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REVIEW ARTICLE

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Quantitative modelling approaches for lean manufacturing under uncertainty

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ABSTRACT

Lean manufacturing (LM) applies different tools that help to eliminate waste as well as the operations that do not add value to the product or processes to increase the value of each performed activity. Here the main motivation is to study how quantitative modelling approaches can support LM tools even under system and environment uncertainties. The main contributions of the article are: (i) providing a systematic literature review of 99 works related to the modelling of uncertainty in LM environments; (ii) proposing a methodology to classify the reviewed works; (iii) classifying LM works under uncertainty; and (iv) identify quantitative models and their solution to deal with uncertainty in LM environments by identifying the main variables involved. Hence this article provides a conceptual framework for future LM quantitative modelling under uncertainty as a guide for academics, researchers and industrial practitioners. The main findings identify that LM under uncertainty has been empirically investigated mainly in the US, India and the UK in the automotive and aerospace manufacturing sectors using analytical and simulation models to minimise time and cost. Value stream mapping (VSM) and just in time (JIT) are the most used LM techniques to reduce waste in a context of system uncertainty.

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Lean manufacturing; production management; optimisation; modelling; uncertainty; review

Acronyms:

5S	seiri, seiton, seiso, seiketsu, shitsuke
AM	analytical model
ANFIS	adaptive neurofuzzy inference system
ANP	analytic network process
CLTWN	cosorganisational labelled time workflow nets
CM	cellular manufacturing
DEA	data envelopment analysis
DES	discrete events simulation
DMAIC	define, measure, analyse, improve, control
DOE	design of experiments
DR	distributed robotics
DRC	dual resource constrained
EPQ	economic production quantity
ERP	enterprise resource planning
FISM	fuzzy interpretive structural modelling
FMEA	failure mode and effects analysis
FMONLP	fuzzy multi-objective non-linear programming
GRAI	graphs with results and actions interrelated
HS	hybrid simulation
IPA	intuitive and pragmatic approach
IRP	interpretive ranking process
ISIC	International Standard Industrial Classification
ISM	interpretive structural modelling
JIT	just in time
LM	lean manufacturing
LPS	last planner system
LSS	lean six sigma
MAS	multi-agent systems
MCDM	multiple criteria decision making
MH	metaheuristics
MICMAC	cross-impact matrix multiplication applied to classification
MILP	mixed integer linear programming
MLP	multilayer perceptron
MO	multi-objective model
NFMS	net framework and Microsoft SQL server 200
PDCA	plan-do-check-act
PLS	partial least squares
PSO	particle swarm optimisation
QFD	quality function deployment

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RBF	radial basis function
SC	supply chain
SCMD	CAE system
SCOR	supply chain operations reference
SD	system dynamics
SEM	structural equation modelling
SMED	single minute exchange of die
SMMs	small and medium sized manufacturers
S&OP	sales & operation planning
SPC	statistical process control
SPSim	Siemens plant simulation
SPSS	statistical package for social sciences
SSCM	sustainable supply chain manager
TPS	Toyota production system
TOC	theory of constraints
TOPSIS	technique for order of preference by similarity to ideal solution
TPM	total productive maintenance
TQM	total quality management
UML	unified modelling language
VDC	virtual design and construction
VSM	value stream mapping
WF	workflow
WIP	work in progress

1. Introduction

Lean manufacturing (LM) techniques, widely extended by Womak, Jones, and Roos (1990), address tools that help companies to reduce losses and generate added value for customers through the well-known just in time (JIT) production system, based mainly on pull of demand to generate orders. LM is emphasised in manufacturing industries, such as automotive (Holweg 2007), textile (Hodge et al. 2011), technology (Lu, Yang, and Wang 2011), among others, but also in service industries in developed countries (Maware, Okwu, and Adetunji 2022). Lu, Yang, and Wang (2011) indicates that the LM philosophy is a systematic approach that helps to identify and eliminate waste through the application of continuous improvement by seeking to enhance processes to meet customer requirements. According to Baliga, Raut, and Kamble (2020), LM practices are a combination of techniques followed to improve productivity, reduce production costs and environmental impacts, and provide greater social sustainability. Accordingly, Kamble, Gunasekaran, and Dhone (2020) define ten dimensions to classify LM practices based on the following four factors (supplier, process, control and human, customer) defined by Sanders, Elangeswaran, and Wulfsberg (2016). Here we structure some of the 20 best known LM techniques inspired by these dimensions and factors, as follows:

- Supplier: JIT (Sugimori et al. 1977; Tortorella et al. 2018).
- Planning: enterprise resource planning (ERP) (Sharma, Dixit, and Qadri 2016); sales & operation planning (S&OP) (Oleghe and Salonitis 2016); and Hoshin Hairi (Gupta, Gupta, and Parida 2017).
- Process: kanban (Sugimori et al. 1977; Noha and Abderrazak 2019); cellular manufacturing (CM) (Gutierrez 2014); Heijuka (Zuniga, Moris, and Syberfeldt 2017); seven waste (Sugimori et al. 1977); Toyota production system (TPS) (Sugimori et al. 1977; Bhamu and Singh Sangwan 2014; Hiraoka, 1989) and theory of constraints (TOC) (Goldratt 1988; McWilliams and Tetteh 2009).
- Continuous flow: value stream mapping (VSM) (Gomero-Campos et al. 2020); and visual control (Hodge et al. 2011); and standardisation work (Houshmand and Jamshidnezhad 2006).
- Setup time reduction: single minute exchange of dies (SMED) (Johansen 1986,; Rabii, Naoufal, and Omar 2018); and takt time (Nallusamy and Saravanan 2018).
- Maintenance: total productive/preventive maintenance (TPM) (Mahfouz, Shea, and Arisha 2011); and failure mode and effects analysis (FMEA) (Chase et al. 2009).
- Quality: total quality management (TQM) (Samson and Yao 1990; Besseris 2014); statistical process control (SPC) (Shewhart and Deming 1967; Gutierrez Pulido and de La Vara Salazar 2014; Pérez Vergara and Rojas López 2019); six sigma (Zhao, Ye, and Gao 2012); plan, do, check and act (PDCA) (Henríquez-Alvarado et al. 2019); Ishikawa (Kindlarski 1984; Agnetis, Bianciardi, and Iasparra 2019); Pareto (Schumpeter 1949; Yang et al. 2020); five whys (Chaple et al. 2018b); and Jidoka (Sugimori et al. 1977; Noha and Abderrazak 2019).
- Employee involvement: 5S (Singh and Kumar 2020), kaizen (Allnoch 1998; Jayamaha, Grigg, and Pallawala 2018); poka-yoke (Tayyab, Sarkar, and Ullah 2018); andon or visual control (Rabii, Naoufal, and Omar 2018); and brainstorming (Misselhorn 1978; Agnetis, Bianciardi, and Iasparra 2019).
- Customer: pull system (PS) (Lu, Yang, and Wang 2011); and quality function deployment (QFD) (Schauerman and Peachy 1994; Aldana de Vega 2011).

