo do processo de pesquisa, no qual avanços conceituais e empíricos retroalimentam o desenvolvimento metodológico, culminando na consolidação da abordagem proposta.

Figura 3.1 – Fases de Execução do Projeto de Pesquisa



Fonte: Os autores

A seguir, cada fase do estudo é descrita de forma sintética, destacando seus objetivos metodológicos e os principais resultados conceituais alcançados em cada etapa.

Tabela 3.1 – Fases, métodos, objetivos específicos e disseminação do conhecimento

Fase	Métodos e Técnicas	Objetivo Específico Atendido	Disseminação do Conhecimento
1. Investigação e análise da literatura	Revisão sistematizada da literatura	Sistematizar e analisar a literatura sobre quantificação do risco em investimentos produtivos, com ênfase em abordagens baseadas na geração de cenários e na modelagem estocástica de variáveis econômicas relevantes.	Artigo 1
2. Desenvolvimento conceitual e computacional	Modelagem conceitual e desenvolvimento exploratório	Propor e estruturar um modelo conceitual para a quantificação do risco em investimentos na indústria de transformação, definindo seus principais componentes, fluxos e relações para a geração de cenários estocásticos de longo prazo.	Artigo 2
3. Aplicação e evidenciação empírica	Modelagem computacional, projeção estocástica e validação empírica	Desenvolver, aplicar e avaliar um modelo computacional para a geração de cenários estocásticos multivariados de longo prazo, analisando sua capacidade de representar incertezas e dependências relevantes ao contexto de investimentos produtivos.	Artigo 3
4. Disseminação do conhecimento	Organização, submissão e publicação científica	Sistematizar e disseminar os resultados obtidos ao longo do desenvolvimento da pesquisa, integrando os produtos científicos à dissertação.	Artigos 1, 2 e 3

Fonte: Os autores

Fase 1 – Investigação e análise da literatura

A primeira fase consiste em uma revisão sistematizada da literatura voltada à análise de investimentos produtivos sob incerteza, com ênfase em abordagens de quantificação do risco e geração de cenários estocásticos. Essa etapa teve como objetivo estabelecer o enquadramento teórico do trabalho, identificar métodos recorrentes na literatura e eviden-

ciar lacunas relacionadas à representação probabilística conjunta de variáveis econômicas ao longo de horizontes de longo prazo.

Como resultado dessa fase, foi possível sistematizar o estado da arte sobre a análise econômica de investimentos sob risco, evidenciando limitações das abordagens tradicionais baseadas em projeções determinísticas ou em medidas de risco desvinculadas de representações probabilísticas consistentes. Os resultados dessa etapa deram origem ao **Artigo 1**, que fundamenta conceitualmente o desenvolvimento metodológico subsequente.

Fase 2 – Desenvolvimento conceitual e computacional

A segunda fase dedica-se à proposição de um modelo conceitual para a projeção estocástica multivariada de variáveis econômicas relevantes à análise de investimentos produtivos. Com base nos achados da revisão da literatura, essa etapa teve como objetivo estruturar conceitualmente o problema de pesquisa, definindo os principais componentes do processo de geração de cenários e suas inter-relações.

Nesta fase, foi elaborada uma primeira formulação conceitual da abordagem proposta, com caráter exploratório, resultando no **Artigo 2**. Essa formulação incluiu uma abordagem inicial para a desenvolvimento técnico-teórico do processo produtivo, projeção de séries temporais, e análise dos cenários gerados, cuja função principal foi organizar o arcabouço conceitual e orientar o avanço da pesquisa. A análise dessa etapa evidenciou limitações técnicas e teóricas na abordagem inicial de projeção, particularmente no que se refere à representação adequada da incerteza e da dependência entre séries temporais em horizontes de longo prazo.

Fase 3 – Aplicação e evidenciação empírica

A terceira fase concentra-se no refinamento metodológico e na aplicação empírica da abordagem proposta. A partir das limitações identificadas na fase anterior, especialmente na componente de projeção de séries temporais, essa etapa envolveu a reformulação e o aprofundamento do modelo computacional, culminando no desenvolvimento da versão metodológica definitiva.

O modelo refinado foi aplicado a dados reais, permitindo avaliar sua capacidade de gerar cenários estocásticos multivariados coerentes e compatíveis com a dinâmica observada das variáveis econômicas analisadas. Essa fase resultou no **Artigo 3**, no qual a abordagem consolidada é apresentada e sua aplicação empírica é demonstrada, evidenciando a evolução metodológica em relação à formulação inicial.

Fase 4 – Disseminação do conhecimento

A fase final corresponde à consolidação e disseminação dos resultados obtidos ao longo do desenvolvimento da pesquisa. Os produtos científicos gerados nas etapas anteriores foram organizados na forma de artigos científicos, submetidos e publicados em periódicos especializados, e integrados à presente dissertação. Esse processo possibilitou a comunicação dos resultados à comunidade acadêmica e a incorporação de contribuições decorrentes do processo de avaliação por pares.

Síntese metodológica das fases

De forma integrada, as fases metodológicas adotadas refletem um processo de pesquisa progressivo e iterativo, no qual a investigação teórica, a formulação conceitual, o desenvolvimento computacional e a aplicação empírica se articulam de maneira coerente. A Fase 1 estabeleceu a base conceitual do estudo; a Fase 2 permitiu estruturar o problema por meio de um modelo conceitual exploratório; a Fase 3 consolidou a abordagem metodológica por meio de sua reformulação e aplicação empírica; e a Fase 4 assegurou a sistematização e disseminação do conhecimento gerado.

Essa estrutura metodológica evidencia que o trabalho não se limita à aplicação direta de um modelo previamente definido, mas documenta o processo de desenvolvimento e refinamento metodológico que culmina na proposição de uma abordagem consistente para a projeção estocástica multivariada de séries temporais econômicas aplicadas à análise de investimentos produtivos.

4 Artigo 01 - Economic Feasibility Analysis In The Manufacturing Industry – A Literature Review

Este artigo foi aceito para publicação pela revista GEPROS (Journal of Production, Operations and Systems Management) com coautoria do professor Dr. Enzo M. Frazzon.

Abstract

Purpose

The development of companies in the manufacturing industry and determining their viability is challenging. This article reviews the most applied methodologies to facilitate investment decision-making in resource allocation within the supply chain.

Methodology/Approach

The PRISMA 2020 methodology was applied, using Web of Science and Scopus as sources, analyzing articles up to April 2024, and rigorously following inclusion and exclusion criteria.

Findings

The study included 16 articles, exhaustively extracting bibliographic metadata and detailing, particularly the methodologies applied in each study. It identified approaches such as the most used methods, variables, main objectives, optimization goals, and methods for validating results.

Research, practical & social implications

This article identified dominant approaches and research gaps within its scope, providing a guide for researchers interested in studying the relationship between supply chain risks and investments. The results support decision-making and indicate the most used methods for investment evaluation.

Originality/ Value

The article contributes to the consolidation of knowledge on risk analysis methods and economic feasibility, also highlighting the application of these tools in the manufacturing industry. This systematic review offers a critical analysis of existing studies, points out directions for future research, and supports the development of the field.

Keywords: Investments; Supply Chain; Risks; Technical-Economic Feasibility; Decision Methods

4.1 Introduction

Developing new companies is a complex challenge, particularly due to uncertainties that can hinder decision-making (Gopika; Resmi, 2024). Raw material prices, demand issues, logistics costs, selling prices, the emergence of technologies, and new competitors are only a few examples of uncertainty that affect the supply chain (SC) directly (Zhang; Shang; Li, 2011). External factors can also disrupt the SC significantly. Environmental disasters, economic crises, legislative updates, and geopolitical issues can equally affect investments and, to some extent, are unpredictable (Roscoe *et al.*, 2022; Yilmaz, 2024). Another crucial factor is the payback period of allocated resources (Kondaveeti *et al.*, 2023), which can exceed a decade in the case of investments for creating or expanding companies, and changes related to the aforementioned points can make resource allocation unsustainable (Bocken, 2015).

Such concerns are not new, and several researchers have dedicated efforts to developing methods aimed at assessing these uncertain scenarios. Therefore, this study involves in-depth research aimed at analyzing and compiling existing knowledge to facilitate the use of these tools in future studies in the field. Integrating such knowledge into a single study also contributes to identifying research gaps, highlighting the most used methods and those that require further investigation.

This systematic review aims to contribute to scientific knowledge by classifying and analyzing studies dedicated to enforcing methods applied in the manufacturing industry supply chain's investment risk assessment. It also seeks to determine how these investments are addressed by researchers and facilitate the work of future researchers interested in this topic. Thus, this article aims to answer the following questions:

- a. What is the current state of the literature on economic feasibility analysis methods in the manufacturing industry?
- b. What have been the main methods and metrics employed in existing studies?

This article is structured as follows: Chapter 1 introduces the topic and points out the research questions that will be answered throughout this work. Then, it substantiates the methodology for including and excluding articles composing the database, which is followed by the execution of such process. Chapter 3 details the data extraction process required to answer the research questions. Chapter 4 presents the results and compiles data collected in the previous phases. Chapter 5 presents the conclusion, limitations, suggestions for future research, and acknowledgments.

4.2 Methodology

The bibliometric analysis complied with the PRISMA 2020 guidelines (Page *et al.*, 2021). Studies were retrieved from the Web of Science and Scopus databases on April 18, 2024, covering the entire time span available. We restricted the search to terms present in titles, abstracts, and keywords. These databases were chosen due to their breadth and strict journal inclusion criteria (Singh *et al.*, 2021).

Articles written in languages other than English and Portuguese were retained in the database if they could be translated adequately through automated tools such as Google Translate. These articles were also retained if they had official translations available (Steigerwald *et al.*, 2022).

Reference management and data deduplication were performed using the Ferramenta Parsival (2024), with default analysis settings. Articles identified as duplicates were also reviewed manually before being removed.

The analysis and selection procedure for all articles followed criteria defined in this methodology. All excluded articles were documented along with the respective exclusion rationale. This information is available in detail at <https://osf.io/fnyzh>.

4.2.1 Inclusion Criteria

The database was formed by articles that contribute to answering the research theme, “analysis of the relationship between supply chain risks and the effectiveness of investments in the manufacturing industry of consumer goods.” To this end, the following string was developed according to the guidelines suggested by Vaz and Uriona Maldonado (2017) for conducting a comprehensive and robust search.

(“connect*” OR “contact” OR “network” OR “relation*” OR “acquaintance” OR “associate*”) AND (“risk” OR “danger” OR “exposure” OR “hazard” OR “Threat”) AND (“Supply Chain” OR “SC”) AND (“Effectiv*” OR “convenci*” OR “persuasiv*” OR “strength” OR “validity”) AND (“investment” OR “asset” OR “purchase” OR “transaction” OR “venture” OR “Funding” OR “Capital Allocation”) AND (“Manufacturing” OR “Production” OR “Fabrication” OR “Industry”) AND (“goods” OR “product” OR “amount” OR “brand” OR “commodity” OR “production”)

4.2.2 Exclusion Criteria

The first analysis performed involved excluding duplicate articles, references that are not journal articles, and articles in languages not covered by the research, as defined earlier. In accordance with PRISMA 2020, we screened titles, abstracts, and keywords to identify whether they fit the scope of this systematic review. To assist in this task, enable replicability, and

document the criteria adopted, we created an Excel spreadsheet and searched for the following topics in titles, abstracts, and keywords:

- a. Relationship Analysis
- b. Risks
- c. Supply Chain
- d. Effectiveness
- e. Investments
- f. Manufacturing Industry
- g. Consumer Goods

Each criterion was assigned a weight of 1 (meets the criterion), 0.5 (partially meets the criterion), and 0 (does not meet the criterion). After tallying up the points average of each item, we carefully reviewed articles whose average exceeded 0.6 by reading them in full. Our detailed analysis is available at <https://osf.io/ma76d>.

Continuing with PRISMA 2020, we performed a full reading of the remaining articles, which were classified according to their quality and fit to the researched topic and quality. In this quality assessment, authors answered the ten questions in Table 4.1 based on a thorough reading of the articles.

Each question was assigned a weight of 1 (yes), 0.5 (partial), and 0 (no) according to their fit to the topic. After tallying up the scores of all questions, articles whose score exceeded seven points were deemed suitable for data extraction. The detailed assessment is available at <https://osf.io/gn98u>. If the analysis scored zero on all requirements, the article did not fit the research scope.

4.2.3 Execution of the article selection process

In the study selection process, 118 articles were found on Scopus and 39 on Web of Science, of which 27 were duplicates. After screening titles, abstracts, keywords, and document type, 110 articles were excluded. Of these, 75 did not fit the scope, 28 were gray literature (conference papers, symposia, conferences, or retracted), and five were systematic reviews. At this stage, 22 articles remained for full reading and evaluation, of which four were excluded due to lack of full access. Among the remaining articles, two were discarded after full reading due to lack of fit with the research scope. Data and metadata were extracted from the 16 articles that passed the exclusion criteria. This process is illustrated in Figure 1, with the full analysis available at <https://osf.io/msrfj>.

Table 4.2 introduces the authors of articles that were selected and will be assessed throughout this study. The table also contains the articles identification code (ID), which will

Table 4.1 – Quality assessment criteria

ID	Questions for analysis
Q1	Are the objectives clearly described, specific, and measurable? (Dybå; Dingsøy, 2008 apud Dermeval <i>et al.</i> , 2018)
Q2	Are the methods used adequately, clearly, and precisely described? (Achimugu <i>et al.</i> , 2014 apud Dermeval <i>et al.</i> , 2018)
Q3	Are the metrics used in the study clearly defined and aligned with the proposed objectives? (Petticrew; Roberts, 2008; Slawson, 1997 apud Kitchenham <i>et al.</i> , 2010)
Q4	Were the databases collected appropriately? (Petticrew; Roberts, 2008; Slawson, 1997 apud Kitchenham <i>et al.</i> , 2010)
Q5	Is there an adequate description of the context (industry, laboratory setting, products used and so on) in which the research was carried out? (Dybå; Dingsøy, 2008; Mahdavi-Hezavehi; Galster; Avgeriou, 2013 apud Dermeval <i>et al.</i> , 2018)
Q6	Are the variables used in the study adequately measured?
Q7	Is the data analysis consistent and transparent, enabling replication of the results? (Petticrew; Roberts, 2008 apud Kitchenham <i>et al.</i> , 2010)
Q8	Were all proposed questions answered? (Kitchenham <i>et al.</i> , 2010)
Q9	Are the limitations of the study discussed and were solutions proposed for these limitations?
Q10	Does the study present a critical and unbiased analysis of the included studies, considering possible selection, publication, and methodological biases (Petticrew; Roberts, 2008 apud Kitchenham <i>et al.</i> , 2010)

assist in subsequent results, and the quality score of each article according to the questions introduced in the previous section of this paper.

4.3 Data Extraction

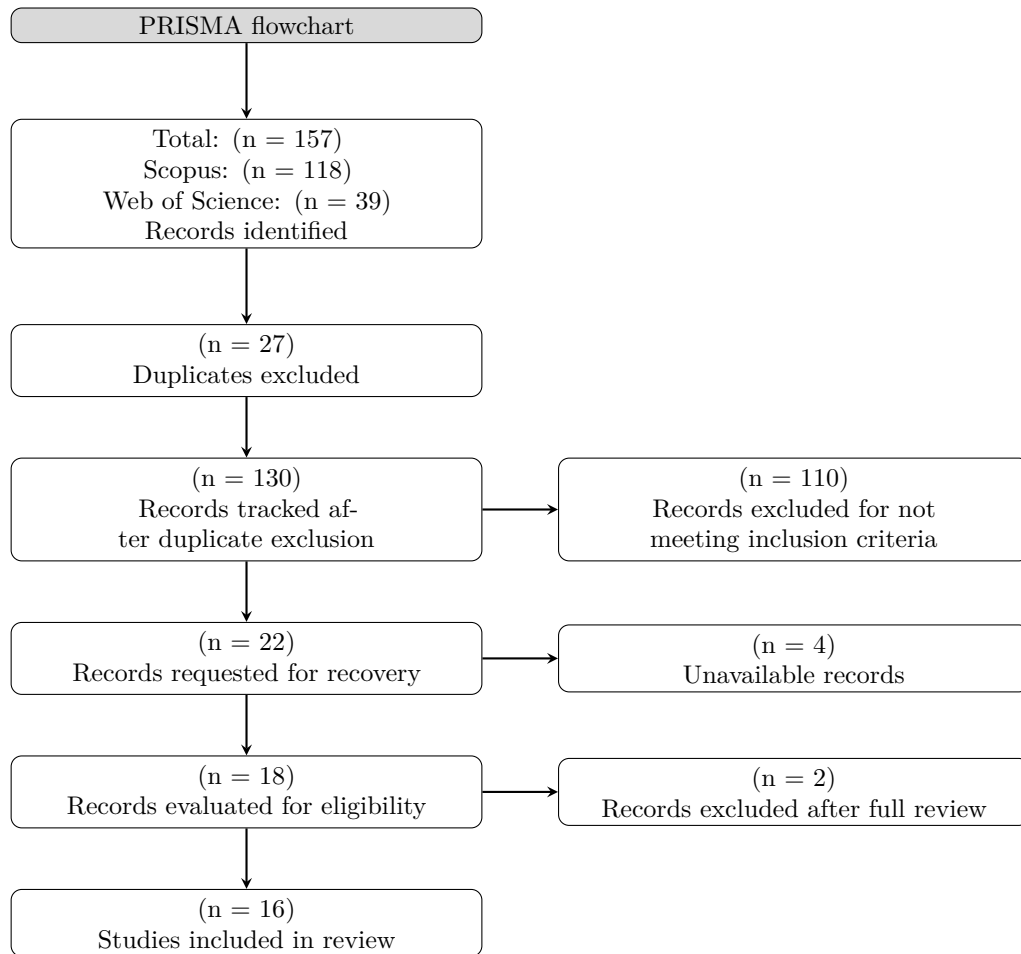
For data extraction, the selected articles were analyzed and classified according to criteria adapted from Resende, Lima-Junior, and Carpinetti (2023), which helped answer the research questions proposed throughout the project development. The following paragraphs describe the criteria used in this task:

Purpose: Assesses the main purpose of the study. First, it divides articles into two groups: Articles aimed at designing investment projects, and articles aimed at assessing investment results. In the first category, we assessed four points based on the purpose of the article: The definition of metrics, how to operate, when to implement, and how much to invest. In the second category, we assessed two subcategories: Metrics definition and results analysis.

Application scenario: Whether the study considered real scenarios or hypotheses.

Application sector: Identifies which industrial sector was evaluated, such as the food,

Figure 4.1 – Flow of record inclusion and exclusion



petrochemical, or pharmaceutical industry.

Optimization objective: Classifies the objectives of models proposed in articles based on the parameters the study aims to optimize. Articles can be classified according to optimization objectives, for example, profit maximization, cost reduction, resilience maximization, and maximization of return on investments.

Parameter selection: Evaluates criteria used by researchers to establish which parameters to use, for example, opinions from specialists and business models recommended by the author or selected from other studies.

Parameters used: Identifies which parameters researchers used throughout the study. Parameters are the variables, metrics and criteria used in analyses.

Data source: Analyzes the source of data used to feed models, for example, historical data, simulated data, specialist opinions and whether they were selected from other studies.

Type of method used: Classifies the study according to the proposed decision-

Table 4.2 – Selected articles

ID	Autor	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Pt.
S01	DAL-MAS et al., 2011	1	1	1	1	1	1	1	1	0	1	9.0
S02	FANG; KANG; LU, 2023	1	1	1	1	1	1	1	1	0	1	9.0
S03	GEBRESLASSIE; YAO; YOU, 2012	1	1	1	1	1	1	1	1	0	1	9.0
S04	HU et al., 2019	1	1	1	1	1	1	1	1	1	1	10
S05	JAIN; HAZRA, 2017	1	1	1	1	1	1	1	1	0	1	9.0
S06	KWON; NGAN DO; KIM, 2022	1	1	1	1	1	1	1	1	1	1	10
S07	LI; LIU; YANG, 2023	1	1	1	1	1	1	1	1	0.5	1	9.5
S08	MAKRIDIS; MAVREPIS; KYRIAZIS, 2023	1	1	1	1	1	1	1	1	1	1	10
S09	NGAN et al., 2020	1	1	1	1	1	1	1	1	0.5	1	9.5
S10	QUIGLEY et al., 2018	1	1	1	1	1	1	1	1	1	1	10
S11	SIMIC, 2019	1	1	1	1	1	1	1	1	1	1	10
S12	SURYAWANSHI et al., 2021	1	1	1	1	1	1	1	1	9.5	1	9.5
S13	TALLURI; NARASIMHAN; CHUNG, 2010	1	1	1	1	1	1	1	1	0	1	9.0
S14	VICCARO et al., 2019	1	0.5	1	0.5	0.5	1	0.5	1	0	1	7.0
S15	YODER et al., 2015	1	1	1	1	1	1	1	1	0	1	9.0
S16	ZHU; CAO, 2021	1	1	1	1	1	1	1	1	0.5	1	9.5

making method, for example, Multi-Criteria Decision Making (MCDM), stochastic, mathematical programming, statistics, and artificial intelligence.

Decision-making method(s): Identifies which specific method(s) were used to assist in decision-making.

Number of methods: Determines the number of methods used in articles, given that studies may apply only one method or combine multiple methods.

Validation approach: Establishes which methods were used to validate results.

Risk quantification approach: Identifies the specific methods used to quantify or determine risk in each study, including financial risk measures, dispersion-based metrics, sensitivity analyses, and other approaches employed to assess uncertainty or exposure to adverse outcomes.

