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Algorithm-Driven SME Evolution: Optimising Automotive Supply Chains from Industry 4.0 to 5.0

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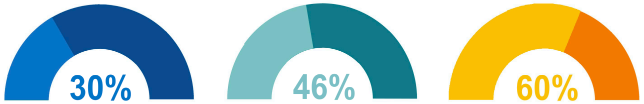
SMEs represent 90% businesses world wide
accounting for 50% of employment [1]

1. Introduction

Understanding the transition from Industry 4.0 to 5.0, SMEs—which make up a **vast majority of global businesses**—encounter significant challenges in adopting new technologies. Despite a **large number of automotive manufacturers moving towards smart factory integrations**, a relatively **small fraction of SMEs have embraced advanced algorithmic models** for optimising their supply chains. This highlights a crucial opportunity for growth, particularly as **consumer preferences shift towards more sustainable and value-driven choices**. For SMEs in the automotive sector, leveraging these technological advancements to meet evolving consumer expectations is not merely a technological upgrade but a strategic move towards sustainability and enhanced efficiency in a competitive landscape.



SME Utilise Advanced Algorithms for Supply Chain [2]
Automotive Manufacturers Embrace Innovation by 2022 [3]
Consumer Prioritise Value-driven Metrics Since 2020 [4]

2. Aim & Objectives

Investigate the adaptation and scalability of algorithmic models to assist SMEs in the automotive industry during the transition from Industry 4.0 to 5.0, with emphasis on optimising supply chain performance with value-driven metrics.

Identify Criteria
Success criteria and requirements for supply chain algorithms

Optimize Performance
Apply adapted algorithm to enhance SME supply chain efficiency and responsiveness.

Develop Adoption Strategies
Strategies for SMEs to adopt and implement the adapted algorithms.

Customize for SMEs
Select and adapt algorithms specifically for SME use in the automotive industry.

Value-driven metrics
Integrate sustainability and ethical metrics into supply chain optimization.

3. Methodology

1 Comprehensive Literature Synthesis
Conduct literature review, identify optimization requirements, Industry 4.0 to 5.0 transition, and SME needs in the automotive sector, focusing on theories and current practices.

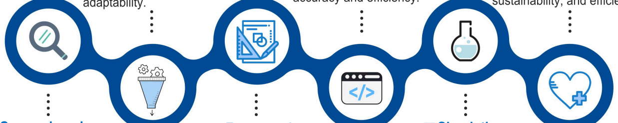
2 Algorithm Criteria Algorithm Pool
Identify key criteria from the literature review, compile a pool of algorithms meeting these criteria, focusing on SME adaptability.

3 Framework Development
Develop a framework to adapt a chosen algorithm from the pool to SME needs, considering SME constraints, industry challenges, and Industry 5.0 principles.

4 Python Implementation
Adapted algorithm in Python, using its libraries for data processing, algorithm development, and optimising accuracy and efficiency.

5 Simulation Testing
Conduct simulation testing with SME data, including cost, customer satisfaction, and delivery time, to assess the algorithm's supply chain optimization performance.

6 Value Metrics Adoption Strategies
Integrate value-driven metrics and create an adoption strategy for SMEs, focusing on scalability, sustainability, and efficiency.



4. Literature Review

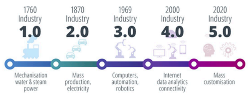


Figure 1: Industry Transition [6]

Evolution : Industry 4.0 to 5.0 [5]
- Automation to human creativity and machine efficiency.
- Emphasises sustainability and personalization.
- Challenges SMEs to adapt with human-machine collaboration.
- Need for adaptable, value-driven strategies in the automotive sector.

Impact of Industrial Transition on SMEs [7]
- Industry 5.0 demands technological adoption and cultural shifts towards human-centric values.
- Emphasises flexibility and customisation.
- SMEs leverage close customer relationships.
- Encourages blending innovation with human-centricity for competitive edge.

Supply Chain Optimization Algorithms [8]
- Minimizing costs and maximizing efficiency.
- Predictive algorithms and machine learning drive these improvements.
- High computational demands pose challenges for SMEs.
- Highlights the need for scalable, cost-effective solutions tailored to SMEs' constraints and goals.

Criteria for Optimal Supply Chain Optimization in SMEs Versus Large Corporations [9]
- Optimization criteria vary between SMEs and large corporations.
- **SMEs**—agility and flexibility; lean practices and JIT inventory.
- **Large corporations**—scalability and efficiency with advanced technologies.
- Both value sustainability and customer satisfaction.

Challenges and Possibilities for SMEs in Developing, Adapting, or Scaling Models [10]
- Algorithmic models in SME supply chains enhance efficiency and responsiveness.
- SMEs confront resource constraints and scalability challenges.
- Issues include technology access, implementation expertise, and adaptability.