Other classifications of LM tools can be found in Hodge et al. (2011), who identify 20 lean tools that they stratify into six categories: visual management, policy deployment, quality methods, standardised work, JIT and improvement methods. Valamede and Akkari (2020) relate, in the lean industry 4.0 context (Hines et al. 2023), the interactions of digital technologies like big data analytics, cloud computing, virtual simulation and augmented reality, and multilevel circle diagrams with LM tools, namely kaizen, kanban, poka-yoke and VSM. Pagliosa, Tortorella, and Ferreira (2019) classify LM tools according to citation frequency and the value stream level application. Patel et al. (2021) identify barriers and drivers to effectively implement LM through the following factors: employee involvement, stability and automation, collaborative relationship, benchmarking, TQM, effective leadership, highly skilled human resources, and adequate management commitment and transparency at the workplace. In terms of research methodologies, Bhamu and Singh Sangwan (2014) showed that a quarter of the reviewed LM articles are conceptual or descriptive in nature, three quarters of them deal with the verification of theories based on empirical or cross-sectional exploratory studies rather than longitudinal and other approaches by further identifying that most research is based on cross-sectional exploratory studies and a few studies combine several research methodologies. Here, like Pearce and Pons (2019), we identify the missing link between LM and quantitative approaches in the existing lean literature, and highlight the need to improve the performance and success of LM practices in industry. We also state the necessity and relevance of quantitative LM approaches to be applied under uncertainty conditions.

Galbraith (1973) defines uncertainty as the difference between the amount of information needed to perform a task and the amount of possessed information. There are two main types of uncertainty: system uncertainty and environmental uncertainty. System uncertainties relate to the uncertainties inherent to the production process itself, such as machine breakdowns or quality defects, while environmental uncertainties include those that arise beyond the production processes, such as uncertainty of demand and supply (Ho 1989). Mula et al. (2006) offer an extensive literature review on models for production planning under uncertainty that has being considerably cited in over 300 international journals. According to Mula et al. (2006), uncertainty can be completely removed from supply chains (SCs), and also from each link of SCs. Therefore, new optimisation approaches in the SC production planning context and, hence, under uncertainty conditions, are generally demanded to manage uncertainty in each company of the SC. Moreover, in the contemporary global economy characterised by the impact of the postCOVID-19 pandemic, coupled with military conflicts, more uncertainty is being created in SCs. So it is timely to revisit this body of knowledge. Indeed more research into new approaches to uncertainty modelling is required. In the LM context, Qiu (2011) suggests applying last planner system (LPS) to identify uncertainties, improve quality and increase productivity, which is based on learning from past planning errors and involves project participants. In other contexts, like lean project management (Qiu 2011), lean startup (Silva et al. 2020) and lean product and process development (Dullen et al. 2021), other reviews have addressed uncertainty. Regarding the decision level, LM is applied at the strategic level (Rossini et al. 2022) in the SC management context with the tactical level being the most frequent (Reyes, Mula, and Díaz-Madroñero 2021), whereas operational LM techniques focus on the productive use of resources in enterprise systems (Sanchez and Nagi 2001). Therefore, considering uncertainty at the strategic and tactical decision levels is commonplace, but it is just as important to demonstrate LM dynamics under uncertainty also at the operational level to, for example, eliminate waste by reducing customer demand uncertainty and internal variability, such as machine availability conditions (Deif 2012).

The main contributions of this article to scholarly knowledge are to: (i) propose analytic categories of research taxonomy by addressing LM works under uncertainty in terms of aims, application context, research methodology, modelling approach, software tool, LM techniques/tools, decision variables, type of LM waste, and type of uncertainty; (ii) identify and classify the quantitative models used for LM with uncertainty approaches into four main groups of models: analytical, artificial intelligence, conceptual and simulation; and (iii) provide results and a conceptual framework for future LM quantitative modelling with uncertainty research. Yet to the best of our knowledge, no reviews that provide new insights into the use of quantitative methods for optimisation and simulation of LM problems under uncertainty have been carried out to date. Therefore, this study conducts a systematic literature review based on the context-intervention-mechanism-outcome (CIMO) structure provided by Kitchenham (2004) to formulate review questions (Denyer, Tranfield, and van Aken 2008). Thus we formulate the main review question to focus on investigating how quantitative approaches behave in LM environments under uncertainty to identify their practical relevance that favours the application of LM in industrial companies to improve manufacturing performance. Here the context refers to order entry points, the intervention is related to quantitative approaches, the mechanism focuses on LM tools and the outcome contemplates manufacturing performance. Consequently, the purpose of this paper is to identify, select and classify the most relevant research into quantitative models of decision support in LM environments in industrial firms under uncertainty. This literature review is intended as a conceptual framework for researchers, academics and practitioners to reveal managerial insights based on research methodologies and modelling approaches, LM techniques, LM waste, and the software tools used by economic sectors of the reviewed literature to make progress in LM production systems in an uncertainty context.

The remainder of the paper is structured as follows. Section 2 presents the review methodology. Section 3 classifies and studies the reviewed articles by means thematic and content analysis. Section 4 discusses the results of the present study. Finally, Section 5 provides conclusions and directions for future research on the addressed topic.

2. Review methodology

Here a systematic literature review is performed based on the methodology proposed by Denyer and Tranfield (2009) and applied by Novais, Maqueira, and Ortiz-Bas (2019) and Llaguno, Mula, and Campuzano-Bolarin (2022), among others. This methodology includes five steps to: (i) formulate research questions; (ii) search for and locate relevant articles to answer the research questions; (iii) select and evaluate the located articles; (iv) analyse and synthesise the selected articles; and (v) present the literature review results and identify research gaps and further research.

In the first step, the general research question to be answered is about the current state of research into quantitative modelling approaches for LM under uncertainty. This general research question is divided into the following two specific questions: RQ1. How is it possible to categorise the selected articles?; RQ2. What are the research gaps and future research on quantitative modelling approaches for LM under uncertainty from the existing literature?

The second step searches for and locates relevant articles to answer the research questions. To do so, the research questions are converted into keywords and synonyms, which represent CIMO, by relating them to Boolean operators. The search was done by using the multidisciplinary databases Scopus and Web of Science (WoS) Core Collection, which are leading scientific databases in indexed documents and citations in all research fields, especially in engineering, technology, among others (Bartol et al. 2014). Table 1 shows the keyword combinations defined according to the CIMO structure and based on Dekkers, Carey, and Langhorne (2022). Appendix 1 presents the search formulas of the articles to locate.