4.3.1 Metadata

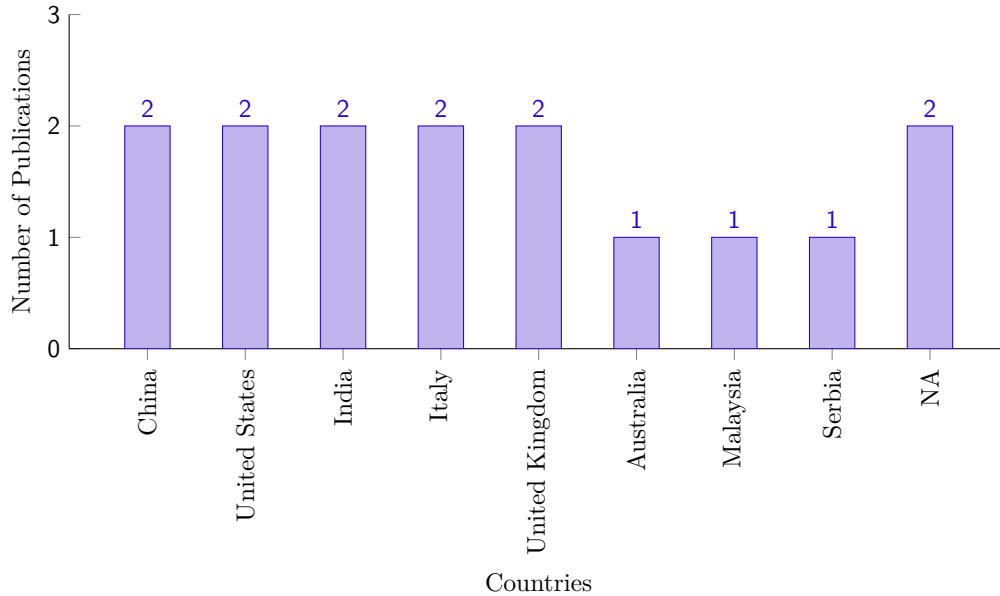
Studying article metadata is important not only for indicators of quality and relevance but also for additional information that can improve understanding of the results. To this end, we analyzed number of citations (Cit.), publication year, country of main authors, journal, CiteScore (Scopus) and Impact Factor (IF) of journals, which are all provided in Table 4.3.

Figure 4.2 facilitates visualization of the publication numbers by providing the history of publications by author nationality. This chart indicates that nationality is homogeneous across authors, pointing toward a global concern regarding risks and economic feasibility regarding investment projects within this industry.

Table 4.3 – Analyzed articles metadata

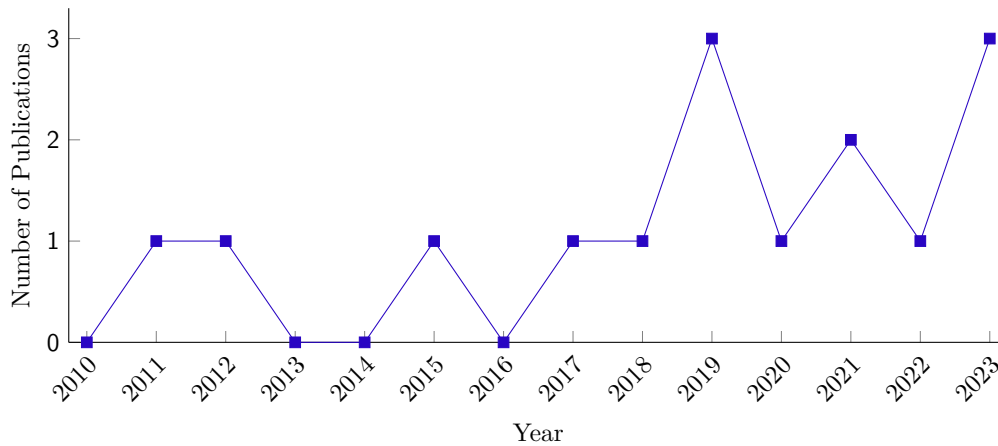
ID	Cit.	Year	Countries	Journal	CiteScore	IF
S01	166	2011	Italy	Biomass and Bioenergy	11.5	6.00
S02	0	2023	United States	Journal of Financial Stability	7.7	5.4
S03	199	2012	Australia	AIChE Journal	7.1	NA
S04	33	2019	United Kingdom	Supply Chain Management: An International Journal	16.7	8.80
S05	26	2017	India	International Journal of Pro- duction Economics	21.4	12.0
S06	5	2022	South Korea	Journal of Industrial and Engi- neering Chemistry	10.4	6.1
S07	4	2023	China	International Transactions in Operational Research	7.8	3.1
S08	1	2023	N/A	Machine Learning	NA	4.3
S09	37	2020	Malaysia	Renewable and Sustainable En- ergy Reviews	31.2	15.9
S10	37	2018	United Kingdom	European Journal of Opera- tional Research	11.9	6.4
S11	13	2019	Serbia	Environmental Modelling & As- sessment	NA	2.7
S12	23	2021	India	Sustainable Production and Consumption	17.4	12.1
S13	103	2010	United States	European Journal of Opera- tional Research	11.9	6.4
S14	34	2019	Italia	Journal of Cleaner Production	20.4	11.1
S15	12	2015	NA	BioEnergy Research	NA	3.1
S16	16	2021	China	Transportation Research Part E: Logistics and Transporta- tion Review	16.2	10.6

Figure 4.2 – Number of published articles by author nationality



In the same regard, Figure 4.3 provides the number of publications by year. Among the articles analyzed, the oldest was published in 2011. Since then, the number of published articles rose until 2023, however, the number of articles analyzed is still small, which hinders the development of a trendline with an acceptable degree of reliability.

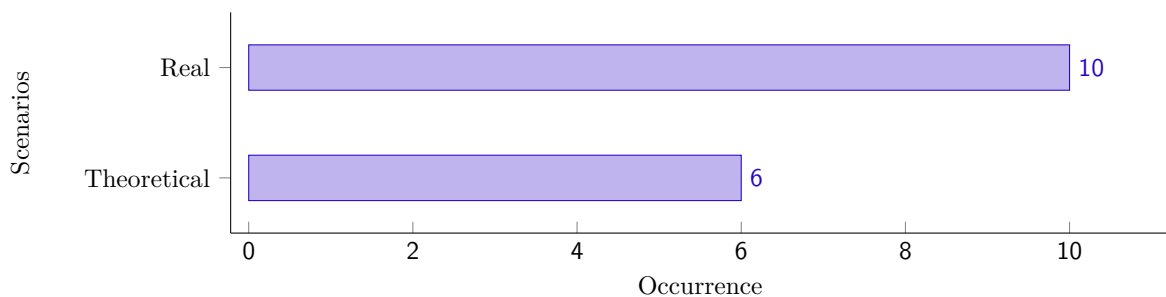
Figure 4.3 – Number of publications by year



4.3.2 Data

Most articles applied methods to real scenarios (about 62%, 10 articles), as shown in Figure 4.4. This preference may be justified by natural economic volatility, such as price and demand variations, natural disasters, technological changes, among others (Choi; Wallace; Wang, 2016). The difficulty of simulating these variables complicates purely theoretical models (about 37%, 6 articles), though these studies remain relevant. Other parameters did not vary significantly by scenario, except for data sources, which showed a strong relationship with the application scenario.

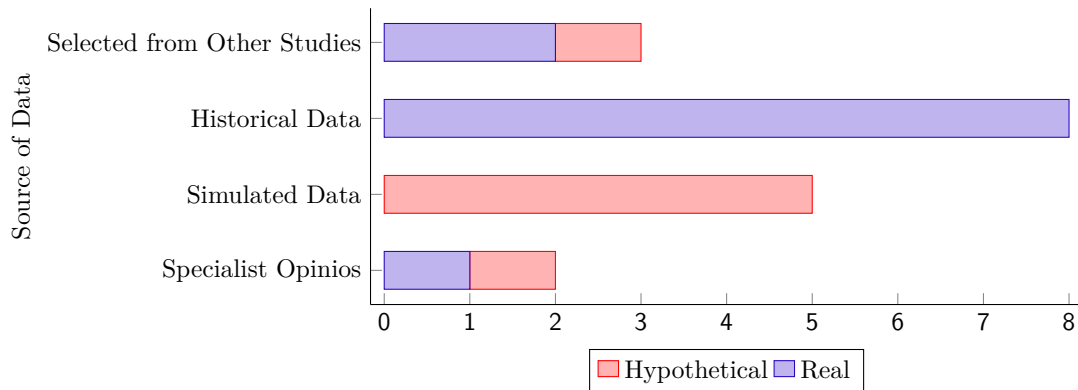
Figure 4.4 – Application scenario



As shown in Figure 4.5, all studies using historical data evaluated real scenarios, while all studies using simulated data focused on theoretical scenarios. Two-thirds of the studies using data selected from other studies analyzed real cases, while one-third used hypothetical scenarios. For studies using specialist opinions as a data source, 50% analyzed real cases and 50% theoretical cases.

A noteworthy detail is that some studies used more than one source of data. Across all articles, 50% used historical data; 31% simulated data; 19% data selected from other studies; and 12% specialist opinion. Two studies used more than one source: One combined historical data with data selected from other studies, and the other used specialist opinions with data obtained from other studies.

Figure 4.5 – Occurrences by source of Data



Regarding variable definition, Figure 4.6 presents the methods used. In 50% of cases, variable selection was based on the business plan proposed by the authors; 38% used a mix of specialist opinion and prior studies; and the remaining 12% split between variables selected solely by specialists or solely based on other studies.

Figure 4.6 – Method of variable definition



This study also identified the most relevant parameters used in each article – 120 parameters were used across articles as shown in Table 4.4. Of these, 62% used infrastructure and operating costs, the most frequent parameter. The second most frequent was production volume (50%). Product price, logistics costs, raw material costs, and demand appeared in 44% of the studies. Other parameters, such as invested capital, investment period, financial cost, geographic position of facilities, geographic position of suppliers, geographic position of distribution centers, and inventory levels, appeared with frequencies from 37% to 25%.

Less frequent parameters included firm size, investment rate, government incentives, estimated financial risk, quality, product, operational loss costs, supplier determination, and effectiveness (19% - 12%). Several other parameters occurred at a 6% frequency in the studies assessed.

The cataloging of most used methods identified a total of 27 distinct methods. Two-Stage Stochastic Programming was the most used—present in 19% of the articles and accounting for 11% of all methods applied. Tools such as Monte Carlo Simulation, Mixed-Integer Linear

Table 4.4 – Parameters used in the models

Parameters / Articles	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11	S12	S13	S14	S15	S16	Freq.
Infrastructure and Operating Costs	X	X	X			X					X	X	X	X	X	X	10
Production Volume	X	X	X		X	X			X		X				X		8
Price	X	X			X	X			X					X	X		7
Logistics Costs			X				X				X	X	X		X	X	7
Raw Material Costs	X					X			X		X	X	X	X			7
Demand	X		X		X		X		X		X	X					7
Invested Capital		X	X		X	X	X						X				6
Investment Period		X		X				X	X					X	X		6
Financial Cost		X			X	X								X		X	5
Geographical Position of Facilities	X	X		X			X					X					5
Efficiency				X	X	X			X						X		5
Geographic Position of Suppliers	X	X				X	X					X					5
Geographic Position of Distribution Centers	X	X					X					X					4
Inventory Levels			X			X				X	X						4
Firm Size		X			X	X											3
Investment Rate		X			X											X	3
Government Incentive			X						X					X			3
Estimated Financial Risks											X	X			X		3
Quality								X		X		X					3
Product							X	X									2
Operational Loss Costs												X				X	2
Supplier Determination							X						X				2
Efficiency				X	X												2
Value of Information										X							1
Financial Distress Cost		X															1
Payment Policies		X															1
Deadlines												X					1
Geographic Position of Customers												X					1
Raw Material Exploration			X														1
Effectiveness										X							1
Recoverability Difficulty																X	1
Severity																X	1
Disruption Start Time																X	1
Profitability		X															1
Climatic History															X		1

Programming (MILP), and Linear Programming were also prominent, each appearing in 12% of the studies and representing 7% of the methods. Many other methods were identified (individually 6% of articles; jointly 67% of all methods). This may be due to the wide range of methods and their variations. See Figure 4.12 for details.

Grouping the methods by type provides a clearer view of the approaches conducted by the authors in their studies. Figure 4.7 shows that the stochastic method was the most used: Present in 56% of the articles and representing 33% of the methods used. Mathematical programming methods corresponded to 30% of the methods and appeared in half of the articles.

Calculation-based and statistical studies used these tools in 25% of cases, and this method amounted to 15% of the methods used. Artificial Intelligence tools, Multi-Criteria Decision Making (MCDM) and “others” were used in 12% of the studies, amounting, individually, to 7% of the methods used..

The study also demonstrated the clear difference of approaches by authors regarding the

Figure 4.7 – Types of modeling method

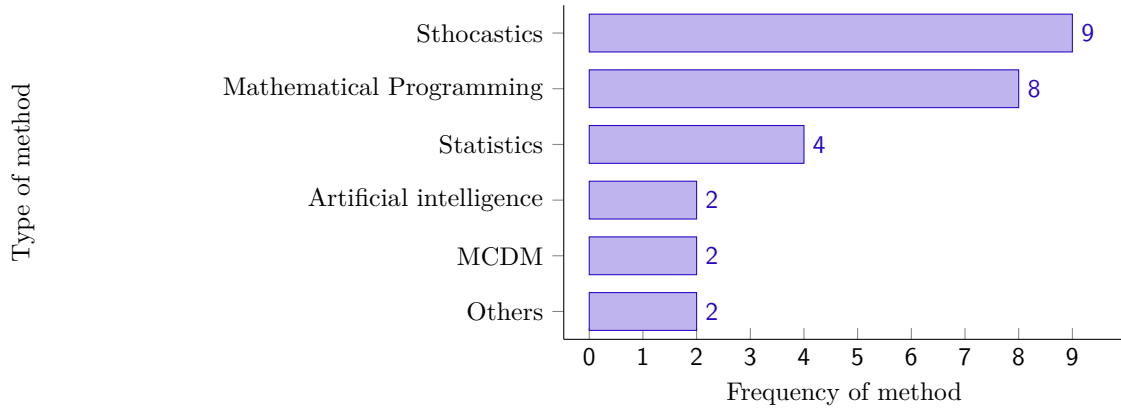
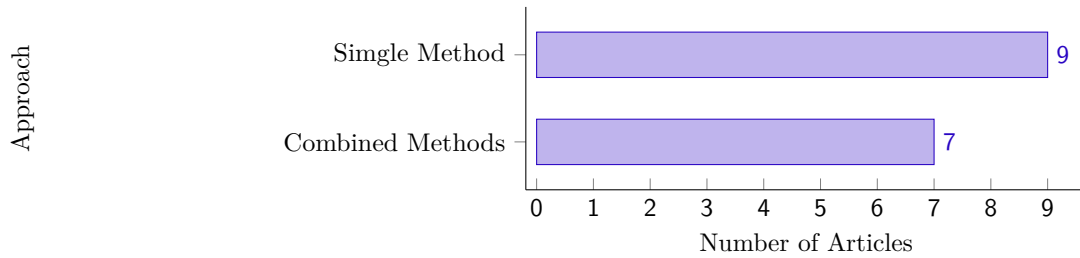
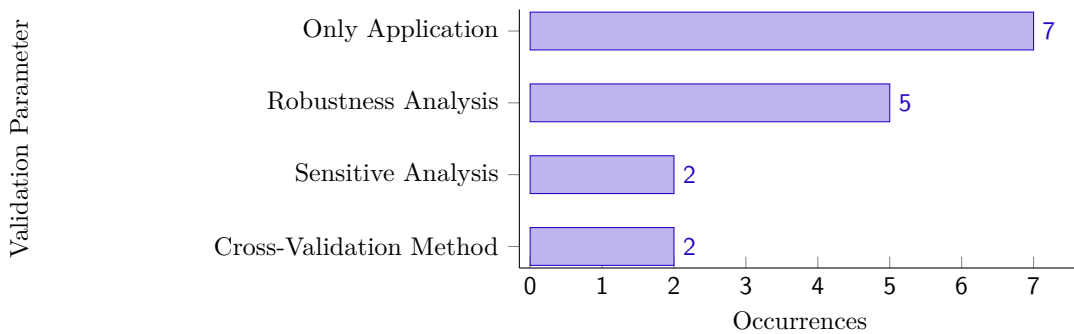


Figure 4.8 – Variety of methods per study



number of methods used in each study, as seen on Figure 4.8. Regarding the number of analysis methods per study, 56% of the papers used a single method, while 44% combined two or more models.

Figure 4.9 – Result Validation Approach

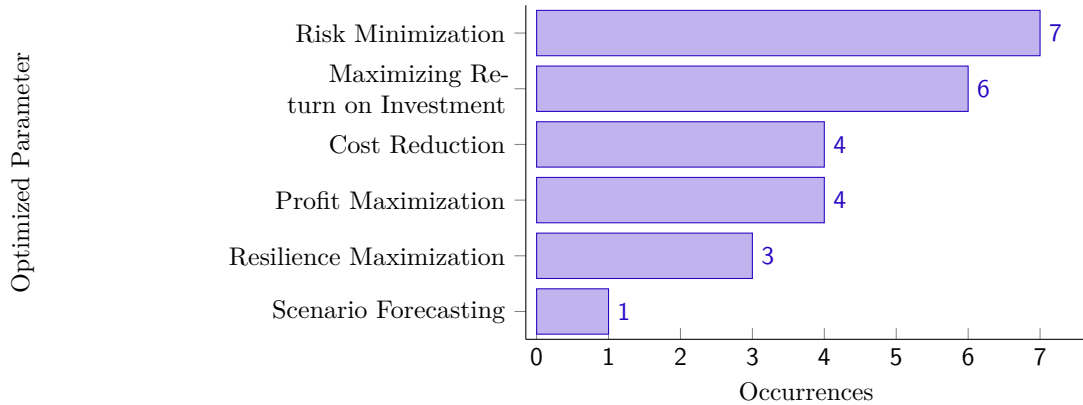


Upon analyzing authors' result validation approaches, 44% of the studies did not apply a validation method. Robustness analysis was the most common validation technique (31%). Finally, 12% applied cross-validation or sensitivity analysis, as seen on Figure 4.9.

Regarding optimization objectives, we identified 25 objectives across the articles. Seven papers had at least two objectives, of which four authors combined risk minimization with another objective.

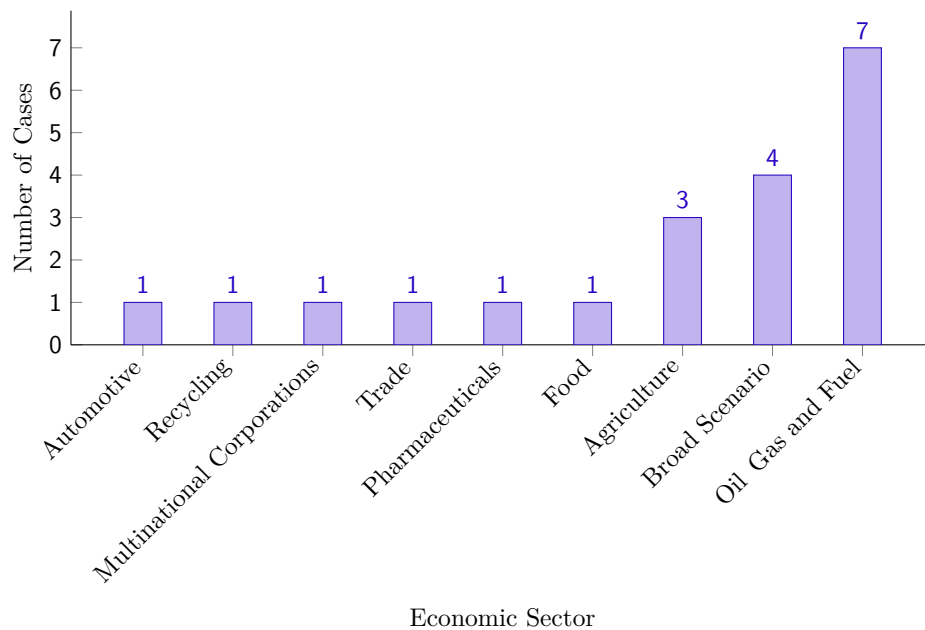
Risk minimization was the most frequent objective (28% of objectives; present in 44% of articles). Return On Investment maximization appeared in 37% of papers, which amounts to 24% of optimization objectives. Cost reduction and profit maximization appeared in 25% of

Figure 4.10 – Objetivos de Otimização



studies, amounting individually to 16% of objectives. Resilience maximization was sought in 18% of studies (12% of optimization objectives). Finally, only one study focused on scenario forecasting without optimizing a variable. These results can be seen on Figure 4.10.

Figure 4.11 – Sectors where studies were applied



These objectives were applied to 20 types of industrial scenarios, with some articles addressing more than one type or linking sectors. For example, Viccaro *et al.* (2019), Yoder *et al.* (2015) and Ngan *et al.* (2020) addressed similar sectors related to oilseed agriculture for bioenergy supply chains.

In our sample, 35% of the industries analyzed were fuel production, included in 44% of the articles. Broad scenarios or undefined industrial sectors represented 20% of companies and were present in 25% of studies, all theoretical. Agribusiness represented 15% of sectors, always linked to biofuels, representing 19% of the articles. Sectors such as automotive, recycling, multinational corporations, trade, pharmaceuticals, and food were analyzed in only one study each and together represented 30% of sectors. This data can be seen on Figure 4.11.

Table 4.5 – Motivating purpose of the study

ID	Formulation				Evaluation	
	Definition of metrics and inter-relationships	How to act	When to implement	How much to invest	Definition of metrics and inter-relationships	Analysis of results
S01		X	X	X		
S02						X
S03		X		X		
S04					X	X
S05	X	X		X		
S06		X	X	X		
S07		X		X		
S08		X				
S09	X					
S10				X		
S11	X	X				
S12		X				
S13				X		
S14		X				
S15	X	X				
S16				X		

We also analyzed articles from the motivating purpose perspective. First, we filtered studies that aimed to formulate scenarios linked to future strategies or scenarios linked to past strategies. From this perspective, only two articles evaluated scenarios, and both analyzed results; in addition, one of them also searched for the best metrics to evaluate results. Such studies account for 12% of the sample.