5. Algorithm Criteria

Resource Utilisation
Low — Importance Meter
CPU and Memory Usage
Dependent against other critical criterias

Computational Efficiency
Mid — Importance Meter
Time to Solution (TTS)
Swift and efficient data handling for real-time decision-making

Industry 5.0 Alignment
Mid — Importance Meter
Industry 5.0 Technology Integration Index
Algorithm alignment with future industry standards and practices

Scalability
Mid — Importance Meter
Data Volume Handling Capacity
Accommodate the growth and varying sizes of SMEs

Resilience
Mid — Importance Meter
Downtime and Recovery Time
Ensure algorithm can withstand disruptions throughout its operation

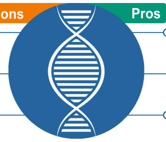
Adaptability
High — Importance Meter
Customization Flexibility Score
Algorithm effectiveness as industry conditions evolve

Accuracy
High — Importance Meter
Error Rate
Direct impact on decision-making quality

Real-Time Processing
High — Importance Meter
Latency
Keeping pace with the fast-moving automotive industry

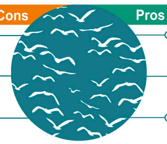
6. Algorithm Pool

NSGA-II
Non-Dominated Sorting Genetic Algorithm II
NSGA-II excels in solving multi-objective optimization problems, generating diverse Pareto-optimal solutions using evolutionary principles. [11]



Cons	Pros
Intensive computations	Diverse solutions
Needs parameter tuning	Handles multi-objectives
Slow convergence risk	Good for complex problems

PSO
Particle Swarm Optimisation
PSO leverages swarm intelligence to find optimal solutions in continuous spaces, balancing global exploration with local exploitation. [12]



Cons	Pros
Prone to local minima	Fast convergence
Variability in performance	Simple parameters
Limited by problem type	Versatile in applications

MILP
Mixed-Integer Linear Programming
MILP optimizes complex systems with linear objectives and constraints, efficiently handling both discrete and continuous variables for precise decision-making. [13]

Cons	Pros
Not scalable	Exact solutions
High complexity	Wide applicability
Linear constraints only	Clear problem formulation

7. NSGA-II Overview and SME Adaptation

General form of NSGA-II algorithm, additionally adapting NSGA-II for SMEs showcasing its potential in optimizing supply chains for the automotive industry, aligning with the transformative goals of Industry 5.0. [14]

NSGA-II General Model

Input
Identify Objectives (e.g., minimize cost) & Constraints (e.g., production capacity)

Initialisation
Generate initial population of supply chain configurations (e.g. production cost + delivery + inventory)

Evaluate Individual Fitness
Assess each population individual against objective

Ranking
Non-dominated sorting the population into fronts based on Pareto dominance.

Diversity
Calculate crowding distance within each front to maintain solution diversity.

Selection
Perform binary tournament selection based on rank and crowding distance. Population +1

Crossover and Mutation
Apply genetic operators to selected individuals to create a new generation.

New Generation Formation
Combine parent and offspring populations, then select the best individuals for the next generation.

No

Population reached? Yes

Termination Check
Check if the maximum number of generations has been reached. If not, return to step 3.

No

Generation reached? Yes

Output
Analyze the Pareto front solutions for trade-offs between objectives.

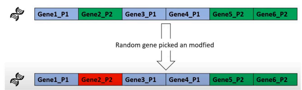


Figure 4: Example of Crossover Mutation in Gene Algorithm [15]

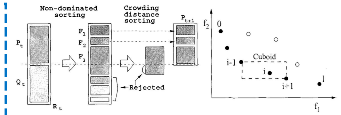


Figure 2: NSGA-II Crossover and Mutation & Crowding Distance [14]

Adaptation Proposal

- SME-specific constraints and objectives. User-friendly
  Example: Prioritize cost efficiency, accounting for smaller budgets.
- Initial solutions based on SME operations.
  Example: Solutions reflecting limited logistics an warehousing capabilities.
- Measure performance using metrics relevant to SMEs.
  Example: Focus on cash flow stability and short-term ROI.
- Feedback loop to modify **real-time** parameters as SME conditions change.
  Example: Inventory diruption; Price changes
- Select solutions offering flexibility in uncertain markets.
  Example: Choose configurations that easily adapt to supplier changes.
- Preserve solutions with attributes aiding SME survival.
  Example: Favor solutions with low upfront investment requirements.
- Feedback loop to gather performance data, and refine the problem definition, objectives, and constraints. Initiating a new iteration if needed.

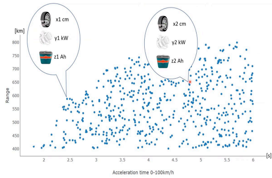


Figure 3: Example of NSGA-II Chart Population [15]

8. Inclusion of Value-driven Metrics

Value-driven metrics integrate sustainability, social responsibility, and operational resilience into business strategies, enhancing long-term success and ethical impact.

Sustainability
Measures aimed at reducing environmental impact, like carbon footprint and waste reduction.

Constraint & Objectives

Social Responsibility
Metrics that consider the welfare of employees, communities, and the broader society, such as fair labor.

9. Future Work

- **Finalize Adapted Algorithm Framework**: Convert the theoretical NSGA-II framework into a comprehensive Python codebase.
- **Integrate Value-driven Metrics**: Apply value-driven metrics into simulation code
- **Real-world Simulation**: Implement the algorithm with real-world data to simulate supply chain optimization scenarios.
- **Extensive Testing**: Test the algorithm against diverse operational parameters to ensure robustness and reliability.

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