Table 1. Search keywords statement.

Mechanisms		Intervention		Outcome
Quantitative approaches		Lean manufacturing		Manufacturing performance
Quantitative OR Modelling OR Variables OR Optimisation OR Uncertainty modelling	AND	Lean	AND	Manufacturing

The third step selects the located articles by firstly filtering by the years between 2006, because quantitative modelling of uncertainty had previously been addressed in a comprehensive review (Mula et al. 2006), and 2021, when this search process was carried out; secondly, by removing duplicate articles from the two scientific databases, Scopus and WoS; finally, by defining the inclusion and exclusion criteria related to the scientific research categories, as shown in Figure 1. Then, a review of abstracts was carried out to select those related to the posed research questions. Following the search and review of article abstracts, a selection of those most closely related to the research objective (quantitative approaches for LM under uncertainty) was made. As a result, 89 selected references were obtained, and ten articles were added using cross references based on the same criteria. In all, this literature review is based on 99 reviewed articles, a list of which is provided in Table 2.

In Phase 4, analysis and synthesis, the selected articles are reviewed with a thematic and content analysis (Section 3). Finally, Phase 5 (presenting the results and research gaps) is addressed and discussed in Section 4.

3. Literature review

3.1. Thematic analysis

Appendix 2 shows the source of the reviewed papers: the International Journal of Lean Six Sigma accounts for 7.07% of the reviewed articles, followed by the International Journal of Advanced Manufacturing Technology with 4.04%. Proceedings and conferences represent 26.26% if we consider that lean is a current topic dealt with in these events.

As a further complement, a bibliometric analysis was conducted using the VOSviewer software and the Scopus database to quantify and analyse research and scientific publication patterns. Thus a co-occurrence matrix showing the frequency with which each pair of keywords appears together was created to show the network map (Figure 2). Each keyword is represented as a node, and links between nodes represent the co-occurrence relations among keywords (Strozzi et al. 2017). The size and colour of each node reflect the frequency of occurrence

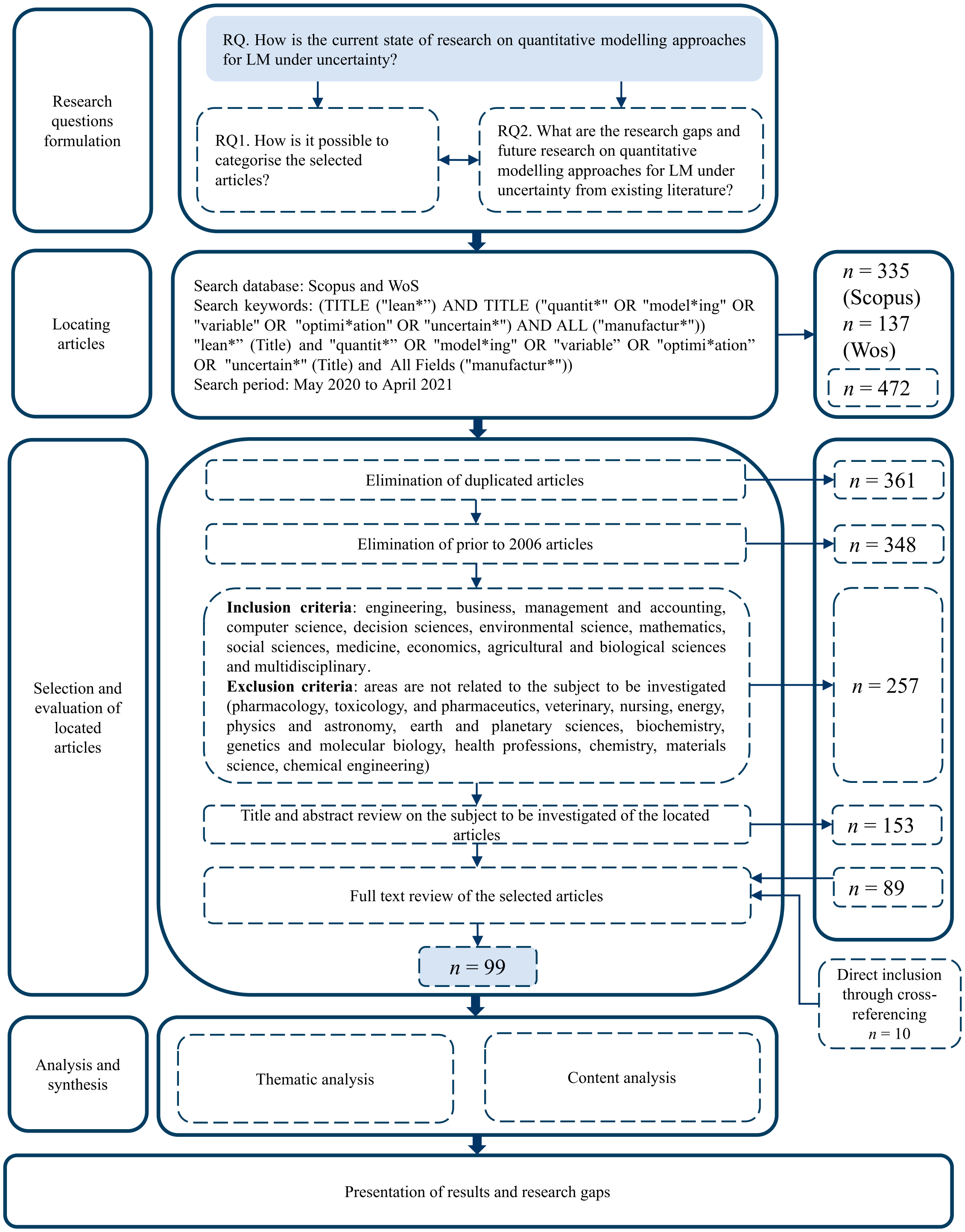

Figure 1. Summary of the review methodology.

of a keyword in publications, and the thickness of links between nodes reflects the strength of the co-occurrence relation. Essentially, this methodology allows the extraction and cleaning of data from scientific publications, followed by the construction of networks based on co-citation, co-authorship or co-occurrence of keywords to identify significant trends, relations and clusters in a research field (Ball 2018).

Figure 2 shows six trends related to research in the area, which can be detailed as: (i) LM, optimisation, agile manufacturing systems, VSM (in red); (ii) related to lean production, concepts around lean construction, structural equation modelling (SEM), performance (in green); (iii) terms related to lean, decision making, SC management, efficiency (in blue); (iv) trends around terms related to six sigma, LSS, process engineering (in yellow);

Table 2. Selected literature.