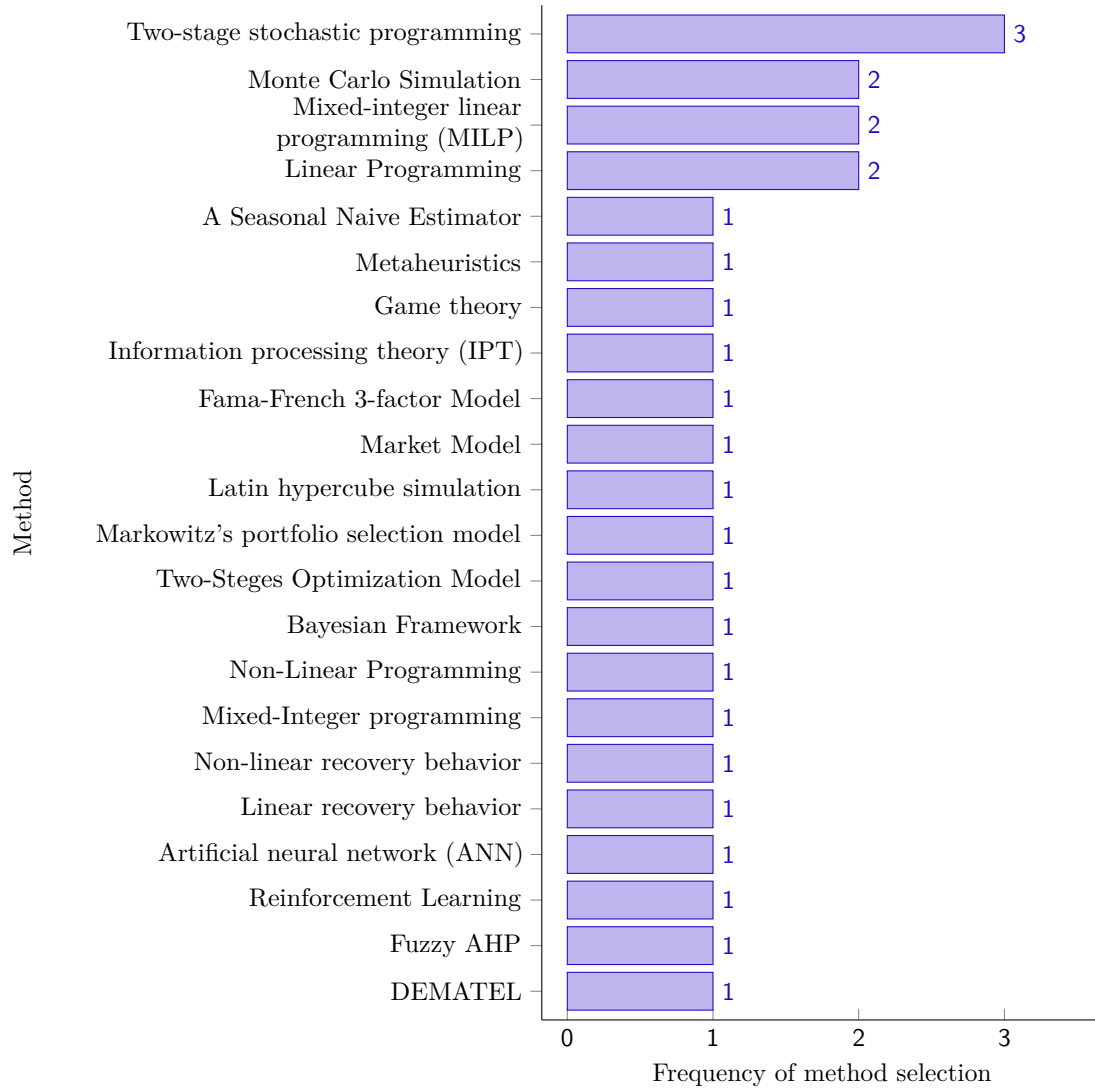
Among the articles, 14 sought to formulate actions, amounting to 87% of the sample. Of these, 71% sought to improve the method of executing actions and defining strategies; 57% sought to determine how much to invest; 25% sought to define the best metrics to use in analyses; and, finally, 12% sought to define the best investment period. Such data can be seen on Table 4.5.

Regarding approaches for risk quantification or determination, Figure 4.13 present the methods identified in the analyzed studies, ordered by decreasing frequency. Conditional Value-at-Risk (CVaR) was the most frequently reported method, appearing in 22.22% of the articles (six occurrences). Net Present Value (NPV) appeared in 14.81% of the studies (four occurrences). Variance analysis, sensitivity analysis, and standard deviation each appeared in 11.11% of the articles (three occurrences each). Internal Rate of Return (IRR) was identified in 7.41% of the studies (two occurrences). The remaining methods — multivariate analysis, downside risk, Information Processing Theory (IPT), Poisson–Gamma distribution, covariance analysis, and Payback Period — each appeared once, corresponding to 3.70% of the analyzed articles.

4.4 Results

The literature review presented a satisfactory outcome, with a bibliographic base composed of articles published in high-impact journals. Standouts include *Renewable and*

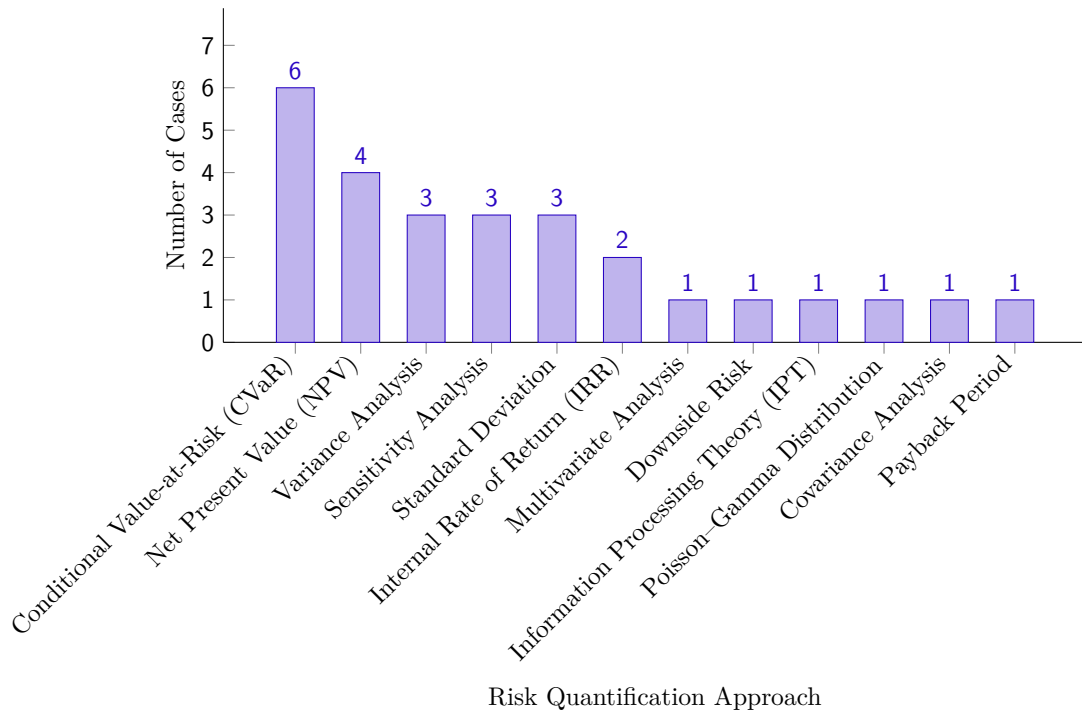
Figure 4.12 – Type of Model



Sustainable Energy Reviews, *International Journal of Production Economics* and *Journal of Cleaner Production*, among others. Citation counts vary widely – from zero (newer papers) to 199 (older papers). Articles span from 2010 to 2023, with a gradual increase in publications. While articles written 13 years ago are not deemed current, the fact that the oldest article in the database dates to 2010 indicates topic relevance. Combined with the quality of journals willing to publish such work and the growing number of publications on this topic, this suggests demand for more studies to support investment decision-making. Additionally, there is considerable diversity in authors' nationalities, indicating global concern for the topic.

Most studies focused on real investment projects. The main objectives were to determine the best positioning relative to the supply chain, to determine how much should be invested, and, to a lesser extent, to define the metrics used in analyses and the investment implementation period, addressing core decision-making issues. Researchers translated these questions primarily into objectives of risk mitigation coupled with Return On Investment maximization, cost reduction, and profit maximization. For these analyses, parameters were defined based on business plans developed by the authors and, to a lesser extent, selected from other studies or via specialist

Figure 4.13 – Approaches for risk quantification or determination



consultation.

Although a wide variety of specific parameters were used, and this article compiled them, parameters can be grouped into costs, revenues, and demand. This indicates a greater emphasis on quantitative rather than qualitative variables. Many authors highlighted the volatility of these parameters; consequently, there was a preference for stochastic models, mathematical programming, and statistics, sometimes combined. Articles applied to real cases showed greater concern with validation of results: 70% used some validation method.

Theoretical scenario studies relied on simulated data; 67% focused on determining investment amounts and, to a lesser extent, on identifying the best variables to use. These studies often analyzed broad investment sectors without specifying an industry. Variables and selection methods did not differ significantly from real-case studies. However, only four of the six theoretical articles used a validation method, and the other two applied robustness analysis.

4.5 Conclusion

This review contributes to scientific knowledge by classifying and analyzing studies on methods for determining risk and technical-economic feasibility of investments in the manufacturing industry, facilitating future work by researchers interested in this and related themes. This review addressed matters relating to metadata (publication year, citations, publishing journals, authors' nationalities, and article quality) and specific methodological aspects (nature of methods employed, supply chain sectors studied, variables used in models, validation methods, application scenarios, data sources, and methods for determining which data to use).

The research followed PRISMA 2020 (Page *et al.*, 2021) guidelines for systematic reviews and applied rigorously detailed inclusion and exclusion criteria, ensuring that only relevant articles were included in the database of analyzed articles. Data analysis revealed that most studies were applied to real scenarios, used stochastic methods, relied on historical data, determined variables from author-developed business models, sought to minimize risk and maximize return on investment, validated primarily via robustness analyses, and focused on oil, gas, and fuels supply chains. The substantial number of variables used in each model highlights the complexity of investment planning models.

4.5.1 Limitations and future research

Although the criteria and exclusions were described and applied rigorously, with particular care regarding evaluation biases, systematic reviews remain subject to errors, which can hinder reproducibility and weaken results. Generalization of results is also limited by the researchers' focus on specific contexts.

One noteworthy finding was the number of articles focusing on energy and fuel sectors. Future research may identify the drivers behind the interest in assessing economic feasibility and investment-related risks in these areas.

Additionally, future studies may continue updating the database underpinning this review, either targeting more specific sectors or broader scopes. It is also possible to apply the most-used methods indicated here to validate the results obtained by the researchers, as well as to test methods not yet explored in past studies, thereby expanding the knowledge base.

4.5.2 Acknowledgements

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5 Artigo 02 - Risk Quantification In Manufacturing Industry Investments: A Stochastic Approach With Artificial Intelligence

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Abstract

Manufacturing investment decisions are often hindered by significant uncertainty. This paper introduces a conceptual model that integrates stochastic simulation with machine learning to quantify investment risk. Our hybrid approach employs a Monte Carlo simulation using time series data of fixed, variable, and investment costs as inputs. To enhance the simulation's realism, Long Short-Term Memory (LSTM) recurrent neural networks forecast the trend components of these series, while a Vector Autoregression (VAR) model captures their inter-correlations. This framework generates a multitude of potential scenarios, each evaluated through a mathematical model of the supply chain to produce a distinct cash flow. The subsequent application of investment metrics, such as Net Present Value (NPV) and Discounted Payback, to the distribution of these cash flows enables a comprehensive statistical analysis of the investment's risk profile, thereby providing robust support for strategic decision-making.

Palavras-chave: Investments, Supply Chain, Risk Evaluation, Techno-Economic Feasibility, Decision-Making Methods

5.1 Introduction

Investment risks in the manufacturing industry are significant due to various intrinsic characteristics of the production chain. The central position of the manufacturing sector within the supply chain makes it particularly sensitive to fluctuations in the supply of raw materials and changes in demand. This sensitivity is further intensified by the highly specialized nature of its production processes (Wang; Zhou, 2024). Consequently, structural changes in the supply chain often require substantial investments to adapt production processes.

In addition to these factors, a wide range of risks can affect the supply chain, including regulatory changes, natural disasters, disruptions in logistics systems, shifts in consumer preferences, wars, and deliberate attacks on industrial infrastructure. These events are often unpredictable and their consequences uncontrollable (Oliveira; Júnior; Caetano, 2023; Zykiene *et al.*, 2023).

Therefore, investments in the manufacturing industry require extensive planning, encompassing a minimum time horizon to ensure return on investment. Motivated by this need, several researchers have developed methods for quantifying investment risks and supporting decision-making (Silva; Santos, *et al.*, 2023).

Among these efforts, stochastic approaches have stood out for assessing investment risks. However, there remains a research gap regarding the application of neural network tools for this purpose (Silva; Frazzon, 2025). This integration is essential, as artificial intelligence techniques excel at identifying patterns, while stochastic methods are particularly effective in analyzing scenarios under uncertainty. The current context is especially conducive to the development of such approaches, due to advances in computational capabilities, improvements in programming libraries and languages, and the growing popularity of artificial intelligence.

Given this context, this study proposes a conceptual model that integrates neural networks and stochastic methods to quantify investment risks in the manufacturing industry. This paper is organized as follows: Chapter 5.2 presents the theoretical background of the components of the model; Chapter III introduces the proposed conceptual model; Chapter IV provides the results and discussions approach; and Chapter V provides the concluding remarks. This study is limited to the proposal of a conceptual model, presenting its structure, tools, and implementation methods. However, the implementation of the proposed method is beyond the scope of this article and will be addressed in future research.

5.2 Theoretical Reference

5.2.1 Monte Carlo Method

The Monte Carlo method is a computational approach based on simulations generated from random numbers applied to probabilistically defined models. It has proven effective in analyzing complex systems where deterministic models are infeasible or inaccurate. Its flexibility and ability to handle uncertainty have made it widely adopted in various fields (Zhang, 2021).

For instance, it is used in finance for pricing financial options, portfolio evaluation, and risk analysis; in engineering for system reliability assessment and maintenance planning (Gebreslassie; Yao; You, 2012; Ngan *et al.*, 2020); and in computer science for high-dimensional integration and machine learning algorithms (Ingelaere; Maes; Samaey, 2024).

For investment risk assessment in the manufacturing industry, the Monte Carlo method can handle volatility in commodity prices, finished goods, and operational costs. This flexibility in modeling multiple variables is crucial in sensitive environments such as investment evaluation. Its strength becomes even more evident when integrated with other methods, such as Vector Autoregression (VAR), enabling multivariate analyses (Yoder *et al.*, 2015). Correlation analyses between variables are essential for investment assessment, especially considering the interdependence of products within supply chains (Kwon; Suh, 2005). Given that uncertainty in time series tends to increase over time, Monte Carlo simulations are well-suited for long-term projections, as they naturally account for increasing volatility (Tian *et al.*, 2018).

The Monte Carlo method typically follows a systematic structure that may vary by context but often includes: problem definition, statistical analysis, random number generation, scenario simulation, and result analysis (Platon; Constantinescu, 2014). The process begins by defining the scope and identifying initial parameters and variables. Statistical analysis includes data collection, preliminary analysis, and fitting statistical distributions. To incorporate uncertainty, random numbers are generated according to these distributions (Capuozzo *et al.*, 2021). Each set of random numbers produces a new simulated scenario. Simulation results are compiled to compute metrics such as mean, median, variance, and confidence intervals (Platon; Constantinescu, 2014; Capuozzo *et al.*, 2021).

In the context of time series analysis, a typical Monte Carlo modeling approach involves decomposing the series into trend, seasonality, and residual components, as expressed in Equation 5.1.

$$Y_t = Trend_t + Seasonality_t + X_t \quad (5.1)$$

Where: The $Trend_t$ represents the systematic behavior of a variable, ignoring cyclical variations and noise. It can be modeled using linear, exponential, polynomial trends, or more advanced methods such as neural networks (West, 1997); The $Seasonality_t$ refers to predictable, cyclic components of the time series, often linked to natural, social, or economic events. Unlike trends and residuals, seasonality occurs at fixed intervals (e.g., days, months, years) (West, 1997). And the Residuals (X_t) capture unpredictable variations not explained by trend or seasonality. These components reflect external or internal conditions and exhibit no clear periodicity or dependency over time (West, 1997).

If residuals follow a normal distribution, they can be modeled as white noise – $\epsilon \sim (0, \sigma^2)$. For highly volatile systems with cumulative noise, Brownian noise (or Brownian motion) is more appropriate, as it better describes the long-term stochastic behavior of asset time series. As shown in Equation 5.2 the noise at time is the sum of white noise and the accumulated noise from the previous time step (Heinäkoski, 2018).

$$X_t = X_{t-1} + \epsilon_t \quad (5.2)$$

Where:

- X_t : noise value at time t ;
- X_{t-1} : noise value at time $t - 1$;
- ϵ_t : white noise at time t .

5.2.1.1 Time Series Decomposition

Each time series component must be treated individually in the analytical process. Therefore, decomposing the time series into trend, seasonality, and noise components is essential. One effective method for this task is STL decomposition (Seasonal and Trend decomposition using Loess), which presents several advantages: robustness to non-stationary data, flexibility in handling complex seasonal patterns, resistance to noise and structural changes, and the direct extraction of trend, seasonality, and residual components through iterative optimization (Krake *et al.*, 2024; Leite Coelho da Silva *et al.*, 2025). However, it requires careful parameter tuning, entails higher computational complexity, assumes constant seasonality, and may encounter limitations with very short or very long time series (Phungtua-eng; Yamamoto, 2024).

The STL decomposition process begins by defining the cycle length of the time series. For monthly data, the cycle is typically annual, resulting in a period of 12 months. Equation 5.3 calculates the initial seasonal component, which serves as the basis for the first iteration. This involves summing all observations that occur in the same position within each cycle (e.g., every January), and dividing by the number of complete cycles.

The next step involves centering the initial seasonal values using Equation 5.4, which removes bias and ensures that the seasonal component does not interfere with other components of the time series.

$$S_i = \frac{1}{N} \sum_{t \in \text{cycle } i} Y_t \quad (5.3)$$

$$S_t = S_i - \frac{1}{p} \sum_{i=1}^p S_i \quad (5.4)$$

Where:

- S_i : estimated seasonal component at position i within the cycle;
- N : total number of complete cycles in the time series;
- Y_t : value at time t ;
- p : number of periods within one cycle.

The trend is calculated by subtracting the seasonal component from the original series, as shown in Equation 5.7 resulting in the adjusted series 5.7, which contains both noise and trend. The Loess method is then applied to Y_t'' , to remove the noise and extract the smoothed trend component, as shown in Equation 5.8.

$$Y_t' = Y_t - S_t \quad (5.5)$$

$$T_t = \text{Loess}(Y_t') \quad (5.6)$$

Since the initial seasonal estimate may include elements of trend and noise, STL applies Equation 5.7 to subtract the extracted trend from the original time series, yielding the intermediate series Y_t'' . Loess is then applied again to this intermediate series to refine the seasonal component, as shown in Equation 5.8 (Zhang; Huo; Shao, 2023)

$$Y_t'' = Y_t - T_t \quad (5.7)$$

$$S_t = \text{Loess}(Y_t'', \text{periodicity } p) \quad (5.8)$$

The residual component (noise) is calculated by subtracting both trend and seasonal components from the original time series, as given in Equation 5.9. STL is an iterative method, and Equations 5.5 through Equation 5.9 must be repeated iteratively, where k represent the current iteration.

$$\epsilon_t = Y_t - T_t - S_t \quad (5.9)$$

$$(\sum \epsilon_t^2)^{(k)} - (\sum \epsilon_t^2)^{(k-1)} > \text{Error}_{\max} \quad (5.10)$$

The number of iterations can be adjusted based on criteria such as the threshold defined by Equation 5.10, where the stopping condition is determined by the difference in the sum of squared residuals between two consecutive iterations. Additional parameters may also be set, such as a maximum number of iterations, in order to stop the process in cases of non-convergence (Zhang; Huo; Shao, 2023).

5.2.2 Recurrent Neural Networks And Lstm

The architecture of traditional multilayer perceptrons (MLPs) includes a fixed number of input neurons defined by the dataset's dimensionality. Each input is connected to all neurons in the hidden layers, which means the data is processed independently - ignoring the temporal structure of sequential data (Gardner Jr; McKenzie, 1985). Furthermore, traditional networks lack memory mechanisms and cannot retrieve previous computations, making them unsuitable for

tasks such as time series modeling or natural language processing. To address these limitations, Recurrent Neural Networks (RNNs) were introduced by Rumelhart, Hinton, and Williams (1986). Despite improvements over traditional networks, RNNs face training challenges when dealing with long sequences. Recurrent weights are multiplied across many time steps, leading to vanishing or exploding gradients, which hinder convergence (Giles *et al.*, 1995).

To address this, Sepp Hochreiter and Jürgen Schmidhuber proposed the Long Short-Term Memory (LSTM) network in 1997, introducing the concepts of cell state and gates (Hochreiter; Schmidhuber, 1996). The cell state and hidden state give LSTM the ability to store both long- and short-term dependencies - often referred to as the network's "memory." Gates, typically controlled by sigmoid activations, act as dynamic weights that determine which information to retain, discard, or update. These innovations make LSTM networks more robust against gradient problems and capable of adaptively learning patterns in sequential data (Schmidhuber; Hochreiter, *et al.*, 1997).