Author/s	Document title
Agarwal, Shankar, and Tiwari (2006)	Modelling the metrics of lean, agile and leagile supply chain: An ANP-based approach
Goldsby, Griffis, and Roath (2006)	Modelling lean, agile, and leagile supply chain strategies
Houshmand and Jamshidnezhad (2006)	An extended model of design process of lean production systems by means of process variables
Meade, Kumar, and Houshyar (2006)	Financial analysis of a theoretical lean manufacturing implementation using hybrid simulation modelling
Ajaefobi and Weston (2007)	Enterprise modelling in support of the application of lean manufacturing in SMEs
Evans and Alexander (2007)	Using multicriteria modelling and simulation to achieve lean goals
Holweg (2007)	The genealogy of lean production
Li and Zhu (2008)	Research on multi-objective optimisation of lean construction project
Machado and Pereira (2008)	Modelling lean performance
Machado and Tavares (2008)	Value streams-based strategy: modelling for lean management performance
Siomina and Ahlinder (2008)	Lean optimisation using supersaturated experimental design
McWilliams and Tetteh (2009)	Managing lean DRC systems with demand uncertainty: an analytical approach
Hodge et al. (2011)	Adapting lean manufacturing principles to the textile industry
Lu, Yang, and Wang (2011)	A lean pull system design analysed by value stream mapping and multiple criteria decision-making method under demand uncertainty
Mahfouz, Shea, and Arisha (2011)	Simulation based optimisation model for the lean assessment in SME: a case study
Ma, Wang, and Xu (2011)	Modelling and analysis of workflow for lean supply chains
Qiu (2011)	Uncertainty in project management based on lean construction implementation
Deif (2012)	Dynamic analysis of a lean cell under uncertainty
Dotoli et al. (2012)	A lean manufacturing strategy using value stream mapping, the unified modelling language, and discrete event simulation
Vinodh and Aravindraj (2012)	Axiomatic modelling of lean manufacturing system
Vinodh and Joy (2012)	Structural equation modelling of lean manufacturing practices
Zhao, Ye, and Gao (2012)	Research on process optimisation for equipment maintenance based on lean six sigma management
Anvari, Zulkifli, and Yusuff (2013)	A dynamic modelling to measure lean performance within lean attributes
Wasim et al. (2013)	An innovative cost modelling system to support lean product and process development
Abbasian-Hosseini, Nikakhtar, and Ghoddousi (2014)	Verification of lean construction benefits through simulation modelling: A case study of bricklaying process
Besseris (2014)	Multi-factorial lean six sigma product optimisation for quality, leanness and safety: A case study in food product improvement
Elmaraghy and Deif (2014)	Dynamic modelling of impact of lean policies on production levelling feasibility
Sękala et al. (2014)	Optimisation of the lean production process using the virtual manufacturing cell
Dubey and Singh (2015)	Understanding complex relationship among JIT, lean behaviour, TQM and their antecedents using interpretive structural modelling and fuzzy MICMAC analysis
Tortorella et al. (2015)	The impact of contextual variables on learning organization in firms that are implementing lean: a study in Southern Brazil
Wang et al. (2015)	Lean principles and simulation optimisation for emergency department layout design
Wang (2015)	Optimisation study based on lean logistics in manufacturing enterprises
Yang et al. (2015)	Lean production system design for fishing net manufacturing using lean principles and simulation optimisation
Kumar and Kumar (2016)	Analysis of significant lean manufacturing elements through application of interpretive structural modelling approach in Indian industry
McLeod, Stephens, and McWilliams (2016)	Empirical modelling of lean adoption in small to medium size manufacturers
Nguyen and Dao (2016)	Robust optimisation for lean supply chain design under disruptive risk
Oleghe and Salonitis (2016)	Variation modelling of lean manufacturing performance using fuzzy logic based quantitative lean index
Sharma, Dixit, and Qadri (2016)	Modelling lean implementation for manufacturing sector
Soni and Kodali (2016)	Interpretive structural modelling and path analysis for proposed framework of lean supply chain in Indian manufacturing industry
Tajri and Cherkaoui (2016)	Modelling the complexity of the relationship (lean, company, employee and cognitive ergonomics) case of Moroccan SMEs
Uriarte et al. (2016)	Lean, simulation and optimisation: A win-win combination
Vasanthakumar, Vinodh, and Ramesh (2016)	Application of interpretive structural modelling for analysis of factors influencing lean remanufacturing practices
Azadeh et al. (2017)	Performance optimisation of integrated resilience engineering and lean production principles
Bocanegra-Herrera and Orejuela-Cabrera (2017)	Cellular manufacturing system selection with multi-lean criteria, optimisation and simulation
Gupta, Gupta, and Parida (2017)	Modelling lean maintenance metric using incidence matrix approach
Khalili, Ismail, and Karim (2017)	Integration of lean manufacturing and quality management system through structural equation modelling
Kumar and Kumar (2017)	Application of interpretive structural modelling approach for the analysis of barriers affecting lean manufacturing implementation in Indian manufacturing industry
Mandujano et al. (2017)	Modelling virtual design and construction implementation strategies considering lean management impacts
Nagi, Chen, and Wan (2017)	Throughput rate improvement in a multiproduct assembly line using lean and simulation modelling and analysis
Zarrin and Azadeh (2017)	Simulation optimisation of lean production strategy by considering resilience engineering in a production system with maintenance policies
Zuniga et al. (2017)	Integrating simulation-based optimisation, lean, and the concepts of industry 4.0
Basu, Ghosh, and Dan (2018a)	Structural equation modelling based empirical analysis of technical issues for lean manufacturing implementation in the Indian context
Basu, Ghosh, and Dan (2018b)	Using structural equation modelling to integrate human resources with internal practices for lean manufacturing implementation

(*continued*)

Table 2. Continued.