Mathematically, the forget gate is defined in Equation 5.11, controlling how much of the previous cell state is retained. Simultaneously, the input gate (Equation 5.12) and candidate cell state (Equation 5.13) determine the contribution of new information. The updated cell state is calculated using Equation 5.14.

$$f_t = \sigma(w_f[h_{t-1}, x_t]) + b_f \quad (5.11)$$

$$i_t = \sigma(w_i[h_{t-1}, x_t]) + b_i \quad (5.12)$$

$$\tilde{C}_t = \tanh(w_{\tilde{C}}[h_{t-1}, x_t]) + b_{\tilde{C}} \quad (5.13)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (5.14)$$

Where:

- σ : sigmoid function;
- w : gate weight;
- b : bias weight;
- $\tanh$: tanh function;
- $\odot$: element-wise multiplication.

The hidden state reflects the current output of the LSTM cell and is calculated using Equation 5.15, combining the output gate (Equation 5.16) and the updated cell state:

$$o_t = \sigma(w_o[h_{t-1}, x_t]) + b_o \quad (5.15)$$

$$h_t = o_t \odot \tanh(C_t) \quad (5.16)$$

In this way, LSTM networks are capable of modeling long-range dependencies in sequential data, overcoming the limitations of traditional feedforward and basic RNN architectures. They are widely used for time series forecasting and sequence modeling with high efficiency and precision (Yu *et al.*, 2019).

5.2.3 Var-Cholesky Method

The Vector Autoregressive (VAR) method was introduced by Sims (1980) through the publication *Macroeconomics and Reality*. It evolved from the autoregressive (AR) model and allows for the simultaneous modeling of lagged interdependencies among multiple time series.

In this framework, all variables are treated as interdependent, eliminating the need to distinguish between dependent and independent variables (Sims, 1980). However, the method presents some limitations, such as sensitivity to the number of lags chosen, which can lead to overparameterization or under parameterization.

Another limitation arises from the potential high dimensionality when the number of endogenous variables and lags is large, requiring a substantial amount of data (Stock; Watson, 2001). Additionally, The VAR method assumes that the time series is stationary, meaning its statistical properties (such as mean, variance, and covariance) must remain constant over time (Canova, 1999).

In this study, STL decomposition is proposed to separate the trend and seasonality from the time series, with the expectation that the resulting residuals will be stationary.

The mathematical foundation of the VAR method is based on vectors and matrices. Vectors represent the values of the variables over time, while matrices contain the coefficients that describe variance and covariance among these variables across different time lags. This interaction is modeled through a linear equation, as presented in Equation 5.17 which captures the mutual influence among variables over time (Canova, 1999).

$$Y_t = C + \sum_{i=1}^p \Phi_i Y_{t-i} + \epsilon_t \quad (5.17)$$

Onde:

- Y_t : vector of endogenous variables;
- Φ : coefficient matrices;
- C : constant vector;
- ϵ_t : vector of error terms;
- p : model order (number of lags).

Expanding this equation for all time periods with T observations, one can stack the equations corresponding to periods $t = p + 1$ to T into a matrix form, as shown in Equation 5.18. This reformulation allows all observations to be treated simultaneously, enabling a direct solution using the Ordinary Least Squares (OLS) method (Kohli; Garcia; Pourahmadi, 2016; Kavaklioglu, 2019).

$$Y = Z\Theta + E \quad (5.18)$$

Where:

- Matrix of Dependent Variables (Y): Composed of transposed vectors of endogenous variables $Y_{p+1}^T, Y_{p+2}^T \dots Y_T^T$, with dimensions $(T - p) \times N$;
- Matrix of Constants and Lagged Variables Z : Concatenates a vector of constants (C) and lagged endogenous variables, with dimensions $(T - p) \times (N \cdot p + 1)$;
- Matrix of Coefficients (Θ): Composed of the transposed constant vector (C^T) and the coefficient matrices Φ_1 to Φ_p , with dimensions $(N \cdot p + 1) \times N$;
- Matrix of Residuals (E): Organizes the transposed error terms ϵ^T from period $p + 1$ to T , with dimensions $(T - p) \times N$.

Equation 5.19 is derived by isolating the error matrix E da equação 5.18 from Equation 18 and substituting it into the minimization of the sum of squared residuals $S(\Theta) = E^T E$, according to the OLS method. Thus, $\hat{\Theta}$ represents the theoretical coefficients that minimize $S(\Theta)$, corresponding to the values that minimize the squared error between observed and predicted values (Kavaklioglu, 2019).

$$\hat{\Theta} = (Z^T Z)^{-1} Z^T Y \quad (5.19)$$

By substituting $\hat{\Theta}$ into Equation 5.18, one obtains the estimated residual matrix ($\hat{E}$), which contains the differences between observed values and model-adjusted values for each of the $T - p$ periods. Then, Equation 5.20, can be applied to calculate the sample covariance matrix of the residuals, describing the variability and dependency structure among the residuals of the VAR model's endogenous variables (Kohli; Garcia; Pourahmadi, 2016).

$$\widehat{\sum}_{\epsilon} = \frac{\hat{E}^T \hat{E}}{T - p} \quad (5.20)$$

Where:

- $\widehat{\sum}_{\epsilon}$: estimated covariance matrix of the residuals;
- T : total number of time periods;

- E^T : transposed matrix of residuals.

This process captures the correlation, magnitude, and direction of the model residuals, where each element $\widehat{\sum_{\varepsilon}^{ij}}$ represents the covariance between residuals i and j . In this context, both the residual matrix and the residual covariance matrix provide a deep understanding of the unexplained component of the model.

To incorporate this unexplained behavior into simulations, the Cholesky decomposition is applied to the covariance matrix of the residuals, as shown in Equation 5.21. This factorizes a symmetric positive definite matrix into the product of a lower triangular matrix and its transpose (Lütkepohl, 2001).

$$\sum_{\varepsilon} = LL^t \quad (5.21)$$

5.2.4 Financial Mathematical Modeling

The most fundamental concept for developing a financial mathematical model lies in understanding the concepts of revenue, fixed costs, variable costs, investment expenses, debt payments, and dividend distributions. These can be detailed as follows:

- Cash Inflows (Lucko, 2013):
 - Sales Revenue: Refers to income generated from product sales, with the amount received varying directly with the quantity of goods and services sold;
 - Financial Revenues: Arise from financial activities, such as interest from investments, dividends on equity, foreign exchange gains, among others;
 - Other Operating Revenues: These are part of the company's cash flow but are not related to its core business activities. Examples include rental income, proceeds from by-products, compensation received, etc.
- Cash Outflows (Briciu, 2008):
 - Fixed Costs: Recurring expenses necessary for maintaining the company's operations that do not vary with production volume. Examples include rent, insurance, and salaries;
 - Variable Costs: Costs directly related to the production volume, such as raw materials, supply expenses, and sales commissions;
 - Investment Expenses: Expenditures on tangible or intangible assets aimed at generating future financial returns, such as spending on new projects, equipment, or capacity expansion;
 - Financial Expenses: Costs related to debt service, such as loan repayments and interest payments.

These concepts are structured in various ways to report business performance. However, the cash flow statement and the balance sheet are the most basic tools for financial evaluation. The following sections briefly explain these tools, highlighting their main characteristics, advantages, and limitations.

The cash flow (CF) statement is a financial tool that records all of the company's cash inflows and outflows. It is divided into three categories: operating cash flow (OCF), investing cash flow (ICF), and financing cash flow (FCF), as expressed in Equation 5.22 (Simons, 1994).

$$CF_t = OCF_t + ICF_t + FCF_t \quad (5.22)$$

The OCF includes all financial movements related to the company's core activities. It consists of both operating revenues and expenses. Revenues mainly stem from product and service sales, including by-product sales, freight charges, and additional services. Expenses include payments to suppliers, wages and payroll charges, infrastructure costs, taxes on sales, and commercial expenses (Simons, 1994). This is modeled by Equation 5.23. If this indicator remains negative for extended periods, it threatens the company's viability.

$$OCF_t = \text{Operating Cash Inflows}_t - \text{Operating Cash Outflows}_t \quad (5.23)$$

The ICF accounts for financial movements involving the acquisition or disposal of long-term assets, including financial investments. Inflows originate from asset sales, proceeds from financial applications, or divestments. Outflows cover the purchase of machinery, buildings, participation in other businesses, and infrastructure investments (Simons, 1994). According to Equation 5.24, a positive ICF indicates disinvestment, while a negative value suggests active long-term investment.

$$ICF_t = \text{Investment Inflows}_t - \text{Investment Outflows}_t \quad (5.24)$$

The FCF relates to the company's financing activities and capital structure. Inflows include borrowed capital, equity issuance, or capital contributions from shareholders. Outflows include debt repayments, interest payments, dividend distributions, and share buybacks (Simons, 1994).

$$FCF_t = \text{Financing Inflows}_t - \text{Financing Outflows}_t \quad (5.25)$$

While OCF and ICF are directly interpretable, FCF requires more nuanced analysis. A positive FCF indicates the company is taking on debt, which may be strategic if occasional (e.g., leveraged investment). However, recurring positive FCF values may indicate over-reliance on debt to sustain operations. A negative FCF typically reflects debt repayment and shareholder returns, often interpreted as a positive indicator.

5.2.4.1 Financial Analysis Tools

Cash flow and the balance sheet form the basis for various financial analyses. Below are tools used to assess investment risks and project viability

Net Present Value (NPV)

NPV calculates the difference between the present value of expected cash flows and the initial investment, as defined in Equation 5.26 (Lucko, 2013).

$$VPL = \sum_{t=0}^n \frac{FC_t}{(1+i)^t} - I_0 \quad (5.26)$$

Where:

- t : Time period;
- FC_t : Cash flow in period t ;
- i : Discount rate or minimum acceptable rate of return;
- I_0 : Initial investment.

NPV yields three main interpretations for investment decisions: a positive NPV indicates financial viability, where the project's net income exceeds its cost; a negative NPV implies economic inviability; and an NPV close to zero suggests the investment merely breaks even (Shou, 2022).

When applied in Monte Carlo simulations, NPV is calculated for each generated scenario, allowing for statistical analysis across scenarios (mean, standard deviation, quartiles) (Shaffie; Jaaman, 2016).

Probability of Positive Return (PPR)

PPR is a probabilistic economic viability metric that evaluates the likelihood of a project yielding positive returns over a specified time horizon. Using stochastically generated scenarios, each case is evaluated for profitability (e.g., whether $VPL > 0$). The proportion of positive-return scenarios among all simulations is calculated, as shown in Equation 5.27 (Ronyastra; Saw; Low, 2024).

$$PPR = \frac{\text{Number of Scenarios with Positive Return}}{\text{Total Number of Simulated Scenarios}} \quad (5.27)$$

Discounted Payback Period

The Discounted Payback Period estimates the time required to recover an investment, accounting for a discount rate. It is computed by identifying the minimum T where the cumulative present value of cash flows exceeds the initial investment, as shown in Equation 5.28 (Kijo-Kleczkowska; Bruś; Więciorkowski, 2022).

$$\text{Discounted Payback} = \min \left\{ T : \sum_{t=1}^T \frac{FC_t}{(1+i)^t} \geq I_0 \right\} \quad (5.28)$$

In Monte Carlo simulations, this metric is applied to each individual scenario. Results are then statistically analyzed to derive metrics such as average payback time, standard deviation, and quartiles (Ronyastra; Saw; Low, 2024).

5.3 Materials And Methods

The proposed conceptual model, as illustrated in Figure 5.1, is structured into three stages, classified according to the nature of their activities.

5.3.1 Production Chain

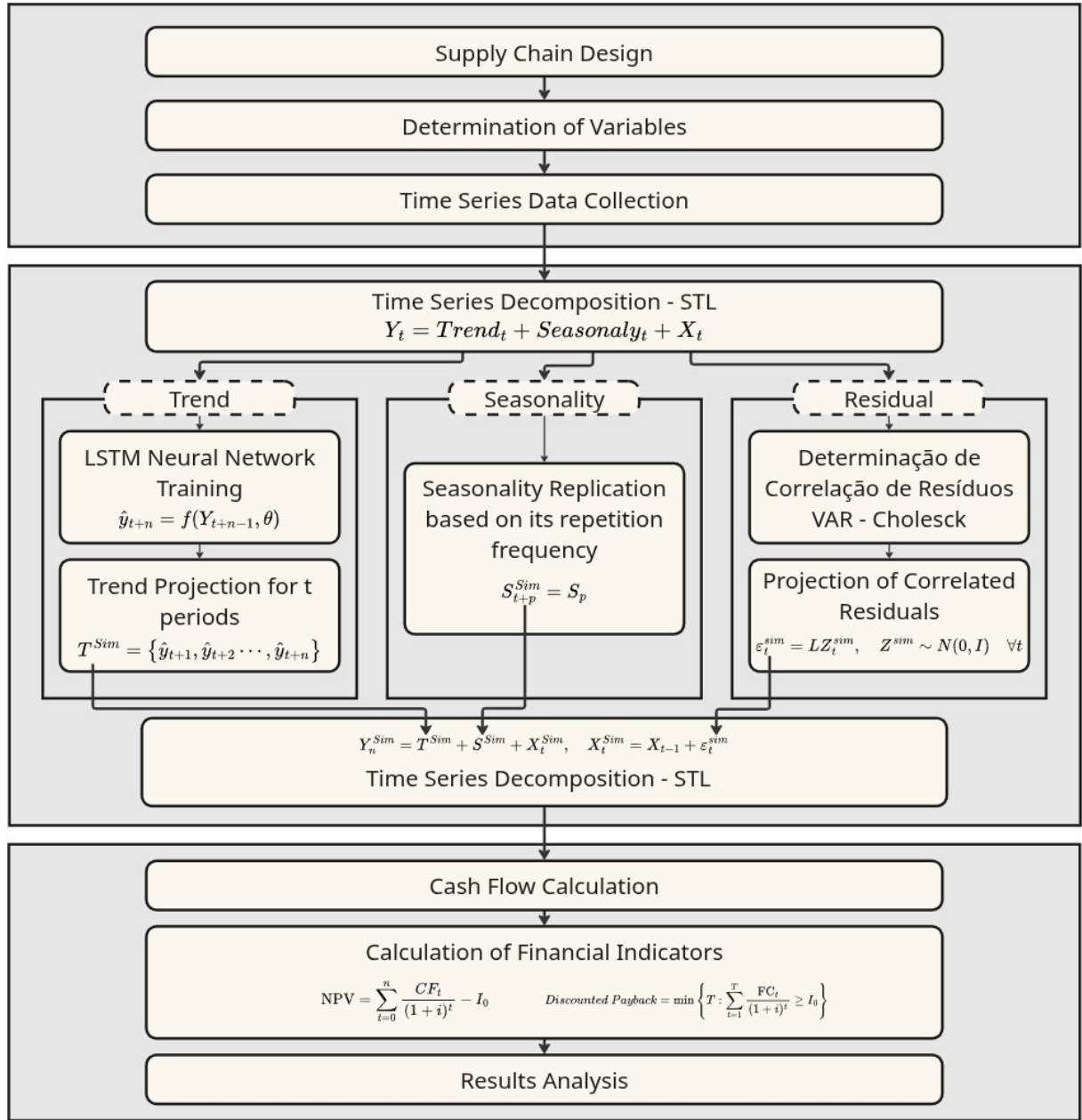
The first stage involves the design of the production chain to be analyzed. Although this work does not delve deeply into the theoretical basis of this step, a general overview is provided based on the evidence discussed in Silva and Frazzon (2025). At least three different approaches can be used to structure this production chain:

Based on an existing supply chain: Analyzing existing supply chains is useful for business planning, as it enables incorporating validated strategies and empirical knowledge, a process commonly referred to as benchmarking. This approach is not limited to companies within the same industry as the target project but can also draw from firms in different sectors within the same region.

Based on expert opinion: Expertise should not be overlooked. Even with rigorous studies and sound project management methods, subtle nuances may be missed. Expert reviews help identify waste, challenges, design flaws, and other risks. Specialist consultation is also essential in adjacent areas, such as taxation, environmental regulations, and legal compliance.

Based on academic studies: Research-based development enables innovation in investment projects, whether related to product design or process improvement. Academic literature reviews and the synthesis of scholarly knowledge provide an innovative foundation that may help establish a competitive edge. Innovation is crucial for the success of new ventures that lack economies of scale or an established market. Without some form of product or process innovation, new companies often face severe market entry difficulties.

Figure 5.1 – Conceptual Model



Source: Os autores

From this production chain layout, it is possible to identify the key project variables, including fixed costs, variable costs, revenues, and investments. Additional data may also be needed, such as historical inflation rates, currency exchange rates (e.g., USD), among others. Collecting these time series can be challenging and may require collaboration with companies or institutions, as access to such data is often restricted.

5.3.2 Time Series Forecasting

Once the production chain is defined and data collected, the model proceeds with the decomposition of time series using the STL method. As described for Krake *et al.* (2024),

STL decomposes each time series into trend, seasonal, and residual components in a unified manner. This joint decomposition is highly desirable. Applying different methods to extract each component separately introduces different parameters and biases, potentially resulting in overlap between trend and residual components. STL's unified decomposition improves model stability by avoiding such issues.

Another advantage of STL is its ability to produce stationary residuals, which is crucial for analyzing residual correlation. Verifying stationarity is essential and should be done using tests such as the Dickey-Fuller Test, KPSS Test, and Phillips-Perron Test. If residuals are found to be non-stationary, STL parameters can be adjusted and reapplied, avoiding the need for additional transformations such as differencing, log transformations, or the Box-Cox transformation - which may be methodologically costly and risk information loss, ultimately reducing model robustness.

After decomposition, the model separately forecasts each of the three components.

Trend forecasting is performed using Long Short-Term Memory (LSTM) neural networks, chosen for their capacity to capture both long- and short-term dependencies in financial time series (Sunki *et al.*, 2024).

Prior to training, the time series data undergoes preprocessing. A common step is normalization, which scales values to a 0–1 range, preventing large-scale numbers from disproportionately influencing training (Agarwal *et al.*, 2024).

Another preprocessing step involves converting dates into sequential integers. For example, neural networks may struggle to interpret the transition from month 12 (December 2024) to month 01 (January 2025). Using sequential numeric encoding and reverting it during postprocessing improves interpretability. Additionally, a cyclical temporal component, such as a sine or cosine function, can be included to help the network detect seasonal patterns not fully captured by STL (Arthur; Yudistira; Dewi, 2024; Zhang; Wang, *et al.*, 2025). During network configuration, key parameters must be defined:

- Batch size: number of samples processed simultaneously;
- Timesteps: length of time intervals processed as a unit;
- Features: number of correlated variables used as input.

LSTM architecture parameters include:

- Number of units: neurons per layer;
- Activation functions: typically tanh and sigmoid;
- Number of layers;
- Dropout rate: to prevent overfitting by randomly disabling neurons during training.

Training parameters (also known as learning parameters) include the definition of training, validation, and test sets, as well as:

- Loss function: measures the difference between predicted and actual values;
- Optimizer: updates weights and biases based on the loss.

Let T be a trend vector composed of x values over n time periods, as in Equation 5.29:

$$T = \{x_{t-n}, x_{t-n+1}, \dots, x_{t-1}, x_t\} \quad (5.29)$$

This vector T is input into an LSTM network, which forecasts the trend's future trajectory by iteratively adjusting weights and biases via the internal operations of the LSTM cell. These are represented by Equations 5.11, 5.12, 5.14 and 5.15, involving forget gate (f_t), input gate (i_t), output gate (o_t), and cell state update (C_y).

Two common issues may arise during training:

- Overfitting: the model memorizes patterns specific to the training data but fails to generalize;
- Underfitting: the model fails to capture meaningful patterns.
- These are mitigated by fine-tuning the above parameters (Li *et al.*, 2024).

The forecast for the next time step is given by Equation 5.30:

$$\hat{y}_{t+n} = f(Y_{t+n-1}, \theta) \quad (5.30)$$

Onde:

- y_{t+n} : Forecasted value for period $t + n$;
- Y_{t+n-1} : Vector of previous values, including both actual and predicted data;
- f : Function learned by the LSTM network;
- θ : Parameters (weights and biases) of the trained model.

After training is complete, the model forecasts the full trend sequence over n periods, as shown in Equation 5.31

$$\hat{Y} = \{\hat{y}_{t+1}, \hat{y}_{t+2}, \dots, \hat{y}_{t+n-1}, \hat{y}_{t+n}\} \quad (5.31)$$

5.3.2.1 Seasonality Forecasting

As previously mentioned in Section 5.2.1.1, the STL decomposition method produces a well-defined seasonality pattern, which facilitates the extrapolation of this periodic behavior into future cycles.

Delving deeper into the seasonality projection methodology, after the time series is decomposed, each seasonal component S_t is associated with a corresponding time point within the cycle. The cycle length defines the number of seasonal values in a full cycle for monthly series with yearly seasonality. The seasonal pattern is represented by a sequence of P values, $S = \{S_1, S_2, \dots, S_P\}$, where each value corresponds to a specific position within the cycle. For future time points $t > T$, where T is the last observed value of the series, seasonality is projected using Equation 5.32 (Phungtua-eng; Yamamoto, 2024).

$$S_{t+p} = S_p \quad (5.32)$$

Onde:

- S_{t+p} : forecasted seasonal value;
- S_p : value from the seasonal cycle, with p ranging from 1 to P .

In cases where seasonality exhibits non-stationary behavior, regression-based models may be applied to dynamically adjust the amplitude of seasonal components over time (So; Chung, 2014).

5.3.2.2 Residual Forecasting

The VAR-Cholesky method was selected for modeling the correlation between residuals due to its ability to capture interdependencies among multiple time series, including time lags (Demetrescu; Salish, 2024). This characteristic is essential for generating robust feasibility forecasts.