Author/s	Document title
Camuffo and Gerli (2018)	Modelling management behaviors in lean production environments
Chaple et al. (2018a)	Interpretive framework for analyzing lean implementation using ISM and IRP modelling
Chaple et al. (2018b)	Modelling the lean barriers for successful lean implementation: TISM approach
Faisal (2018)	Predictive simulation modelling and analytics of value stream mapping for the implementation of lean manufacturing: A case study of small and medium-sized enterprises (SMEs)
Garzaniti, Golkar, and Fortin (2018)	Optimisation of multi-part 3D printing build strategies for lean product and process development
Ghobakhloo et al. (2018)	Modelling lean manufacturing success
Jayamaha, Grigg, and Pallawala (2018)	The effect of uncertainty avoidance on lean implementation: a cross cultural empirical study involving Toyota
Khalili et al. (2018)	Soft total quality management and lean manufacturing initiatives: model development through structural equation modelling
Nallusamy and Saravanan (2018)	Optimisation of process flow in an assembly line of manufacturing unit through lean tools execution
Rabii, Naoufal, and Omar (2018)	Model of a maintenance process improvement approach inclusioning lean six sigma and preventive maintenance optimisation
Ramadas and Satish (2018a)	Identification and modelling of employee barriers while implementing lean manufacturing in small- and medium-scale enterprises
Ramadas and Satish (2018b)	Identification and modelling of process barriers: implementing lean manufacturing in small-and medium-sized enterprises
Singh and Singru (2018)	Graph theoretic structural modelling based new measures of complexity for analysis of lean initiatives
Solke and Singh (2018)	Analysis of relationship between manufacturing flexibility and lean manufacturing using structural equation modelling
Tayyab, Sarkar, and Ullah (2018)	Sustainable lot size in a multistage lean-green manufacturing process under uncertainty
Tortorella et al. (2018)	Lean manufacturing implementation: leadership styles and contextual variables
Uriarte, Ng, and Moris (2018a)	Lean, simulation and optimisation: a maturity model
Uriarte et al. (2018b)	Supporting the lean journey with simulation and optimisation in the context of industry 4.0
Uriarte et al. (2018c)	Improving the material flow of a manufacturing company via lean, simulation and optimisation
Wickramasinghe and Wickramasinghe (2018)	Variable pay and job performance of shop-floor workers in lean production
Agnetis, Bianciardi, and Iasparra (2019)	Integrating lean thinking and mathematical optimisation: a case study in appointment scheduling of hematological treatments
Alkaabi et al. (2019)	A review on the implementation of system modelling techniques in lean healthcare applications
Ajmera and Jain (2019)	A fuzzy interpretive structural modelling approach for evaluating the factors affecting lean implementation in Indian healthcare industry
Eel Kihel et al. (2019)	Implementation of lean through VSM modeling on the distribution chain: automotive case
Henríquez-Alvarado et al. (2019)	Process optimisation using lean manufacturing to reduce downtime: case study of a manufacturing SME in Peru
Mohammad and Oduoza (2019)	Interactions of lean enablers in manufacturing SMEs using interpretive structural modelling approach. A case study of KRI
Noha and Abderrazak (2019)	Toward a global approach for value chain optimisation, based on lean management concept
Oleghe and Salonitis (2019)	Hybrid simulation modelling of the human-production process interface in lean manufacturing systems
Pérez Vergara and Rojas López (2019)	Lean, six sigma and quantitative tools: a real experience in the productive improvement of processes of the graphic industry in Colombia
Sarhan et al. (2019)	Framework for the implementation of lean construction strategies using the interpretive structural modelling (ISM) technique: a case of the Saudi construction industry
Shrafat and Ismail (2019)	Structural equation modelling of lean manufacturing practices in a developing country context
Sindhwani et al. (2019)	Modelling and analysis of barriers affecting the implementation of lean green agile manufacturing system (LGAMS)
Singh et al.	Modelling the barriers of lean six sigma for Indian micro-small medium enterprises: an ISM and MICMAC approach
Solke and Singh (2018)	Analysis of relationship between manufacturing flexibility and lean manufacturing using structural equation modelling
Baliga, Raut, and Kamble (2020)	The effect of motivators, supply, and lean management on sustainable supply chain management practices and performance: systematic literature review and modelling
Cuesta et al. (2020)	Optimisation of assembly processes based on lean manufacturing tools. case studies: television and printed circuit boards (PCB) assemblers
Gomero-Campos et al. (2020)	Lean manufacturing production management model using the Johnson method approach to reduce delivery delays for printing production lines in the digital graphic design industry
Gomez Segura, Oleghe, and Salonitis (2020)	Analysis of lean manufacturing strategy using system dynamics modelling of a business model
Greinacher et al. (2020)	Multi-objective optimisation of lean and resource efficient manufacturing systems
Kant, Pattanaik, and Pandey (2020)	Sequential optimisation of reconfigurable machine cell feeders and production sequence during lean assembly
Kumar, Mathiyazhagan, and Mathivathanan (2020)	Modelling the interrelationship between factors for adoption of sustainable lean manufacturing: a business case from the Indian automobile industry
Narottam, Mathiyazhagan, and Kumar (2020)	Modelling the common critical success factors for the adoption of lean six sigma in Indian industries
Vaishnavi and Suresh (2020)	Modelling of readiness factors for the implementation of lean six sigma in healthcare organizations
Yang et al. (2020)	A lean production system design for semiconductor crystal-ingot pulling manufacturing using hybrid Taguchi method and simulation optimisation
Gürsoy and Soner Kara (2021)	Modelling of just-in-time supply chain network under raw material quality and time constraints
Kristensen (2021)	Enabling use of standard variable costing in lean production

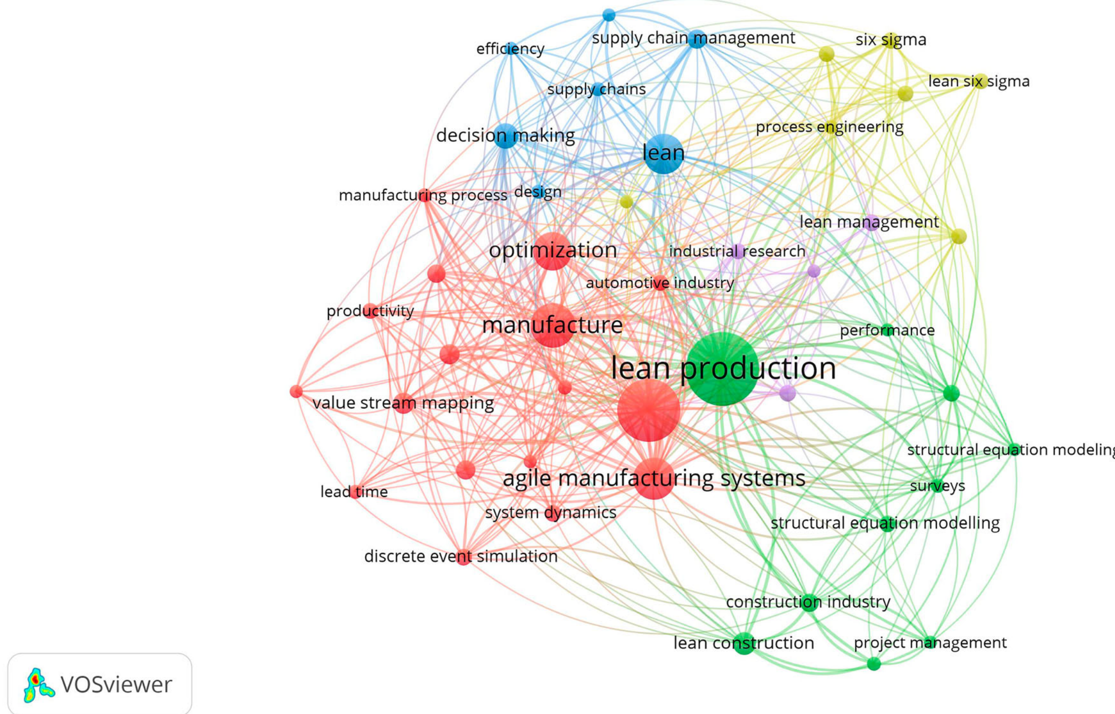

Figure 2. Co-occurrence analysis map.