To illustrate the importance of properly identifying correlation among series, consider a yogurt manufacturing plant. One can reasonably expect a correlation between the price of raw milk (a commodity) and the final price of yogurt. These prices may be influenced by external factors not fully captured in the model, the residuals. If residual correlations are ignored, the simulation may generate inconsistent results, where one variable fluctuates independently of the other, leading to unreliable viability projections.

Residual forecasting begins by applying the Monte Carlo method as described in Section II.4, resulting in the residual correlation matrix L . This matrix is multiplied by a standardized random variable vector (Z^{sim}), producing a simulated residual vector (ε_t^{sim}) for each period t . This process is repeated for T periods to cover the desired simulation horizon. The results for all simulations can be stored in a residual simulation matrix E^{sim} with dimensions $N \times T$ (Chou, 2011).

$$\varepsilon_t^{sim} = LZ_t^{sim}, \quad Z^{sim} \sim N(0, I) \quad \forall t \quad (5.33)$$

These results are equivalent to white noise, but now incorporating the correlation among time series residuals. By applying Equation 5.33 to the Brownian noise formulation in Equation 5.2, the behavior of the residual component in the simulations is fully defined. This process is repeated N times to generate the desired number of Monte Carlo scenarios (Heinäkoski, 2018; Higham; Roj, 2012).

5.3.2.3 Reconstruction Of Forecasted Time Series

After decomposition using the STL method, reconstruction of the forecasted time series is a simple process involving the sum of the trend, seasonal, and residual components. This is represented by Equation 5.34, where n denotes the simulation index (Krake *et al.*, 2024).

$$Y_n^{Sim} = T^{Sim} + S^{Sim} + X_n^{Sim} \quad (5.34)$$

It is important to note that the trend and seasonal components can be treated as constant across all simulations. In other words, their values remain fixed, while the residuals are resampled for each simulation scenario. This separation is computationally efficient: although training the LSTM network and computing autoregressive vectors is resource-intensive, the subsequent steps involve only first-order arithmetic operations.

5.4 Results And Discussions

The evaluation of investment risk begins with the mathematical modeling of cash flow, as represented by the simplified Equation 5.35.

$$FC_t = \text{Revenues}_t - \text{Fixed Costs}_t - \text{Variable Costs}_t \quad (5.35)$$

By applying the forecasted time series to this cash flow equation, we obtain a cash flow projection for each period t and each of the n simulated scenarios.

These projected cash flows are then analyzed using investment evaluation tools such as Net Present Value (NPV) and Discounted Payback Period (Shou, 2022; Kijo-Kleczkowska; Bruś; Więciorkowski, 2022). Since the results are based on a set of simulated scenarios, they can be subjected to statistical analysis.

For example, calculating the lower quartile of NPV yields the Value at Risk (VaR), representing the greatest expected loss at a given confidence level (typically 5% or 1%). Additionally, by counting the number of scenarios in which the NPV is greater than zero, one obtains the probability of positive returns.

From the Discounted Payback results, it is possible to estimate the average time to investment recovery, as well as determine the expected return periods in worst-case scenarios (Ronyastra; Saw; Low, 2024).

5.5 Conclusions

This study introduced a conceptual method for risk assessment in manufacturing investments, contributing with a novel approach that integrates STL, LSTM, and VAR-Cholesky methods to forecast correlated time series of costs and revenues. The model advances investment analysis techniques from both an economic science and a production engineering perspective. While theoretically robust, the model's practical utility must be confirmed through empirical validation in real-world case studies. The primary limitations of the current framework are the unstructured nature of the production chain modeling and the absence of an optimization module. Future work should therefore focus on two key areas: first, developing a more rigorous and detailed modeling process for a generic production chain; and second, incorporating an optimization layer to identify ideal investment strategies. Successfully addressing these points will enhance the model's applicability, potentially establishing it as a valuable tool for feasibility analysis and risk forecasting in the manufacturing sector.

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6 Artigo 03 - Joint Modeling of LSTM Marginals and R-vine Copulas for Long-term Probabilistic Forecasting of Multivariate Time Series

Abstract

Purpose

This study proposes an integrated probabilistic forecasting framework that combines Long Short-Term Memory (LSTM) neural networks with R-vine copulas to model and simulate long-term multivariate dependencies in commodity price series. The purpose is to enhance the robustness of scenario generation for investment and risk-management decisions in agri-industrial supply chains.

Methodology

The methodology decomposes the forecasting task into two layers. First, a probabilistic LSTM learns the Gaussian marginal distributions for each time series, providing parameters (μ_t, σ_t) estimated via maximum likelihood. Second, a R-vine copula structure captures the cross-series dependence from residuals transformed through a Probability Integral Transform (PIT). The predictive quality is evaluated using proper scoring rules Continuous Ranked Probability Score (CRPS), Weighted Interval Score (WIS), Energy Score (ES), and Variogram Score (VS) over 5 and 10 year horizons.

Findings

Compared with linear benchmarks such as VARMA-Monte Carlo, the LSTM-Copula model achieves consistent reductions in CRPS (up to 35%) and ES/VS scores. The results show that the joint model maintains both calibration and sharpness while preserving the nonlinear dependence structure among the series..

Research limitations

The empirical analysis is based on 20 years of monthly data from the wheat and soybean supply chains. Future studies should extend the framework to higher-dimensional settings, non-Gaussian marginals, and real-time adaptive copula updates.

Practical implications

The proposed architecture provides a replicable tool for probabilistic scenario generation

in investment feasibility studies, risk quantification, and long-term planning of industrial supply chains.

Originality

This work advances the literature by structurally integrating dynamic vine-copula dependence modeling with deep probabilistic LSTM marginals within a unified framework for long-horizon multivariate forecasting. The contribution lies in the combined implementation, extended forecast horizon focus, and comprehensive multivariate probabilistic validation, rather than in the introduction of new model classes.

Keywords: Business analytics; Cost analysis; Value chain; Simulation; Stochastic models; Time series

6.1 Introduction

Long-term investments are intrinsically subject to uncertainties arising from market fluctuations. Among the main sources of risk are commodity price volatility (Yıldırım; Erdoğan; Tarı, 2022; Melas *et al.*, 2024), exchange and interest rate oscillations (Araujo; Araújo; Brito, 2023), as well as shifts in consumer demand patterns (Bian, 2024). These variables constitute sources of systemic risk that can significantly affect the profitability of invested capital.

A robust strategy to quantify and mitigate these risks is the **stochastic modeling of time series**, which relies on the historical behavior of data to project multiple plausible future trajectories (Sawik, 2022). This approach enables the generation of diversified scenarios, useful for identifying critical situations, assessing the probability of positive returns, and evaluating the overall exposure of investments to risk (Feng *et al.*, 2023). However, for the simulated scenarios to be realistic, it is essential to incorporate the **correlations among variables**. Neglecting such interdependencies compromises the validity of the analysis and may lead to misguided decisions (Nandi, 1998). This challenge is particularly critical in long-term horizons, where forecast errors tend to accumulate exponentially (Carriero; Marcellino; Tornese, 2023; Iania; Nguyen; Smedts, 2025).

In this study, we propose the **Copulas Multivariate Probabilistic Long Short-Term Memory (CMP-LSTM)** method, which seeks to overcome these limitations by combining two complementary techniques: (i) probabilistic LSTM networks, capable of capturing complex temporal patterns and producing heteroscedastic Gaussian conditional distributions (Toubeau *et al.*, 2018; Mienye; Swart; Obaido, 2024; Kaur; Mohta, 2019); and (ii) R-vine copulas, which flexibly model nonlinear dependencies, asymmetries, and heavy tails across time series (Dissmann *et al.*, 2013; Sun; Yu, 2022; Xu; Ma, *et al.*, 2025). Thus, CMP-LSTM simultaneously preserves marginal calibration and multivariate dependence structures, leading to more realistic and informative probabilistic forecasts.

The main contribution of this work is to empirically demonstrate that integrating probabilistic neural networks with dynamic copulas yields significant improvements in calibration,

sharpness, and robustness compared to traditional multivariate forecasting benchmarks, with particular emphasis on the VARMA–Monte Carlo model. The results obtained have direct applications in risk analysis and strategic planning in supply chains, where decisions rely on reliable forecasts at medium- and long-term horizons.

It is important to clarify that the proposed framework does not introduce a new neural architecture or copula class. Its contribution lies in the structured integration of probabilistic LSTM marginals with dynamic R-vine copulas, with emphasis on long-horizon multivariate forecasting and comprehensive probabilistic evaluation.

The article is structured as follows: Section 2 presents the materials and methods; Section 3 describes the experiments; Section 4 discusses the results; and Section 5 summarizes the conclusions and outlines directions for future research.

6.2 Materials and Methods

This section first positions the CMP-LSTM framework relative to existing multivariate forecasting approaches and then details each methodological component. Modern multivariate probabilistic forecasting approaches often rely on shared latent factors or attention mechanisms to capture cross-series dependence (Toubeau *et al.*, 2018; Salinas *et al.*, 2019). Latent-factor models impose a low-dimensional structure that captures global co-movements but may smooth heterogeneous pairwise relationships (Salinas *et al.*, 2019). Attention-based architectures learn dependence implicitly through shared representations (Roshanpour *et al.*, 2025) yet typically do not provide an explicit multivariate probabilistic structure. In contrast, the CMP-LSTM framework adopts a modular decomposition: marginal dynamics are modeled individually, while cross-series dependence is explicitly specified through a dynamic R-vine copula (Patton, 2012; Czado, 2019; Dissmann *et al.*, 2013). This allows flexible, pair-specific dependence modeling without imposing global factor constraints (Brechmann *et al.*, 2012), while maintaining probabilistic coherence and interpretability (Gneiting; Raftery, 2007). Such a structure is particularly suited to supply-chain systems characterized by hierarchical and asymmetric interactions (Sawik, 2022; Ronyastra; Saw; Low, 2024; Ivanov; Dolgui; Sokolov, 2018).

The proposed method, referred to as **CMP-LSTM**, performs multivariate probabilistic forecasting through the integration of two complementary steps. In the first step, a heteroscedastic probabilistic LSTM model is trained to estimate the Gaussian marginal distributions of each time series, providing trend (μ_t) and dispersion (σ_t) parameters. In the second step, the contemporaneous dependence among series is modeled using R-vine copulas. The combination of these two methodological layers enables the generation of stochastic scenarios that preserve both marginal calibration and multivariate correlation structures.

The use of Gaussian marginals constitutes a deliberate modeling decision, consistent with probabilistic deep forecasting frameworks (Salinas *et al.*, 2019). In long-horizon stochastic simulations, numerical stability and coherent propagation of conditional variance are critical, and heteroscedastic Gaussian specifications provide a parsimonious and well-behaved specification

(Oh; Patton, 2024) for conditional mean and variance dynamics.

Within the CMP-LSTM framework, higher-order dependence features are primarily addressed through the dynamic R-vine copula layer (Czado, 2019; Patton, 2012). This structure allows distributional flexibility at the multivariate level while preserving stability and interpretability in the marginal component, which is particularly relevant for extended risk-oriented forecasting horizons.

This design builds upon advances in probabilistic forecasting with recurrent neural networks (Salinas *et al.*, 2019; Toubreau *et al.*, 2018; Xu; Shi; Ni, 2017) and on the flexibility of copula-based dependence models (Brechmann; Czado; Aas, 2012; Czado, 2019; Dissmann *et al.*, 2013).

Additional related research includes dynamic copula-neural models (Hafner; Manner, 2012; Zito; Kowal, 2025), heavy-tailed probabilistic deep models (non-Gaussian marginal distributions) (Cheng *et al.*, 2025; Wang; Ji; Xie, 2024), long-horizon dependence forecasting (Mallen; Lange; Kutz, 2024; Roshanpour *et al.*, 2025), and economic viability analysis in industrial management (Acciarini *et al.*, 2023; Ivanov, 2023; Kou; Lu, 2025).

The methodological contribution of the CMP-LSTM lies in adapting the residual-based copula modeling paradigm to operate with normalized residuals produced by a Gaussian LSTM. While copula construction from residuals is standard in linear models such as VARMA, GARCH, and VAR, its dynamic application in conjunction with a probabilistic LSTM is still uncommon. This provides an alternative mechanism for combining nonlinear marginal dynamics with a time-varying dependence structure, particularly suited for long-horizon scenario generation.

Although the method is not restricted to industrial time series, it was conceived for variables associated with manufacturing supply chains. So that the resulting multivariate scenarios can be directly integrated into techno-economic feasibility assessments and investment evaluations. This adaptation does not aim to replace established multivariate time-series models but to offer an alternative decomposition of marginal dynamics and cross-series dependence suitable for long-horizon scenario generation.

To evaluate the incremental contribution of the proposed framework, we adopt a VARMA-Monte Carlo specification as the benchmark model. VARMA provides a well-established multivariate structure that captures linear cross-series dependence and shock propagation. Combined with Monte Carlo simulation, it enables coherent long-horizon scenario generation (Athanasopoulos; Vahid, 2008; Düker *et al.*, 2025). This makes it an appropriate and transparent reference for assessing the added value of nonlinear marginals and explicit copula-based dependence modeling.

The following sections detail each component of the CMP-LSTM method: the training of the probabilistic LSTM network (Section 2.1), dependence modeling via R-vine copulas (Section 2.2), and the process of multivariate stochastic scenario simulation (Section 2.3).

6.2.1 LSTM Training

The network used in this study is a heteroscedastic probabilistic LSTM, designed to estimate conditional Gaussian distributions at each forecasting step. Unlike deterministic versions, which return point forecasts, the adopted formulation provides two parameters for each time series at time t : the mean μ_t and the standard deviation σ_t . This approach allows capturing not only the central tendency but also the uncertainty associated with the forecasts, an essential aspect in risk analysis scenarios.

Formally, given a mini-batch $(X_\tau^{(b)}, y_\tau^{(b)})$, we assume

$$y_\tau | X_\tau \sim \mathcal{N}(\mu_\tau, \text{diag}(\sigma_\tau^2)), \quad (\mu_\tau, \sigma_\tau) = g_\theta(X_\tau),$$

where $g_\theta(\cdot)$ represents the LSTM followed by its output heads (one for the mean and another for the standard deviation). The diagonal covariance assumption implies that the series are modeled as conditionally independent, with correlations captured only in the copula stage.

The adopted loss function is the Gaussian *Negative Log-Likelihood* (NLL). For an observation $y_\tau = (y_{\tau,1}, \dots, y_{\tau,D})$, the log-likelihood is given by:

$$\log p(y_\tau | X_\tau) = -\frac{1}{2} \sum_{i=1}^D \left[\log(2\pi) + 2 \log \sigma_{\tau,i} + \frac{(y_{\tau,i} - \mu_{\tau,i})^2}{\sigma_{\tau,i}^2} \right].$$

For a mini-batch of size B , the average NLL is expressed as:

$$\mathcal{L}_{\text{NLL}} = -\frac{1}{B} \sum_{b=1}^B \log p(y_\tau^{(b)} | X_\tau^{(b)}).$$

Minimizing this function induces two desirable behaviors: (i) adjustment of the central tendency, via the normalized quadratic term; (ii) calibration of dispersion, penalized by the $\log \sigma$ term. Thus, the network learns to capture higher uncertainties in volatile contexts and smaller dispersions in stable scenarios, resulting in a well-calibrated heteroscedastic probabilistic regression.

The training of the LSTM is carried out through backpropagation through time (*Back-propagation Through Time* — BPTT), in which the gradients of the loss function are propagated across the temporal steps of the network. This procedure updates the weights $\theta = \{W, b\}$ consistently with the recurrent dynamics, though it is known to face challenges such as exploding or vanishing gradients.

To mitigate these issues and ensure stability during training, we adopt the following mechanisms:

- **Adaptive optimization (AdamW with weight decay)**: combines per-parameter learning rate adaptation with decoupled regularization, reducing overfitting risk and improving generalization.
- **Gradient clipping**: imposes limits on the norm of the gradients during BPTT, preventing numerical explosions in long sequences.

- **Dynamic learning rate scheduling (ReduceLROnPlateau):** automatically reduces the learning rate when validation loss stagnates, allowing refinement in local minima regions.
- **Early stopping:** halts training when no improvement beyond a minimum threshold is observed for a consecutive number of epochs, preserving the best *checkpoint*.
- **Series normalization:** scales historical data to the $[0, 1]$ interval, ensuring comparability across variables and accelerating convergence.

In general, at each training epoch the network is fed with mini-batches of size B . Each batch is propagated through the LSTM, producing estimates μ_t and σ_t , which are then used to compute the NLL loss. Gradients are subsequently backpropagated through the layers and the temporal dimension, and parameters are updated according to the defined optimization scheme. At the end of each epoch, the validation loss is evaluated, dynamically adjusting learning hyperparameters and monitoring stopping criteria.

The mechanism implemented by following the steps represented in the pseudo-code (Algorithm 1), together, allows the probabilistic LSTM to learn calibrated and stable marginal distributions, providing adequate forecasts even for long and highly variable time series.

Hyperparameter Configuration

To ensure reproducibility of the experiments, we highlight the main hyperparameters used in the training of the probabilistic LSTM network. The number of layers was fixed at two, each with 64 hidden units. The mini-batch size was set to 32 samples, and the optimization process was conducted over 150 epochs with an initial learning rate of 10^{-3} , dynamically adjusted by the *ReduceLROnPlateau* scheduler. The *dropout* applied to the recurrent layers was 0.2, while the *weight decay* regularization associated with AdamW was 10^{-4} . The early stopping criterion was activated with a patience of 20 epochs and a minimum tolerance (*min_delta*) of 10^{-4} on the validation loss.

6.2.2 Dependence Modeling via Copulas

Having specified the marginal models, we now describe the dependence modeling stage

With the diagonal Gaussian marginals estimated by the LSTM, the contemporaneous dependence among time series is modeled through copulas, adopting the construction of regular vines (R-vine). This approach allows capturing nonlinear relationships, asymmetries, and heavy-tail dependencies, which are recurrent features in economic and financial time series (Dissmann *et al.*, 2013; Brechmann; Czado; Aas, 2012).

To prevent the copula from modeling residual autocorrelations within each series, we apply a pre-processing step using the Ljung–Box test (lag = 10, $\alpha = 0.05$). When the null hypothesis of no autocorrelation is rejected, an AR(1) model is fitted, and the residuals are

Algorithm 1: Training and inference — Probabilistic LSTM (Gaussian marginals)

Input: data $(X_{\text{tr}}, y_{\text{tr}}), (X_{\text{val}}, y_{\text{val}})$; epochs N ; *patience*, *min_delta*; optimizer AdamW; scheduler ReduceLROnPlateau

Output: parameters $\hat{\theta}$ (best *checkpoint*)

- 1 Initialize LSTM($D, \text{hidden}, \text{dropout}$); heads W_{μ}, W_{σ} ;
- 2 Define optimizer AdamW(θ); scheduler ReduceLROnPlateau;
- 3 $\text{best_val} \leftarrow +\infty, \text{pac} \leftarrow 0$;
- 4 **for** $\text{epoch} \leftarrow 1$ **to** N **do**
- 5 Set $\text{model.train}()$, $\text{loss_epoch} \leftarrow 0$;
- 6 **foreach** (X_b, y_b) **in** *training batches* **do**
- 7 $\text{out} \leftarrow \text{LSTM}(X_b)$;
- 8 $h \leftarrow \text{LayerNorm}(\text{Dropout}(\text{out}[:, -1, :]))$;
- 9 $\mu \leftarrow W_{\mu}(h)$;
- 10 $\sigma \leftarrow \text{softplus}(W_{\sigma}(h)) + \varepsilon$;
- 11 $\ell \leftarrow -\text{mean}[\log \mathcal{N}(y_b; \mu, \text{diag}(\sigma^2))]$;
- 12 Zero gradients, backpropagate ℓ , apply gradient clipping, update parameters;
- 13 $\text{loss_epoch} \leftarrow \text{loss_epoch} + \ell$;
- 14 Set $\text{model.eval}()$; compute $\text{val} \leftarrow$ average NLL on validation;
- 15 Update ReduceLROnPlateau with val ;
- 16 **if** $\text{best_val} - \text{val} > \text{min_delta}$ **then**
- 17 Save θ to *best_model.pth*;
- 18 $\text{best_val} \leftarrow \text{val}; \text{pac} \leftarrow 0$;
- 19 **else**
- 20 $\text{pac} \leftarrow \text{pac} + 1$;
- 21 **if** $\text{pac} \geq \text{patience}$ **then**
- 22 Stop;
- 23 Restore $\hat{\theta}$ from *best_model.pth*; return $\hat{\theta}$;

replaced with the filtered ones. This procedure ensures that the copula primarily describes cross-series dependence, rather than individual temporal dependence.

Next, the pre-processed residuals are transformed into the uniform space $(0, 1)^D$ via the empirical Probability Integral Transform (PIT), computed from ranks:

$$u_{t,i} = \frac{\text{rank}(\mathbf{e}_{t,i}) - 0.5}{n}, \quad t = 1, \dots, n,$$

where $u_{t,i}$ approximates the empirical marginal distribution $F_i(\mathbf{e}_{t,i})$. This procedure eliminates the need for explicit marginal parameterization in the copula stage and is robust to asymmetries.

The multivariate dependence is then modeled using bivariate copulas arranged in a hierarchical R-vine structure. The candidate family set includes elliptical copulas (Gaussian and Student-t) and Archimedean copulas (Clayton, Gumbel, Frank, Joe), covering different symmetry patterns and tail dependencies. For each copula, truncations $\tau = \{1, 2, 3\}$ are tested, which control the depth of the vine tree and, consequently, the complexity of conditional dependence.

The optimal truncation t^* is selected by cross-validation, maximizing the average validation log-likelihood.

This time series of copulas is subsequently combined with the marginals provided by the LSTM to generate multivariate stochastic scenarios.

The R-vine decomposition offers superior flexibility compared to linear correlation models, as it parsimoniously and adaptively represents complex interdependencies. Thus, it ensures that the final forecasts preserve not only the individual distribution of each series, but also the multivariate co-movement patterns, which are essential in applications of risk analysis and supply chain planning. The pseudo-code presented in Algorithm 2 is intended to support the replicability of the study.