(v) co-indications related to lean management, industrial research (in purple).

Moreover, a co-authorship analysis of scientific publications was used to identify and visualise patterns of collaboration between pairs of authors from different countries (Appendix 3). On the network map, each country is represented as a node, and links between nodes represent co-authorship relationships between pairs of countries. The size and colour of each node can be adjusted to reflect the number of authors or publications from that country, and the thickness of links between nodes reflects the strength of the co-authorship relationship. The information from this map identifies five clusters of countries that frequently collaborate on topics of interest to this work, with a particular focus on identifying different collaborations in developed or underdeveloped countries.

3.2. Content analysis

Here the selected articles are then reviewed and stratified according to the analytic categories proposed below:

- Aims. The purposes and main contributions of each reviewed article are described.
- Application context. The following are identified: SC, industry 4.0 and small- and medium-sized manufacturers (SMMs), together with the sector where the proposal of the reviewed article is undertaken and/or applied.
- Research methodology. The research methodologies in the operations management area are identified and classified according to Dangayach and Deshmukh (2001): (i) conceptual, they present and discuss basic or fundamental concepts; (ii) descriptive, they explain or describe process or content, and/or propose performance measurement issues; (iii) empirical, they are based on the experimentation or study of existing databases, literature reviews, case studies and/or taxonomy or typology approaches; (iv) cross-sectional exploratory, they are conducted with surveys at one time point; (v) longitudinal exploratory, where data collection is conducted at two time points or more.
- Modelling approach. They are identified and classified according to Giannoccaro and Pontrandolfo (2001) and Mula et al. (2006) into: conceptual, analytical, artificial intelligence and simulation models. Moreover, the type of representation or formulation is identified; e.g. mathematical relations, as are aspects to be considered in the production system, i.e. discrete events simulation (DES), hybrid simulation (HS), etc. applied in the developed modelling approach.
- LM techniques. Those used in research (i.e. Kanban, JIT, etc.) are identified.
- Decision variables and objective functions. The decision variables or key factors used in the proposed

modelling approaches are described along with the goals pursued by the objective function.

- Types of LM waste. The types of LM waste addressed in the different selected papers are examined. For example, transportation, motion, standby/waiting for time, inventory excess, overproduction, over-processing/rework, process errors/defects (Santosa 2018) and, more recently, non-utilised talent, poor information management and poor supplier quality (Reyes, Mula, and Díaz-Madroñero 2021).
- Types of uncertainty. There are mainly two types, i.e. system uncertainty or environment uncertainty (Ho 1989; Mula et al. 2006), or even a combination of both.
- Software tools. The commercial and non-commercial software tools that allow the proposed models to be solved are identified.
- Novelty. This refers to the originality and innovation provided by research.
- Limitations. They determine the characteristics that hinder or limit the study's development and/or the application of models in different environments.

Appendix 4 groups, graphically, the different analytical categories by dimensions: LM, quantitative approaches and uncertainty.

3.2.1. Aims and application context

Table 3 summarises the main identified aims in the reviewed articles in an aggregate form. In addition, Appendix 5 details the main aim stated by each article considered in this literature review. The identified aims are related mainly to: modelling and its application; improving manufacturing performance by establishing measures to monitor system indicators; followed by proposals for implementing strategies, as well as understanding and comprehending LM-oriented principles. Additionally in some articles, the purpose of applying LM tools according to economic activities coincides, and the aims oriented to propose methods and methodologies for the application of different tools are also identified. Several papers identify the different process variables or relevant lean study parameters. There are two articles on the organisational domain. One examines the relation between two contextual variables (team size and leader's age) and the organisational dimensions in a learning context in companies that implement LM (Tortorella et al. 2015). The other identifies and empirically validates the reactions associated with the adoption of lean systems in specific organisational settings (Camuffo and Gerli 2018).

The International Standard Industrial Classification (ISIC) of all economic activities, which allows the systematic classification and global harmonisation of economic activities, was considered for the classification of economic activities and the sector addressed by the reviewed articles. This classification is summarised in Table 4 and appears in detail in Appendix 5. It should be noted that a few articles are not proposed in a context and/or sector to apply their proposals.

Thus in terms of application sectors, it is worth highlighting studies mainly in manufacturing companies, and also in the automotive, health, construction, agrifood and beverages, graphics, technology, retailing, logistics and maintenance sectors. Regarding manufacturing sectors, the case studies in the metal-mechanical, aerospace and textile sectors stand out, as do other specific studies in the fibreglass, plastics and semiconductor sectors. Hence the automotive and aerospace sectors are expected to be pioneers in LM with uncertainty applications because they are sectors where lean practices were born and developed. It is also worth observing how LM practices have spread to almost all industrial sectors, and also to the health sector. In addition, the application contexts in which the problem under study, LM under uncertainty, is addressed are mainly SMMs (8) and SCs (6). Apart from the interest of SMMs and SCs in the addressed problem, it should be noted that further research is still required in the industry 4.0 context because only two articles address LM under uncertainty. Finally, the applications in the graphics sector are stressed, which is particularly interesting for this

Table 3. Main aims of articles.

Main aim	Number of articles
Modelling the LM system and validating its implementation	30
Assessing LM system performance	18
Proposing and implementing LM strategies	19
Defining management principles	13
Applying LM tools	9
Determining lean process variables	3
Establishing working methods	4
Studying organisational aspects	3

Table 4. Economic activities of articles.

Economic activities	Sector	Number of articles
Manufacturing industries	Manufacturing	27
	Automotive and aerospace	16
	Agrifood and beverages	4
	Graph	4
	Maintenance	1
	Plastic	1
Human health care	Health	6
Construction	Construction	5
Information and communications	Technological	4
Wholesale and retail trade	Retailing	1
Transport and storage	Logistics	1

Table 5. Research methodologies used.

Research methodology	Total
Empirical	59
Cross-sectional exploratory	15
Conceptual	14
Empirical and cross-sectional exploratory	6
Descriptive	5
TOTAL	**99**

research and have not been widely addressed compared to other sectors.

3.2.2. Research methodology, modelling approach and software tools

According to the reviewed articles, the most widely used research methodology is the empirical one, which is applied in 59.6% of the reviewed articles. It is followed by the cross-sectional exploratory methodology, which represents 15.15%, and then by the conceptual methodology with 14.14% (Table 5). The least represented research methodologies in the reviewed articles are descriptive and the combination of empirical and cross-sectional exploratory methodologies.

The modelling approaches identified in the review done of the selected articles are grouped into four groups of models (Giannoccaro and Pontrandolfo 2001; Mula et al. 2006): analytical, artificial intelligence, conceptual and simulation. Table 6 describes the classification of these groups of models and modelling approaches by indicating the number of articles reviewed in this respect. More details of the modelling approaches of the reviewed articles appear in Appendix 6.

The analytical approach models are subclassified into four groups: multivariate statistical, LM techniques, optimisation and other quantitative models. Multivariate statistical models encompass the use of SEM, interpretive structural modelling (ISM), fuzzy interpretive structural modelling (FISM), in addition to combinations of ISM and cross-impact matrix multiplication applied to classification (MICMAC); ISM and fuzzy MICMAC; ISM and interpretive ranking process (IRP); combinations of ISM and SEM applied in survey analyses; virtual design and construction (VDC) implementation strategies and the partial least squares (PLS) method.

The models that apply LM techniques are mainly case studies. Gomero-Campos et al. (2020) apply the model based on 5S, SMED, Johnson method, visual management and improving human resources management to obtain 12% reduction lead times for a printing production line in Peru. Another application in a Peruvian SMM is the implementation of 5S to reduce downtimes due to clutter and lack of cleanliness, which also uses VSM to find the most efficient method to follow processes (Henríquez-Alvarado et al. 2019). El Kihel et al. (2019) take the PDCA approach to implement VSM in an electrical wiring manufacturer for the automotive sector. Nallusamy and Saravanan (2018) apply Kaizen and VSM tools to reduce lead times and to improve productivity in a valve manufacturing industry. Wasim et al. (2013) study LM tools of poka yoke, concurrent engineering and knowledge-based engineering.

The optimisation models include mixed integer linear programming (MILP), multi-objective mixed integer linear programming (MOMILP) and fuzzy multi-objective non-linear programming (FMONLP) to consider the economic quantity of production (EQP) with uncertain demand and fuzzy objective programming, as well as design of experiments (DOE), particle swarm optimisation (PSO), stochastic programming and metaheuristics (MH) algorithms.

Other reviewed analytical models base their applications on: analytic network process (ANP); data envelopment analysis (DEA); graph theory; Markov process and dual resource constrained (DRC); multiple criteria decision making (MCDM); hybrid Taguchi and technique for order of preference by similarity to ideal solution (TOPSIS); cosorganisational labelled time workflow nets (CLTWN) with Petri nets.

The least represented models (2.02%) are those categorised as artificial intelligence. Anvari, Zulkifli, and Yusuff (2013) use a fuzzy logic model, while Azadeh et al. (2017) apply an algorithm composed of radial basis function (RBF), multilayer perceptron (MLP) and adaptive neuro-fuzzy inference system (ANFIS).

Conceptual modelling approaches focus on being a reference roadmap for the application of different techniques to improve manufacturing performance, productivity and efficiency, among other management indicators of different types of goods and services industries. The conducted review finds that 18.18% address this approach related to literature reviews, Holweg (2007) develops the LM genealogy and Alkaabi et al. (2019) base their work on implementing lean techniques in the health sector. Other conceptual models involve axiomatic modelling; a combination of lean and simulation multi-objective optimisation in the industry 4.0 context; a hierarchical approach for LM implementation; integrated sustainable SC management (SSCM); leagile; lean, company, employee and cognitive ergonomics relations; LM optimisation strategies; LM for SMMs; LM for the construction sector; LM for SC; LM for flow management and value chain optimisation; lean maintenance; maturity model of lean, simulation and optimisation.

The simulation models group, which accounts for 19.99%, comprises two subgroups: simulation optimisation, which combines optimisation and simulation

Table 6. Modelling approaches in the reviewed articles.

Models	Modelling approach	Models		Modelling approach	
Analytical	Multivariate statistics	Structural equation modelling (SEM) (17)	Artificial intelligence		Multi-expert decision making and fuzzy averaging (1)
		Interpretative structural modelling (ISM) (11)			Algorithm composed of radial basis function (RBF), multilayer perceptron (MLP) and an adaptive neuro-fuzzy inference system (ANFIS) (1)
		Fuzzy Interpretative structural modelling (FISM) (1)			
		ISM and cross-impact matrix multiplication applied to classification (MICMAC) (1)	Conceptual models		Literature reviews (2)
		ISM and fuzzy MICMAC (2)			Axiomatic modelling (2)
		ISM and interpretive ranking process (IRP) (1)			Combination of lean and simulation multi-objective optimisation in the Industry 4.0 context (1)
		ISM and SEM (2)			Hierarchical approach to LM implementation (1)
		Virtual design and construction (VDC) implementation strategies and partial least squares (PLS) method (1)			Integrated sustainable supply chain management (SSCM) (1)
					Leagile (1)
	LM techniques	5S and value stream mapping (VSM) (1)			Lean, company, employee and cognitive ergonomics relations (1)
		5S, single minute exchange of die (SMED), Johnson method, visual management and improving human resources management (1)			LM optimisation strategies (1)
					LM for Small- and Medium-sized Manufacturers (SMMs) (1)
		Kaizen and VSM (1)			LM for supply chain (SC) (1)
		Plan, do, check, action (PDCA) (1)			LM for the construction sector (1)
		Poka yoke, concurrent engineering and knowledge-based engineering (1)			LM for value chain flow management (1)
	Optimisation	Mixed integer linear programming (MILP) (2)			LM for value chain optimisation (1)
		Multi-objective mixed integer linear programming (MOMILP) (1)			Lean maintenance (2)
					Maturity model of lean, simulation and optimisation (1)
		Fuzzy multi-objective nonlinear programming (FMONLP) (1)			
		Design of experiments (DOE) (6)	**Simulation**	Simulation optimisation	Simulation optimisation and Taguchi method (1)
		Particle swarm optimisation (PSO) (1)			Simulation optimisation (6)
		Stochastic programming and metaheuristic solution algorithm (1)			
	Others	Analytic network process (ANP) (2)		Simulation	Simulation with DOE (1)
		Data envelopment analysis (DEA) (1)			Simulation with variables analysis based on a spreadsheet (1)
		Graph theory (1)			Simulation with VSM (1)
		Markov process and dual resource constrained (DRC) (1)			Discrete events simulation (4)
		Multiple criteria decision-making (MCDM), hybrid Taguchi and technique for order of preference by similarity to ideal solution (TOPSIS) (1)			Multi-agent simulation (1)
		Dynamic systems CLTWN Petri nets (1)			System dynamics (4)