Algorithm 2: Adjustment of R-vine copulas

Input: standardized residuals $\mathbf{e}_{t,i}$; dates $\{\text{date}_t\}$; window W ; candidate families $\mathcal{F}$; truncations $\tau = \{1, 2, 3\}$; folds K

Output: collection $\{M_t\}_t$ of R-vine models per window

```

1 for  $i \leftarrow 1$  to  $D$  do
2   Apply Ljung–Box test on  $\{\mathbf{e}_{t,i}\}$ ;
3   if  $p\text{-value} < 0.05$  then
4     Fit AR(1); replace  $\mathbf{e}_{t,i}$  with residuals  $\mathbf{e}_{t,i}$ ;
5   else
6      $\mathbf{e}_{t,i} \leftarrow \mathbf{e}_{t,i}$ ;
7 Construct  $U \in (0, 1)^{W \times D}$  via PIT by ranks:  $u_{s,i} = (\text{rank}(\mathbf{e}_{s,i}) - 0.5)/W$ ;
8 foreach  $c \in \tau$  do
9   Run  $K$ -fold CV:
10  foreach fold  $k$  do
11    Fit R-vine( $U_{\text{train}}$ ;  $\mathcal{F}$ ,  $\text{trunc} = c$ );
12    Evaluate log-likelihood on  $U_{\text{val}}$ ; save  $\ell_{\text{val}}^{(k)}(c)$ ;
13   $\bar{\ell}_{\text{val}}(c) \leftarrow \frac{1}{K} \sum_k \ell_{\text{val}}^{(k)}(c)$ ;
14  $t^* \leftarrow \arg \max_{c \in \tau} \bar{\ell}_{\text{val}}(c)$  (in case of ties, choose smaller  $c$ );
15 Fit final R-vine on  $U$  with truncation  $t^*$ ;
16 Save  $M_t = \{\text{structure, families, parameters, } t^*, \bar{\ell}_{\text{val}}(t^*)\}$ ;
17 Return  $M_t$ ;
```

6.2.3 Multivariate Stochastic Scenario Simulation

With the Gaussian marginals provided by the LSTM and the adjusted R-vine copula, it is possible to consistently simulate future scenarios. The process begins from an initial historical sequence, which is replicated M times to generate M parallel scenarios. At each forecasting step $k = 1, \dots, n_{\text{steps}}$, the LSTM estimates the parameters $(\mu_{t+k}, \sigma_{t+k})$ of the diagonal Gaussian

marginals, while the R-vine copula fitted is used to capture the multivariate dependence among the series (Salinas *et al.*, 2019; Xu; Shi; Ni, 2017).

Scenario generation follows three main stages:

1. **Dependence sampling:** the selected dynamic copula is used to simulate vectors $u^{(m)} \in (0, 1)^D$, preserving the contemporaneous correlation structure among variables.
2. **Empirical transformation:** each component $u_i^{(m)}$ is mapped to a historical residual through an empirical quantile function. In practice, the sample $\{r_{s,i}\}_{s=1}^n$ is ordered and $u_i^{(m)}$ is associated with the corresponding order statistic, yielding $\hat{r}_i^{(m)}$. This step ensures that the variability observed in the historical data is reflected in the projections.
3. **Series reconstruction:** future values are computed as

$$y_{t+k,i}^{(m)} = \mu_{t+k,i} + \sigma_{t+k,i} \cdot \hat{r}_i^{(m)}, \quad i = 1, \dots, D,$$

which are then incorporated into the LSTM input windows for subsequent iterations.

This procedure is recursive. At each step k , the newly generated values are fed back into the model. This ensures consistency between the temporal evolution of the marginals and the contemporaneous dependence across variables. At the end, a tensor of dimensions (n_{steps}, M, D) is obtained, representing M multivariate stochastic trajectories over the forecasting horizon.

As represented in Algorithm 3, after the simulation in the normalized space, all scenarios are reverted to the original scale through the inverse normalization functions applied to each series individually. This adjustment ensures that the final results are directly comparable with the observed data and quantitatively evaluated by the proposed metrics.

The dynamic integration between LSTM and R-vine copulas thus enables the construction of scenarios that not only respect the individual variability of each series, but also preserve multivariate interdependencies, producing more realistic and informative probabilistic forecasts for supply chain applications.

6.2.4 Computational Complexity

The analysis of the computational complexity of the CMP-LSTM method is essential for assessing its scalability in practical applications. The model integrates two main stages — marginal forecasting via probabilistic LSTM and dependence modeling through R-vine copulas — whose costs are evaluated below.

6.2.4.0.1 LSTM Training.

Let n be the number of historical observations, d the number of time series, and h the number of LSTM hidden units. The per-epoch training cost is on the order of

$$\mathcal{O}(n \cdot d \cdot h^2),$$

Algorithm 3: Simulation of multivariate scenarios (LSTM + R-vine)

Input: LSTM model f_θ ; copulas M_τ ; initial sequence X_0 ; horizon n_{steps} ;
number of scenarios M ; historical residuals R
Output: tensor $Y \in \mathbb{R}^{n_{steps} \times M \times D}$ of simulated scenarios

- 1 Replicate $X \leftarrow \{X_0\}_m$ for $m = 1..M$;
- 2 **for** $k \leftarrow 1$ **to** n_{steps} **do**
- 3 $(\mu_k, \sigma_k) \leftarrow f_\theta(X)$;
- 4 Sample $U^{(m)} \sim M_\tau$, $m = 1..M$;
- 5 **for** $i \leftarrow 1$ **to** D **do**
- 6 Sort $R[:, i]$;
- 7 $\kappa_i^{(m)} \leftarrow \text{empirical quantile}(R[:, i], U_i^{(m)})$;
- 8 $y_k^{(m)} \leftarrow \mu_k + \sigma_k \odot \kappa^{(m)}$;
- 9 Save $Y[k, m, :] \leftarrow \text{inverse_scale}(y_k^{(m)})$;
- 10 **Return** Y ;

since backpropagation through time (BPTT) involves quadratic operations in the number of hidden units and linear operations in the sequence length (Sak; Senior; Beaufays, *et al.*, 2014). In experimental practice, training is accelerated by the use of mini-batches and GPU parallelization, but the order of magnitude remains unchanged.

6.2.4.0.2 R-vine Copula Fitting.

Dependence modeling in windows of size w requires the estimation and selection of copulas within hierarchical structures. Considering a truncation depth τ , the main cost lies in the evaluation of the bivariate copula log-likelihood, of order

$$\mathcal{O}(d^2 \cdot w \cdot \tau).$$

This cost grows quadratically with the number of series and linearly with the window size (Nagler; Vatter, 2023). In practice, $\tau \leq 3$ is sufficient to balance flexibility and computational feasibility.

6.2.4.0.3 Scenario Simulation.

The generation of M stochastic trajectories over H forecasting steps has cost

$$\mathcal{O}(M \cdot H \cdot d),$$

dominated by copula sampling and empirical transformations. This component is linear in all dimensions, making it relatively efficient compared to LSTM training and copula fitting.

6.2.4.0.4 Discussion.

Overall, LSTM training ($\mathcal{O}(n \cdot d \cdot h^2)$) and copula fitting ($\mathcal{O}(d^2 \cdot w \cdot \tau)$) are the most computationally demanding components. However, these processes are performed independently: being

adjusted only once. Thus, the incremental cost per new forecast is relatively low, highlighted by the linear simulation step. ($\mathcal{O}(M \cdot H \cdot d)$). This characteristic makes CMP-LSTM suitable for decision-support contexts and applicable to broader datasets.

6.3 Experiments

To empirically assess the predictive capability of the proposed method, we conducted experiments using price time series from the global soybean and wheat supply chains.

The data were collected from the public UN Comtrade Database, covering January 2005 to March 2025 at monthly frequency, expressed in US dollars per kilogram. This dataset captures multiple stages of the value chains and their associated cross-market dependency structure.

To empirically assess the predictive capability of the proposed method, experiments were conducted using price time series of products belonging to the global soybean and wheat supply chains. The data were collected from the public *UN Comtrade Database*¹, covering the period from January 2005 to March 2025, at monthly frequency and expressed in US dollars per kilogram.

The selection of the series followed two main criteria: (i) global economic relevance of the products considered, and (ii) availability of consistent long-horizon data. For each supply chain, representative products from different stages of industrial transformation were chosen: grain, intermediate processed derivatives, and final products. In the case of soybeans, grain, soybean meal, and soybean oil were considered; in the wheat chain, grain, flour, pasta, and bread. The resulting dataset corresponds to seven distinct time series, detailed in Table 6.1.

HS Code	Description	Exporting Country
Soybean supply chain products		
HS 1201	Soybean grain	Brazil
HS 2304	Soybean meal	Brazil
HS 1507	Soybean oil	Brazil
Wheat supply chain products		
HS 1001	Wheat grain	USA
HS 1101	Wheat flour	Turkey
HS 1902	Pasta	Italy
HS 1905	Bread	Italy

Table 6.1 – Description of the collected data

In total, 1,704 monthly observations were collected, distributed across seven time series and covering a 20-year horizon. This dataset provides a robust empirical basis to compare the performance of CMP-LSTM against traditional models. To capture different degrees of interdependence, the experiments were structured into three evaluation scenarios:

¹ <https://comtradeplus.un.org>, To ensure reproducibility, all datasets used in this study will be made publicly available on an open repository Zenodo after peer review and acceptance. A DOI link will be provided at that stage.

1. Soybean chain (3 series highly correlated with each other);
2. Wheat chain (4 series with intermediate correlation);
3. Combined soybean + wheat set (7 series with lower average correlation).

This experimental configuration allows evaluating the method both in relatively homogeneous chains and in more heterogeneous environments, testing its robustness under different correlation structures.

Reference Method: VARMA–Monte Carlo

For comparison purposes, we adopt the **VARMA–Monte Carlo** model as a benchmark, which combines the multivariate linear structure of the VARMA process with the generation of stochastic trajectories via Monte Carlo simulation.

This choice is justified by the fact that VARMA preserves linear dependencies among multiple time series and incorporates moving-average terms capable of capturing short-term shocks that are not explained by the autoregressive components (Athanasopoulos; Vahid, 2008; Düker *et al.*, 2025). In addition, its well-defined multi-step forecasting properties make it a stable and widely adopted benchmark for multivariate projections across extended forecasting horizons (Lütkepohl, 2006, p. 296 - 299) .

Let $y_t \in \mathbb{R}^d$ denote the vector of d series at time t . A VARMA(p, q) process is defined as:

$$y_t = \mu + \sum_{i=1}^p A_i y_{t-i} + \sum_{j=1}^q \Theta_j \varepsilon_{t-j} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \Sigma),$$

where A_i and Θ_j are coefficient matrices, and Σ is the covariance matrix of the residuals. The process is stable when the roots of the characteristic polynomials lie outside the unit circle, while the residuals are evaluated through autocorrelation (Ljung–Box), normality (Jarque–Bera), and heteroscedasticity (ARCH) tests.

The model was fitted on series previously normalized and differenced until stationarity was achieved. The orders (p, q) were selected according to information criteria (AIC, BIC, and HQ), with estimation performed via maximum likelihood under a state-space formulation.

To obtain the joint predictive distribution, we used conditional Monte Carlo simulation. Given the initial conditions — the last p observed states and, when $q > 0$, the last q estimated residuals — we generated M future trajectories for $h = 1, \dots, H$ using the expression:

$$y_{t+h}^{(m)} = \mu + \sum_{i=1}^{\min(p, h-1)} A_i y_{t+h-i}^{(m)} + \sum_{j=1}^{\min(q, h-1)} \Theta_j \varepsilon_{t+h-j}^{(m)} + \varepsilon_{t+h}^{(m)},$$

where $\varepsilon_{\tau}^{(m)} = L z_{\tau}^{(m)}$, $z_{\tau}^{(m)} \sim \mathcal{N}(0, I_d)$, and $\Sigma = LL^{\top}$ is the Cholesky decomposition of the estimated covariance matrix.

After simulation, the trajectories are transformed back to the original scale of the series (through the inverse normalization and differencing transformations), allowing direct comparison

with the observed values. The VARMA–Monte Carlo thus provides a robust linear benchmark against which we evaluate the gains achieved by the proposed CMP-LSTM method.

6.3.1 Evaluation Protocol

The performance evaluation of the models follows an out-of-sample validation protocol (*holdout*). The time series were divided into two halves: (i) the first 10 years used for model fitting (training), and (ii) the final 10 years reserved for validation. Thus, all forecasts are genuinely prospective, with no reuse of future information, ensuring the impartiality of the evaluation (Oh; Patton, 2024).

It is important to emphasize that the adoption of a 50%/50% sample split constitutes an exceptional evaluation design, employed exclusively for methodological purposes in this study. This choice was motivated by the need to rigorously assess the ability of the proposed method to produce long-horizon forecasts, particularly over a ten-year projection window.

Such an extended validation period is essential to compute and demonstrate both univariate and multivariate predictive accuracy under long-term conditions, which would not be feasible with a substantially smaller out-of-sample segment. In this context, the adopted split enables a stringent and informative evaluation of the probabilistic and dependence-aware forecasting capabilities of the model.

It should be noted, however, that this configuration is not intended as a recommendation for practical applications of the proposed methodology. In real-world forecasting settings, a substantially smaller out-of-sample proportion. Typically between 10% and 20% of the available data—would be more appropriate, balancing model calibration needs and predictive validation under operational constraints (Staněk, 2021; Rossi; Inoue, 2012).

For each forecasting horizon $h = 1, \dots, H$, the models generate an ensemble of simulated trajectories $\{\mathbf{y}_{t+h}^{(m)}\}_{m=1}^M$, which are compared against the realized values $\mathbf{y}_{t+h}$. This procedure allows evaluating not only the point accuracy of the forecasts, but also the probabilistic quality of the predictive distribution.

The metrics are computed in the original units (US\$/kg) after reversing the normalization and differencing transformations, ensuring substantive interpretability. Results are reported in an aggregated manner at two levels:

1. **Temporal aggregation:** average scores across the entire validation horizon;
2. **Cross-series aggregation:** macro-average across all evaluated series.

Additionally, the forecasting horizons are stratified into two blocks in order to capture patterns dependent on temporal distance:

- Medium term: 0–60 months,
- Long term: 0–120 months.

This evaluation structure enables analyzing the robustness of the models at different time scales, while providing a more precise diagnosis of the relative performance of CMP-LSTM and VARMA–Monte Carlo.

Evaluation Metrics

Forecast evaluation is conducted using *proper scoring rules*, which incentivize probabilistically honest predictions by being minimized when the predictive distribution coincides with the data-generating distribution. We adopt a concise and complementary set of metrics that capture both the marginal quality (per series) and the joint quality (multivariate) of the predicted distributions: at the univariate level, we use the **Continuous Ranked Probability Score (CRPS)** and the **Weighted Interval Score (WIS)**; at the multivariate level, the **Energy Score (ES)** and the **Variogram Score (VS)**. For all metrics, lower values indicate better performance.

Intuitively, the CRPS simultaneously evaluates the *calibration* and *sharpness* of the univariate distributions; the WIS summarizes, in a single measure, the width and coverage of multiple prediction intervals (via quantiles). For the joint distribution, the ES generalizes the logic of the CRPS to the space $\mathbb{R}^D$, while the VS specifically focuses on the dependence structure among components, being relatively insensitive to purely marginal errors. Thus, the pair (ES, VS) provides a complementary view of both the overall proximity of the joint distribution and the quality of co-movements.

All metrics are computed after reversing the transformations (normalization/differencing), preserving the *original units* of the data and thereby their substantive interpretability. Practical estimation follows ensemble-based approximations (simulated samples), which is standard in recent literature. This approach allows for a coherent comparison between the proposed method (CMP-LSTM) and the VARMA–Monte Carlo benchmark across different forecasting horizons.

6.3.1.0.1 Continuous Ranked Probability Score (CRPS).

The CRPS evaluates the quality of univariate probabilistic forecasts by comparing the predicted cumulative distribution function (CDF) F with the observed value y . It is a widely used proper scoring rule that summarizes both the calibration and the sharpness of predictive distributions into a single metric (Gneiting; Raftery, 2007). Its integral formulation is given by:

$$\text{CRPS}(F, y) = \int_{-\infty}^{\infty} [F(z) - 1\{z \geq y\}]^2 dz,$$

where $1\{\cdot\}$ is the indicator function.

Equivalently, the CRPS can be expressed as:

$$\text{CRPS}(F, y) = \mathbb{E}_F |X - y| - \frac{1}{2} \mathbb{E}_F |X - X'|, \quad X, X' \stackrel{iid}{\sim} F,$$

which highlights its decomposition into two components: the average proximity between forecasts and observations, and the penalty for excessive ensemble dispersion.

In practical implementation, given a set of M simulated trajectories over T periods, the CRPS at time t is approximated as:

$$\widehat{\text{CRPS}}_t = \frac{1}{M} \sum_{m=1}^M |X_t^{(m)} - y_t| - \frac{1}{2M^2} \sum_{m=1}^M \sum_{m'=1}^M |X_t^{(m)} - X_t^{(m')}|,$$

where $X_t^{(m)}$ denotes the forecast of scenario m at time t , and y_t the realized value.

The final score for each series is obtained through temporal aggregation:

$$\text{CRPS} = \frac{1}{T} \sum_{t=1}^T \widehat{\text{CRPS}}_t,$$

preserving the original data units (US\$/kg). Lower CRPS values indicate better-calibrated forecasts, with distributions placing greater probability mass around the observed values.

6.3.1.0.2 Weighted Interval Score (WIS).

The WIS is a univariate proper score based on prediction intervals, which summarizes in a single metric both the **coverage** and the **width** of multiple confidence intervals. This criterion is particularly useful when forecasts are expressed in terms of quantiles, as is common in recent probabilistic models (Bracher *et al.*, 2022).

Given a set of coverage levels $\alpha \in (0, 1)$, for each central $(1 - \alpha)$ interval, with lower and upper bounds l_α, u_α , the *Interval Score* (IS) is defined as:

$$IS_\alpha(F, y) = (u_\alpha - l_\alpha) + \frac{2}{\alpha} (l_\alpha - y) \mathbb{I}\{y < l_\alpha\} + \frac{2}{\alpha} (y - u_\alpha) \mathbb{I}\{y > u_\alpha\}.$$

The first term penalizes excessively wide intervals, while the additional terms penalize cases where the observed value y falls outside the predicted range.

The WIS is obtained as the weighted average of the scores across different coverage levels, also including the predicted median $\hat{y}_{0.5}$:

$$WIS(F, y) = \frac{1}{K+0.5} \left(0.5 \cdot |y - \hat{y}_{0.5}| + \sum_{k=1}^K w_k IS_{\alpha_k}(F, y) \right),$$

where K is the number of coverage levels considered and w_k are the weights assigned to each interval. In practice, we use symmetric coverage levels of 50%, 80%, and 95%, with equal weights, following recommendations from the epidemiological and economic forecasting literature (Bracher *et al.*, 2022).

The WIS is computed directly from the empirical quantiles of the simulated trajectories, without requiring integrated approximations. Lower WIS values indicate distributions that are simultaneously more **sharp** (narrow intervals) and well-calibrated (high observed coverage rate). As with the CRPS, all values are reported in the original units of the series (US\$/kg), ensuring substantive interpretability of the results.

6.3.1.0.3 Energy Score (ES).

The ES is a multivariate proper scoring rule that generalizes the logic of CRPS to distributions in $\mathbb{R}^D$ (Gneiting; Raftery, 2007). It evaluates the overall quality of the predicted joint distribution. It simultaneously accounts for marginal behavior and cross-series dependence.

Formally, for an observed vector $y \in \mathbb{R}^D$ and a predictive distribution F , the ES is defined as:

$$ES(F, y) = \mathbb{E}_F \|X - y\| - \frac{1}{2} \mathbb{E}_F \|X - X'\|, \quad X, X' \stackrel{iid}{\sim} F,$$

where $\|\cdot\|$ denotes the Euclidean norm. The first term measures the expected distance between simulated samples and the observation, while the second penalizes excessive dispersion in the predicted distribution.

In practice, given an ensemble of M simulated trajectories $\{X_t^{(m)}\}_{m=1}^M$ at time t , the ES is approximated by:

$$\widehat{ES}_t = \frac{1}{M} \sum_{m=1}^M \|X_t^{(m)} - y_t\| - \frac{1}{2M^2} \sum_{m=1}^M \sum_{m'=1}^M \|X_t^{(m)} - X_t^{(m')}\|.$$

The final score is obtained through temporal aggregation:

$$ES = \frac{1}{T} \sum_{t=1}^T \widehat{ES}_t,$$

maintaining the original data units (US\$/kg).

Lower ES values indicate that the predicted joint distribution places greater probability mass close to the actually observed vectors, making it a robust indicator of the overall proximity between forecasts and reality.

6.3.1.0.4 Variogram Score (VS).

While the ES measures the global proximity of the predicted distribution to the observed one, the VS places greater emphasis on co-movement patterns among variables (Scheuerer; Hamill, 2015). As a multivariate proper scoring rule, it specifically evaluates the quality of dependence between forecast components and is relatively insensitive to marginal errors.

For an observed vector $y \in \mathbb{R}^D$ and a predictive distribution F , the VS is defined as:

$$VS(F, y) = \sum_{i=1}^D \sum_{j=1}^D w_{ij} (|y_i - y_j|^p - \mathbb{E}_F |X_i - X_j|^p)^2,$$

where $w_{ij} \geq 0$ are weights (commonly set to 1), and p is a fixed power, usually $p = 0.5$ or $p = 1$.

In practice, using an ensemble of M simulated trajectories, the expectation is approximated as:

$$\mathbb{E}_F |X_i - X_j|^p \approx \frac{1}{M} \sum_{m=1}^M |X_{i,t}^{(m)} - X_{j,t}^{(m)}|^p.$$

The average VS over the validation horizon is obtained as:

$$VS = \frac{1}{T} \sum_{t=1}^T VS_t,$$

with VS_t calculated according to the above formula for each time t .

Lower VS values indicate that the differences between components of the joint forecast are well calibrated with respect to the actually observed differences, signaling accurate reproduction of co-movements across series. Thus, the VS complements the ES: while the ES captures global proximity, the VS specifically focuses on the quality of conditional dependence among variables.

Taken together, the four scores provide a comprehensive evaluation: CRPS and WIS assess marginal calibration, while ES and VS capture the quality of multivariate dependence. This approach ensures that the models are evaluated both in terms of individual forecasts and the global consistency across variables.

6.4 Results

In this section, we compare the proposed method (CMP-LSTM) with the VARMA–Monte Carlo benchmark across two out-of-sample validation horizons: 5 years ($H = 60$ months) and 10 years ($H = 120$ months).

We present results for three datasets: (i) the combined Soybean+Wheat set (7 series), (ii) the Soybean chain (3 series), and (iii) the Wheat chain (4 series). The reported metrics correspond to the four measures described in Section 3, allowing us to evaluate both marginal quality and joint distribution. In all cases, lower values indicate better predictive performance.

We first report aggregated numerical results for each dataset and horizon, followed by a complementary graphical inspection.

Soybean+Wheat Set

The consolidated results for the three evaluated scenarios are presented in Table 6.2. The results indicate systematic improvements of CMP-LSTM relative to the VARMA–Monte Carlo benchmark across most dimensions and horizons evaluated.

At the 5-year horizon, we observe a systematic reduction in marginal probabilistic errors (CRPS and WIS), with improvements ranging from approximately 21% to 25% in the combined Soybean+Wheat dataset. For the multivariate scores (ES and VS), the gains are around 21% to 40%, suggesting that CMP-LSTM not only improves the individual calibration of the series, but also more faithfully reproduces the co-movements among variables. An exception occurs in the case of Soybean Oil, where VARMA shows superior performance, a point discussed later.

At the 10-year horizon, the gains of CMP-LSTM become more pronounced. The average reduction in CRPS and WIS approaches 38% to 43%, while ES and VS show decreases 38% and 57% compared to the benchmark. These results confirm that the integration of probabilistic

Series	Soybean + Wheat											
	5 Years						10 Years					
	LSTM-Copulas		VARMA		% Change		LSTM-Copulas		VARMA		% Change	
	CRPS	WIS	CRPS	WIS	CRPS	WIS	CRPS	WIS	CRPS	WIS	CRPS	WIS
Soybean Grain	0,077	0,247	0,100	0,310	23%	20%	0,065	0,211	0,122	0,411	47%	49%
Soybean Meal	0,026	0,078	0,052	0,180	50%	56%	0,035	0,108	0,076	0,263	54%	59%
Soybean Oil	0,273	0,935	0,182	0,599	-50%	-56%	0,225	0,766	0,228	0,801	1%	4%
Wheat Grain	0,049	0,148	0,059	0,190	18%	22%	0,043	0,134	0,073	0,256	41%	48%
Wheat Flour	0,070	0,220	0,083	0,273	16%	19%	0,055	0,171	0,108	0,383	49%	55%
Pasta	0,069	0,209	0,153	0,526	55%	60%	0,137	0,456	0,198	0,720	31%	37%
Bread	0,207	0,640	0,320	1,154	35%	45%	0,262	0,876	0,459	1,659	43%	47%
Energy Score	0,374		0,489		24%		0,427		0,691		38%	
Variogram Score	0,254		0,422		40%		0,299		0,698		57%	

Table 6.2 – Results for the analyses conducted on the unified Soybean and Wheat datasets, at 5- and 10-year horizons

Series	Soybean											
	5 Years						10 Years					
	LSTM-Copulas		VARMA		% Change		LSTM-Copulas		VARMA		% Change	
	CRPS	WIS	CRPS	WIS	CRPS	WIS	CRPS (+)	WIS (+)	CRPS (+)	WIS (+)	CRPS	WIS
Soybean Grain	0,041	0,127	0,117	0,346	65%	63%	0,039	0,120	0,115	0,357	66%	66%
Soybean Meal	0,022	0,075	0,056	0,181	61%	59%	0,021	0,072	0,070	0,233	70%	69%
Soybean Oil	0,149	0,461	0,186	0,566	20%	18%	0,136	0,419	0,196	0,677	31%	38%
Energy Score	0,159		0,237		33%		0,147		0,239		39%	
Variogram Score	0,059		0,084		30%		0,055		0,077		30%	

Table 6.3 – Results for the analyses conducted on the datasets representing the soybean supply chain, at 5- and 10-year horizons

LSTM and dynamic copulas enhances forecast robustness over long horizons, while preserving both marginal consistency and multivariate dependence structure.

Soybean Chain

In the soybean chain, the gains of CMP-LSTM over the benchmark are consistent (Table 6.3). At the 5-year horizon, on average across the three series, this corresponds to a reduction of approximately 49% in CRPS and 47% in WIS relative to VARMA. At the multivariate level, both ES and VS showed decreases of about 33% and 30%, indicating a better reproduction of the joint structure among soybean grain, meal, and oil.

At the 10-year horizon, the improvements become even more expressive: CRPS decreases by around 56% and WIS by about 58%, while ES shows a reduction of 39% and VS of 30%.

These results highlight that the proposed method preserves both calibration and dependence even at longer horizons.

Wheat Chain

In the wheat chain, the gains were equally robust (Table 6.4). At the 5-year horizon, CMP-LSTM reduced CRPS by approximately 52% and WIS by 56%. The multivariate scores also presented substantial reductions: 48% in ES and 80% in VS, demonstrating strong ability to capture co-movements among wheat grain, flour, pasta, and bread.

At the 10-year horizon, performance remains consistent: average reductions of 49% in

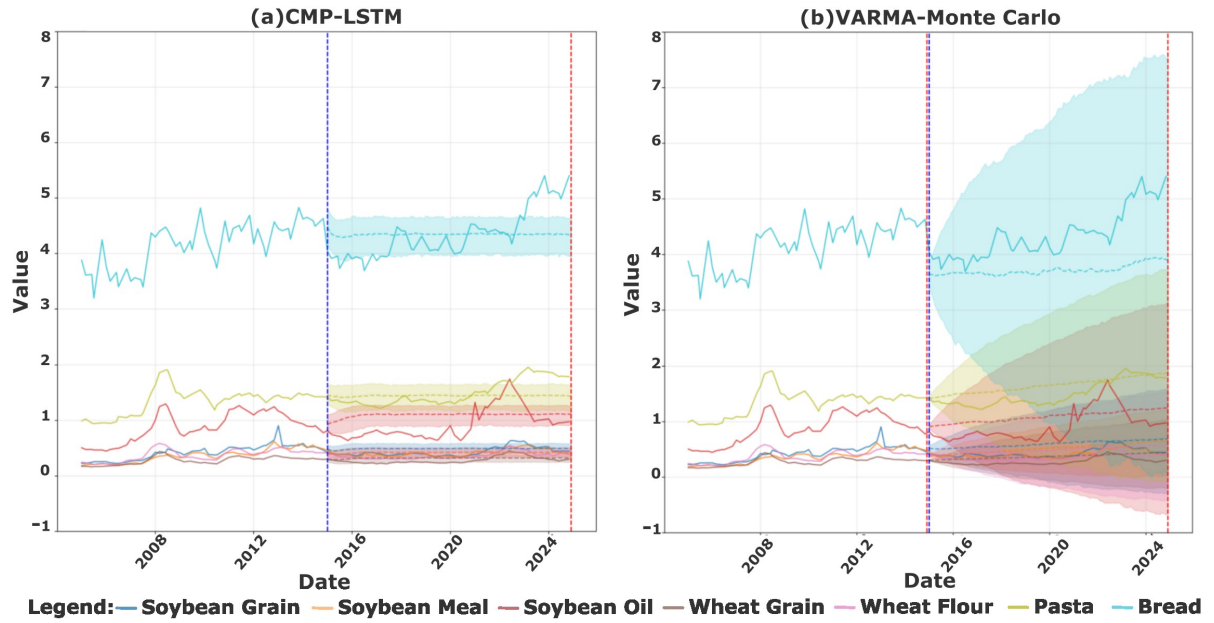


Figure 6.1 – Projection of all analyzed time series jointly (90% prediction interval)

CRPS and 53% in WIS, with decreases of 44% in ES and 72% in VS.

These results reinforce that CMP-LSTM not only improves marginal calibration, but also provides more faithful multivariate representations.

Series	Wheat											
	5 Years						10 Years					
	LSTM-Copulas		VARMA		% Change		LSTM-Copulas		VARMA		% Change	
	CRPS	WIS	CRPS	WIS	CRPS	WIS	CRPS	WIS	CRPS	WIS	CRPS	WIS
Wheat Grain	0,034	0,096	0,069	0,213	51%	55%	0,037	0,112	0,079	0,270	54%	59%
Wheat Flour	0,046	0,132	0,096	0,307	53%	57%	0,042	0,126	0,117	0,405	64%	69%
Pasta	0,062	0,205	0,167	0,564	63%	64%	0,136	0,460	0,211	0,760	36%	39%
Bread	0,166	0,499	0,279	1,017	41%	51%	0,253	0,848	0,439	1,594	42%	47%
Energy Score	0,200		0,386		48%		0,309		0,551		44%	
Variogram Score	0,014		0,070		80%		0,049		0,176		72%	

Table 6.4 – Results for the analyses conducted on the datasets representing the wheat supply chain, at 5- and 10-year horizons

6.4.1 Graphical Analyses

Visual analysis complements the probabilistic scores by enabling inspection of aspects that are not fully captured by numerical metrics. Figures 6.1 presented in this section illustrate 90% prediction intervals and simulated dispersions for representative subsets of the soybean and wheat chains.

In terms of marginal calibration, it is observed that the prediction intervals generated by CMP-LSTM show greater adherence to the realized values, concentrating predictive mass around the observed series without resorting to excessively wide intervals. This pattern confirms the reductions in CRPS and WIS reported earlier, evidencing sharper and better-calibrated distributions.

In the multivariate analyses, the scatter plots (Figure 6.2) highlight that the samples

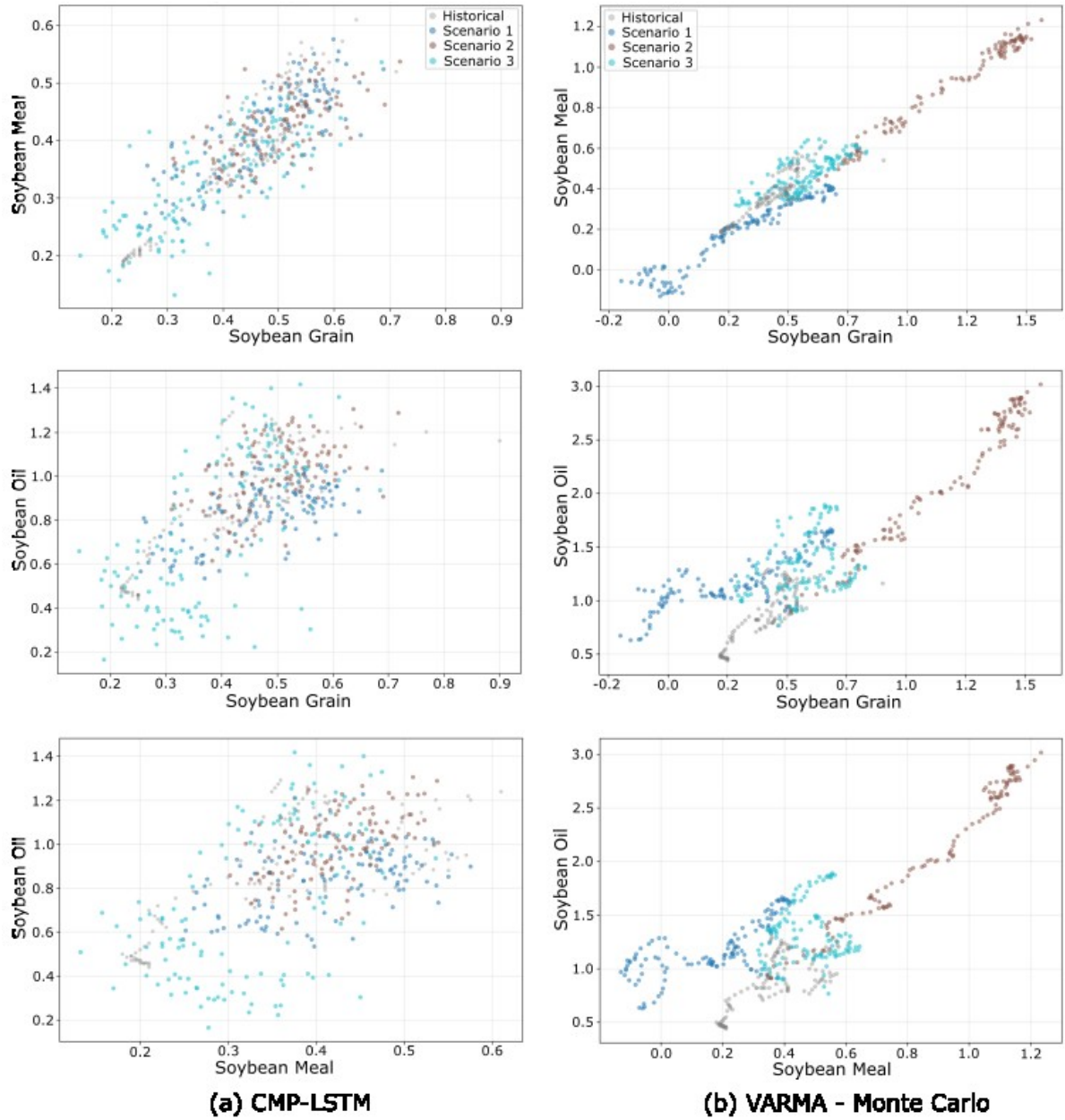


Figure 6.2 – Scatter plot – Representation of the soybean supply chain. The plots correspond to three randomly selected subsets of projection ensembles for each dataset.

simulated by CMP-LSTM more faithfully reproduce the empirical distribution of the data, in contrast to VARMA–Monte Carlo, which tends to underestimate the relative variability among components. This behavior is consistent with the gains observed in ES and, particularly, in VS, reinforcing the method’s ability to capture co-movements.

A specific case is that of Soybean Oil (Figure 6.3), where the metrics indicated lower performance compared to VARMA at the 5-year horizon. Although both methods show similar deviations from the central trend, CMP-LSTM trajectories remain closer to the actually observed values, whereas VARMA tends to overestimate marginal uncertainty. This behavior inflates

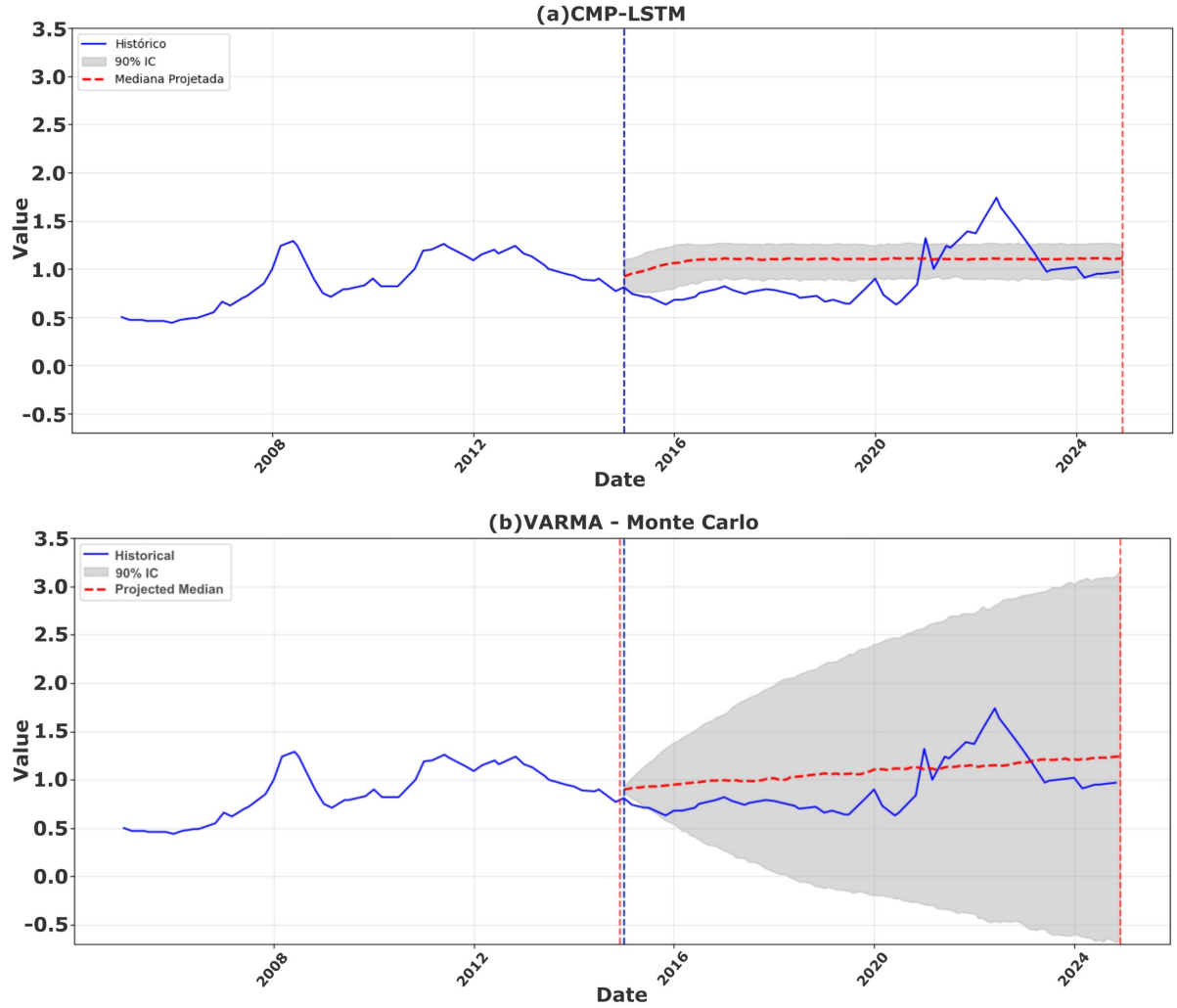


Figure 6.3 – Forecast projections for the Soybean Oil series obtained from the combined datasets (90% prediction interval).

the dispersion of its forecasts, increasing the likelihood of overlap with the actual series and, consequently, favoring its univariate metrics (CRPS and WIS). In the case of CMP-LSTM, the tighter calibration of marginal distributions reduces the width of prediction intervals, but in situations of high variability this may result in lower overlap with observed values, penalizing univariate metrics even when the model remains more faithful to the empirical pattern. This contrast highlights that, in certain contexts, interpreting univariate scores in isolation can be misleading, whereas graphical inspection and multivariate results reveal greater practical and informative consistency of the proposed method.

In summary, the graphical results corroborate the conclusions obtained from the metrics, demonstrating that CMP-LSTM produces more realistic predictive distributions, both at the individual level and in the joint behavior of the series.

Critério	CRPS	WIS	ES	VS
Sequence length	3.3%	4.5%	4.8%	9.2%
Hidden size	11.9%	14.7%	9.5%	12.7%
Number of layers	8.2%	11.9%	6.8%	7.5%
Dropout	1.3%	1.9%	1.0%	2.3%

Table 6.5 – Hyperparameter sensitivity analysis

6.4.2 Sensitivity Analysis

The proposed model exhibited low to moderate sensitivity to variations in its hyperparameters when evaluated using the CRPS, WIS, ES, and VS metrics. Independent perturbations were applied to the following parameters:

- sequence length (1, 6, 12, 24, **36**, 48);
- number of neurons per layer (hidden size) (12, 24, 32, **64**, 128, 256);
- number layers (1, **2**, 3, 4, 8);
- dropout rate (0,10; 0,15; **0,20**; 0,25; 0,30).

The reference architecture was defined with sequence length = 36, hidden size = 64, two layers, and dropout = 0.20, and each hyperparameter was modified individually to isolate its marginal effect on the probabilistic performance metrics.

Table 6.5 summarizes the average variations observed in the CRPS, WIS, ES, and VS indicators. Overall, these metrics remained stable across all combinations tested, with fluctuations that preserved the global performance pattern. This stability does not imply the absence of architectural differences; rather, it indicates that pointwise metrics capture the marginal and joint distributional quality of the forecasts.

This becomes evident when analyzing models parametrized with hidden sizes above 48 and sequence lengths greater than 24. In these configurations, the graphical projections became smoother and structurally more coherent as the number of neurons increased. Hidden sizes above approximately 64 neurons showed a greater ability to capture complex temporal patterns, particularly medium- and long-range dependencies. However, these improvements require a gradual reduction in dropout, since wide networks combined with high dropout tend to underutilize their representational capacity.

Conversely, very large hidden sizes, especially above 128, substantially increase computational cost while providing only marginal gains in predictive quality and little qualitative improvement in the projected trajectories beyond that threshold. This indicates a clear diminishing return in expanding the network’s width indiscriminately.

Regarding the number of layers, architectures with one or two layers produced the most consistent results. Starting from three layers, there was a consistent tendency toward overfitting and overfeat, which reduced the quality of the projected trajectories and increased variance

across runs. Deeper models were unnecessary for the temporal structure of the series analyzed and in some cases were detrimental.

The sequence length also exhibited a dual behavior. Sequences shorter than 24 time steps resulted in loss of temporal memory, causing projections to resemble white-noise patterns even when the probabilistic metrics remained stable. In contrast, very long sequences reduce the effective sample size available for training and weaken the model’s learning capacity. For this reason, `seq_length` proved to be a hyperparameter that requires careful calibration due to its direct impact on the temporal depth accessible to the model.

Finally, dropout was numerically the most stable hyperparameter, with variations below 3 percent across all criteria. Its role was primarily preventive against overfitting and should be adjusted according to network size: moderate dropout works best for compact architectures, whereas wider networks benefit from lower dropout rates to fully leverage their representational capacity.

Taken together, these results reinforce that although CRPS, WIS, ES, and VS are useful, they are not sufficient on their own to assess model quality because they do not capture the full behavioral structure of the projected trajectories. The graphical diagnosis played a crucial role by revealing noise patterns, excessive smoothness, or loss of temporal dependence that would not be detected through metrics alone. The combined quantitative and visual evaluation confirms that the model exhibits global robustness while providing clear guidelines for the appropriate calibration of hyperparameters.

6.4.3 Observed Limitations

Despite the overall favorable results for the CMP-LSTM method, some specific limitations were identified.

Erratic behavior in individual projections: When comparing the unit forecasts generated by CMP-LSTM (Figure 6.4a) with the original series, the presence of multiple peaks and troughs can be observed throughout the forecasting horizon. This pattern reveals greater intra-sample variability, which may be interpreted as a reflection of the model’s heightened sensitivity to local fluctuations. On the other hand, the forecasts derived from VARMA–Monte Carlo (Figure 6.4b) exhibit smoother behavior, resulting from the linear nature of the method and its tendency to overestimate marginal uncertainty.

This contrast highlights that, although CMP-LSTM is more effective in preserving marginal calibration and multivariate dependence structure, it may produce seemingly erratic trajectories in individual scenarios. From the perspective of univariate metrics, this characteristic may be penalized, since greater variability reduces the intersection rate with the observed series. However, in practical terms, such behavior may better reflect the stochastic reality of highly volatile supply chains, even if it lowers performance in univariate scores.

Gaussian LSTM Tail Modeling Limitation: The LSTM model used in this study presents a structural limitation inherent to its probabilistic architecture, which estimates only

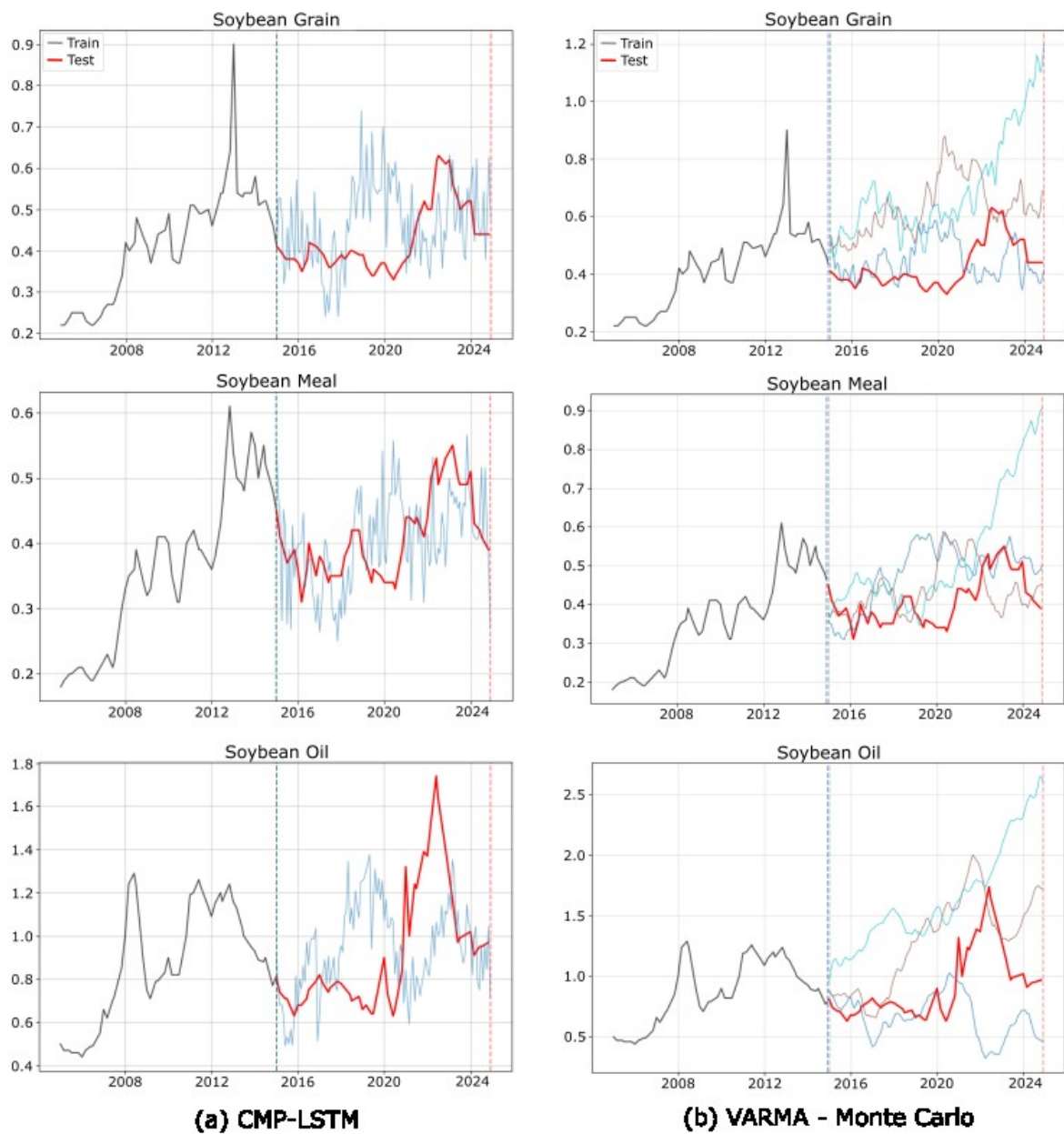


Figure 6.4 – Representative plot of individual forecasts – Sample of projections from the soybean chain, randomly selected

the parameters of a conditional normal distribution. As a result, the marginal modeling cannot represent asymmetry, heavy tails, or extreme events that may occur in industrial time series.

Thus, while the copula component can reproduce complex dependence patterns (Gaussian, t-Student, and Archimedean families), the marginal learned by the LSTM remains restricted to a symmetric, light-tailed form. This limitation may affect marginal accuracy in contexts characterized by abrupt shocks, asymmetry, or tail-driven volatility. Furthermore, the propagation of uncertainty over long horizons remains conditioned by the normality assumption, reducing the model's ability to represent rare events of large magnitude.

6.4.4 Management Implications

The stochastic multivariate forecasts generated by the CMP-LSTM framework have several managerial implications, particularly for decision-making in industrial production systems and capital-intensive investment projects. First, the ability to generate long-term correlated scenarios enables a structured scenario analysis, allowing managers to evaluate how simultaneous changes in key variables (e.g., input prices, production volumes, or market demand) propagate through the system. This is critical for identifying vulnerabilities, stress conditions, and alternative operating strategies.

Second, the projected distributions support investment appraisal by providing probabilistic estimations of future cash flows, production margins, and operating costs. Rather than relying on single deterministic projections, managers can assess expected values, dispersion, and tail risks, resulting in more robust return projections and financial planning.

Third, the multivariate nature of the model makes it possible to estimate future trajectories of revenues, costs, inventories, and receivables jointly, which directly supports the forecasting of working-capital requirements. These estimates allow firms to anticipate capital constraints, liquidity needs, and buffer requirements under uncertainty.

Fourth, the probabilistic structure of the CMP-LSTM allows for the explicit quantification of risk, including downside risk, probability of loss, value-at-risk-type measures, and the distribution of payback times. This facilitates the estimation of payback periods under uncertainty, enabling managers to compare investment alternatives based not only on expected returns but also on the distributional properties of outcomes.

Finally, the model provides a transparent quantitative basis for loan applications and funding requests, as probabilistic financial projections and scenario-based stress tests can be incorporated into risk reports required by banks, development agencies, and internal governance committees. The stochastic outputs of the model can also be integrated into financial and statistical calculations, such as net present value (NPV), internal rate of return (IRR), cost-of-capital assessments, and sensitivity analyses.

Overall, the CMP-LSTM framework enhances decision-making by replacing single-point forecasts with full distributional insights, enabling more informed strategic, operational, and financial evaluations in industrial settings.

6.5 Conclusion

This study introduced the CMP-LSTM method, which integrates heteroscedastic probabilistic LSTM networks with dynamic R-vine copulas for the generation of multivariate stochastic scenarios. The proposal was evaluated on time series from the soybean and wheat supply chains, comparing its performance with the VARMA–Monte Carlo benchmark at 5- and 10-year horizons.

The empirical findings are supported by commodity price data from global soybean and wheat supply chains and therefore reflect the structural characteristics of these markets. Extensions to higher-dimensional systems or to domains with substantially different dependency structures remain an avenue for future research.

The results indicated consistent CMP-LSTM gains in both univariate and multivariate metrics, with average reductions of up to 50% in CRPS and WIS, and up to 70–80% in ES and VS, depending on the horizon and the supply chain analyzed. These advances reflect the method’s ability to simultaneously preserve marginal calibration and multivariate dependence structure, producing more robust and informative probabilistic forecasts. Graphical analysis corroborated these findings, highlighting better-calibrated intervals and multivariate dispersions closer to the observed distribution.

Overall, the comparative results indicate that the performance gains of CMP-LSTM become more pronounced as the forecast horizon increases. While improvements are observed in medium-term projections, the relative advantage is stronger in long-horizon forecasting. These findings support the model’s suitability for extended stochastic scenario generation within the analyzed supply-chain context.

From a practical standpoint, the results suggest that CMP-LSTM represents a promising tool for decision support in supply chains, particularly in medium- and long-term planning scenarios where integrated risk quantification is crucial.

Beyond managerial applications, the findings also have methodological relevance for studies concerned with supply-chain resilience and food-system risk assessment. More reliable long-horizon multivariate forecasting can improve the analytical basis for strategic planning in agro-industrial networks, particularly in environments characterized by price volatility and cross-market dependencies. By enhancing probabilistic calibration and preserving inter-market dependence structures, the proposed framework provides a more consistent foundation for scenario analysis in contexts where uncertainty is structurally significant.

A natural extension is its application to the evaluation of investment projects in the manufacturing industry, where decisions on the implementation of new plants, modernization of equipment, or diversification of production lines depend on the simulation of multiple economic scenarios. Integrating CMP-LSTM with financial and techno-economic feasibility models can enhance risk quantification capabilities and support managers in choosing more robust alternatives under uncertainty.

6.5.1 Future Work

(i) **Improvement of individual forecasts:** results revealed that, in some cases, the unit trajectories generated by CMP-LSTM exhibit more erratic behavior compared to VARMA–Monte Carlo. Future studies may explore alternative architectures incorporating non-diagonal covariance structures, temporal regularization mechanisms, or post-processing smoothing, in order to reduce spurious oscillations without compromising probabilistic calibration.

(ii) **Sectoral applications:** further investigation is recommended into the use of CMP-LSTM in real-world industrial investment analysis contexts, particularly in capital-intensive manufacturing supply chains. Examples include factory modernization projects, production capacity expansions, and integration of agro-industrial chains, where investment decisions rely on realistic forecasts of prices, energy costs, demand, and market risks.

With these developments, CMP-LSTM can evolve from a methodological contribution to an applied tool for risk analysis in manufacturing investment projects, thereby expanding its practical and academic relevance.

(iii) **Gaussian LSTM limitation:** As a limitation, it is noted that the Gaussian LSTM model adopted assumes conditional distributions with approximately constant variance over the forecasting horizon, reflecting the average variability observed under the historical regime. Although this characteristic is consistent with stationary processes, it may limit the model’s ability to capture more persistent local dynamics or gradual changes in the conditional mean in long-term projections.

In this regard, future research may explore replacing the Gaussian LSTM with probabilistic autoregressive approaches, such as the DeepAR method, which has been shown to be more effective in preserving local patterns and dynamically adapting conditional means over time. A comparative analysis of these approaches may contribute to improvements in representing temporal heterogeneity and refining risk analysis over longer forecasting horizons.

(iv) **Expanded Benchmarking:** In addition, a broader benchmarking exercise incorporating alternative probabilistic baselines, such as Gaussian Copula VAR, DeepAR, Vector Error Correction Model (VECM), or Transformer-based forecasting models, would help contextualize the relative contribution of structured copula-based dependence modeling within the broader landscape of modern multivariate probabilistic forecasting methods.

(v) **Ablation Analysis:** several methodological extensions remain open for future research, particularly regarding the isolated evaluation of each component of the CMP-LSTM framework. A systematic ablation analysis, separating the contribution of the Gaussian LSTM from that of the dynamic R-vine copula, would clarify the marginal and joint effects of each module on forecast performance.

(vi) **Generalization to broader multivariate environments:** Although the empirical validation encompassed multiple stages of the soybean and wheat supply chains, including intermediate and processed products, further assessment in substantially higher-dimensional systems or in structurally distinct economic domains would provide additional evidence of the

framework's scalability and adaptability.

6.5.2 Acknowledgments

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7 Síntese e Discussão

Com o objetivo de propor uma *abordagem de inteligência artificial para quantificação de risco na cadeia de suprimentos*, de forma a apoiar o processo de tomada de decisão em investimentos na indústria de transformação de bens de consumo, foram realizadas três atividades consecutivas e inter-relacionadas.

Inicialmente, buscando *compreender as relações entre risco na cadeia de suprimentos e o sucesso de investimentos na indústria de transformação*, foi conduzido um estudo de revisão sistemática da literatura, utilizando-se a metodologia PRISMA (Page *et al.*, 2021). Identificaram-se 16 artigos relevantes dedicados ao estudo de risco em investimentos na indústria de transformação. Após o processo de qualificação, procedeu-se à extração e catalogação dos metadados, com foco nas abordagens e métodos empregados em cada estudo. Foram analisados os principais abordagens de modelagem da cadeia produtiva (ou de determinação das variáveis do estudo), as variáveis mais frequentemente utilizadas, os métodos de análise (simples ou compostos), os setores produtivos mais investigados e os objetivos específicos de cada artigo.

Os resultados dessa revisão indicaram que abordagens estocásticas e de programação matemática foram utilizadas em 62% dos casos. O estudo também indicou que 71% dos estudos desejavam aperfeiçoar os métodos de tomada de decisão e 57% desejavam determinar quanto investir nos projetos. Com as variáveis sendo determinadas em 50% dos casos pela análise de outros estudos ou pela consultoria de especialistas, os 50% restantes das variáveis foram determinadas pelos autores. Com as variáveis mais empregadas sendo: custos operacionais e de infraestrutura, volumes de produção, preços de venda, custos logísticos e de matérias-primas, investimentos de capital e custos financeiros.

Com base nas informações obtidas nessa primeira etapa, passou-se à fase de *identificação e teste de técnicas de inteligência artificial aplicáveis à quantificação de riscos de investimento na indústria de manufatura*. Propôs-se, então, um modelo conceitual sequencial, composto pelas seguintes etapas:

- Desenho do processo produtivo ou identificação das variáveis: realizado por meio da análise de processos produtivos existentes, da consulta a especialistas e da revisão de estudos acadêmicos.
- Projeção estocástica correlacionada de variáveis: baseada em uma abordagem híbrida entre os métodos VAR–Monte Carlo e redes neurais LSTM.
- Avaliação dos cenários projetados: fundamentada na modelagem matemático-financeira do processo produtivo.

Entretanto, essa abordagem apresentou limitações técnicas e teóricas, especialmente na etapa de projeção estocástica de cenários. Do ponto de vista técnico, o método inicial não foi capaz de identificar e se adaptar adequadamente à heterocedasticidade. Em testes preliminares, apresentou desempenho estatístico insatisfatório, tanto na preservação das correlações entre variáveis quanto na estabilidade geral do modelo. Sob a perspectiva teórica, o método tratava os ruídos brancos como processos brownianos, o que resultava em inconsistências conceituais.

Com o intuito de superar essas limitações e *instanciar a aplicação prática da abordagem proposta*, desenvolveu-se um novo método de projeção estocástica correlacionada de longo prazo, denominado CMP-LSTM. O método combina o uso de Copulas R-Vine para determinar as correlações entre séries temporais com redes neurais LSTM gaussianas para a projeção das médias e desvios-padrão.

Para validação da proposta, foram coletados dados reais mensais correspondentes a um período de 240 meses, referentes às cadeias produtivas derivadas do trigo e da soja. Metade desses dados foi utilizada para a aplicação do método, com projeções de 60 e 120 meses. A outra metade, juntamente com os métodos estatísticos CRTM, WIS, ES e VS, foi utilizada para validação e comparação com os resultados obtidos por meio do método VARMA–Monte Carlo.

A avaliação dos resultados estatísticos e gráficos evidenciou melhorias expressivas no desempenho do método CMP-LSTM em relação aos modelos comparativos, tanto sob critérios univariados quanto multivariados. Nos horizontes de 60 meses, observou-se redução média entre 20% e 30% nas métricas marginais (CRPS e WIS) e entre 40% e 60% nas métricas multivariadas (ES e VS), indicando ganhos consistentes de calibração e melhor representação das correlações contemporâneas entre as séries. Já nos horizontes de 120 meses, os ganhos tornaram-se ainda mais pronunciados, com reduções médias entre 35% e 45% nas métricas marginais e entre 60% e 70% nas métricas multivariadas, chegando a 80% no caso do Variogram Score (VS) para a cadeia do trigo.

Esses resultados corroboram a capacidade do método proposto de preservar simultaneamente a calibração marginal das séries e a estrutura de dependência entre variáveis, demonstrando robustez estatística e alta aplicabilidade no contexto da indústria de transformação.

8 Conclusão

Por meio da revisão bibliográfica apresentada no Capítulo 4, foi alcançado o objetivo específico de “*analisar a relação entre riscos na cadeia de suprimentos e o sucesso de investimentos na indústria de transformação de bens de consumo*”. Essa etapa permitiu identificar o *gap* de pesquisa existente e consolidar as bases conceituais que orientaram as abordagens metodológicas adotadas nas fases subsequentes da investigação.

Na sequência, foi atingido o objetivo específico de “*identificar técnicas de inteligência artificial para determinação de riscos na cadeia de suprimentos, de forma a auxiliar o processo de tomada de decisão de investimentos na indústria de transformação de bens de consumo*”, conforme o modelo conceitual desenvolvido no Capítulo 5. Nesse modelo, estruturou-se um processo para: (i) o desenvolvimento teórico de um processo produtivo e a identificação das variáveis que o compõem; (ii) a definição da abordagem para projeção dessas variáveis por meio de ferramentas de inteligência artificial; e (iii) a seleção de técnicas para análise das projeções e quantificação dos riscos associados.

Na etapa final, voltada à aplicação prática, foi cumprido o objetivo específico de “*instanciar a aplicação da abordagem de inteligência artificial em um setor de transformação de bens de consumo*”. Para isso, a metodologia de projeção de séries temporais proposta no modelo conceitual foi aprimorada, resultando no desenvolvimento do método CMP-LSTM, capaz de realizar projeções estocásticas correlacionadas de longo prazo. Essa capacidade foi demonstrada por meio da aplicação do método a dados reais e da comparação de seu desempenho com um método de referência, utilizando métricas estatísticas para avaliar a acurácia e a calibração probabilística das previsões, conforme detalhado no Capítulo 6.

Além do desenvolvimento metodológico, buscou-se disseminar o conhecimento produzido. O artigo *Economic Feasibility Analysis in the Manufacturing Industry* foi aceito para publicação na revista **GEPROS** (Silva; Frazzon, 2025a), enquanto o artigo *Risk Quantification in Manufacturing Industry Investments* foi publicado na revista **IMTE-GAM-JETIA** (Silva; Frazzon, 2025b). Também foi submetido o artigo *Joint Modeling of LSTM Marginals and R-Vine Copulas for Long-Term Probabilistic Forecasting of Multivariate Time Series* à revista **Journal of Modelling in Management**, atualmente em processo de revisão.

Dessa forma, considera-se que tanto o objetivo geral de “*propor uma abordagem de inteligência artificial para quantificação de riscos na cadeia de suprimentos, de modo a apoiar o processo de tomada de decisão de investimentos na indústria de transformação de bens de consumo*”, quanto os objetivos específicos relacionados foram plenamente alcançados.

8.1 Limitações e Futuras Pesquisas

Dentre as limitações identificadas, destacam-se duas principais.

Primeiramente, o método proposto foi testado apenas parcialmente, aplicando-se exclusivamente à etapa de projeção das séries temporais. As etapas de desenho da cadeia produtiva e de avaliação prática dos cenários projetados não foram implementadas em razão de limitações de tempo, decorrentes da complexidade inerente à modelagem detalhada de processos produtivos sob rigor metodológico, incluindo aspectos tributários e normativos. A aplicação incompleta dessas etapas poderia comprometer a precisão e a relevância acadêmica dos resultados.

Além disso, destaca-se como limitação e oportunidade para futuras pesquisas, a aplicação do método CMP-LSTM a bases de dados mais amplas, com o objetivo de avaliar sua robustez e capacidade generalizável. Essa restrição decorre do acesso limitado a séries temporais correlacionadas e confiáveis que apresentassem a janela temporal desejada.

8.2 Considerações finais

Em síntese, apesar de suas limitações, este trabalho contribui para o avanço do uso de técnicas de inteligência artificial na quantificação de riscos de investimentos na indústria de transformação, oferecendo uma metodologia que alia rigor científico e aplicabilidade prática. Espera-se que os resultados aqui apresentados sirvam de base para novas pesquisas que aprofundem a modelagem integrada de riscos e ampliem o uso de abordagens híbridas em contextos industriais diversos. Assim, acredita-se que esta investigação representa um passo relevante na consolidação da inteligência artificial como ferramenta de apoio à tomada de decisão estratégica no setor produtivo.

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