modelling techniques to improve the decision-making processes in terms of obtaining, understanding and evaluating optimal solutions (Buschiazzo, Mula, and Campuzano-Bolarin 2020); and simulation. The simulation optimisation models group is further divided into two main groups: simulation optimisation and Taguchi method; simulation optimisation, which takes a modelling approach by combining lean, simulation and optimisation. The articles in the simulation subgroup are based on modelling approaches related to: simulation with DOE; simulation with a variables analysis based on a spreadsheet; simulation with VSM; DES, which Mahfouz, Shea, and Arisha (2011) combine with experimental design, Dotoli et al. (2012) combine with unified modelling language (UML), and VSM, Uriarte et al. (2016) combine lean, simulation and optimisation; Pérez Vergara and Rojas López (2019) relate modelling to six sigma and LM tools; multi-agent simulation; finally, system dynamics (SD) models.

Table 7 details the software tools used by the authors of the reviewed articles grouped by the modelling approach. Hence the main relation between the modelling approaches and software tools is oriented to use software Statistical Package for Social Sciences (SPSS) (9) and AMOS (9) in the application of multivariate statistical modelling approaches; Arena (5), Matlab (4) and Minitab (4) are the most widespread in the optimisation modelling approach. Furthermore, it is observed that in this modelling approach, there is a diversity of software that can be applied, such as Excel (3), SPSS (3), Simul8® (2); Arena (4) is also one of the most widely used in the simulation optimisation modelling approach in addition to OptQuest (2). AnyLogic and Arena are considered the most widely employed in the simulation modelling

Table 7. Software tools used per modelling approach.

Modelling approach	Amos	AnyLogic	Arena	CAD	Excel	EasyFit	FlexSim	Facts Analyzer	Gams	ILOG CPLEX	Matlab	Minitab	NFMS	OptiSLang	OptQuest	Promodel	SAP	Simul8®	SPsim	SCMD	Smart PLS	SPSS	Tomlab	Visual Basic	Visual SLAM	XRL/Woflan	N/A
	Software Tools																										
Multivariate statistics	9			1	1							2									1	9					18
LM techniques				1			1						1														2
Optimisation				1	1				1	1	2	3	1	1					1			1	1		1	1	4
Artificial intelligence					1						1											1					1
Conceptual models			1															1									16
Simulation optimisation			5		1		1	1							2	1											1
Simulation		2	3		1		1	1				1				1	1							1			4
	9	**2**	**9**	**3**	**5**	**0**	**3**	**2**	**1**	**1**	**3**	**6**	**2**	**1**	**2**	**2**	**1**	**1**	**1**	**0**	**1**	**11**	**1**	**1**	**1**	**1**	**46**

approach. LM techniques, artificial intelligence and conceptual modelling approaches apply fewer software tools in the articles classified in those categories. So the most widely used analytical software tools are SPSS (12) and SPSS Amos (9) given their application in statistical analyses, based mainly on SEM, ISM, total interpretive structural modelling (TISM), among others; Minitab (7) is applied mainly to implement six sigma with the DMAIC methodology; Besseris (2014) adopts Minitab; Khalili et al. (2017, 2018), Solke and Singh (2018) and Kristensen (2021) combine SPSS and the SPSS Amos software. Of the simulation software tools, Arena (12) and FlexSim (3) are the most used; Meade, Kumar, and Houshyar (2006) combine Excel to model resource planning, Promodel applies it to the development and operation of the model's production environment and Visual Basic to connect to systems for schedule dissemination and inventory tracking; Evans and Alexander (2007) employ Arena and EasyFit; Dotoli et al. (2012) use Arena and SAP; Abbasian-Hosseini, Nikakhtar, and Ghoddousi (2014) resort to Arena and EasyFit; Yang et al. (2015) combine Arena and OptQuest, which helps to enhance data analysis capabilities; Nagi, Chen, and Wan (2017) combines software tools Arena and Minitab, as do Pérez Vergara and Rojas López (2019) who combine Minitab and FlexSim. Of the selected articles, 44.44% do not report which software tools they employ in their research, and 17.17% deal with conceptual models, mainly literature reviews. The least referred software tools in the reviewed LM articles are EasyFit, Gams, ILOG CPLEX, Promodel, SIMUL8, Woflan, Smart PLS, Visual SLAM, Visual Basic, among others. More details of the software tools resorted to by the authors of the reviewed articles appear in Appendix 7.

3.2.3. LM techniques and types of LM waste

The most frequently used LM techniques (see Figure 3) in the reviewed research are: VSM (36), JIT (34), TPM (24), Kanban (23), Kaizen (20), 5S (18), pull (18), TQM (16), SMED (14), takt time (14), six sigma (13), CM (12), PDCA (11) and standardisation work (10). Other techniques, such as visual control, poka yoke, statistical process control (SPC), Ishikawa, Pareto, five whys, heijuka, seven waste, FMEA, brainstorming, ERP or S&OP, Jidoka, Hoshin Hairi, Ishikawa, QFD, TOC and TPS, appear in fewer than 10 of the reviewed research works. Appendix 8 details each technique with the respective literature references.

VSM stands out for being used to: assess the current and future states of processes in organisations; compare the results after applying simulation (Lu, Yang, and Wang 2011; Wang et al. 2015; Yang et al. 2015; Zuniga, Moris, and Syberfeldt 2017; Faisal 2018; Uriarte et al. 2018c; Cuesta et al. 2020; and Yang et al. 2020); help to improve efficiency in eliminating waste (Wang 2015); and visualise value and non-value-adding activities (Yang et al. 2015). Hodge et al. (2011) mention that, of the five textile companies that form the case studies, three involve VSM and two companies, 5S, which highlights that VSM is an initial tool to implement LM.

Houshmand and Jamshidnezhad (2006) apply different LM tools in their conceptual model: VSM, which they place at the first level of the model; Kanban, which they use to eliminate waste; QFD, for the product development phase; TPM, to minimise production costs; process flow analysis; JIT; cause–effect analysis or Ishikawa; standardisation work; SMED; pull production system; visual controls, for effective inspection; and SPC to eliminate product non-conformities.

Vinodh and Aravindraj (2012) highlight some LM techniques: VSM, 5S, Kanban, Kaizen, TQM, TPM, SMED, CM, pull production system, poka yoke and visual controls for efficient waste minimisation. Elmaraghy and Deif (2014) integrate into an SD model three lean techniques, JIT, TPM and SMED, for levelling production and associated costs. Wang (2015) recommends

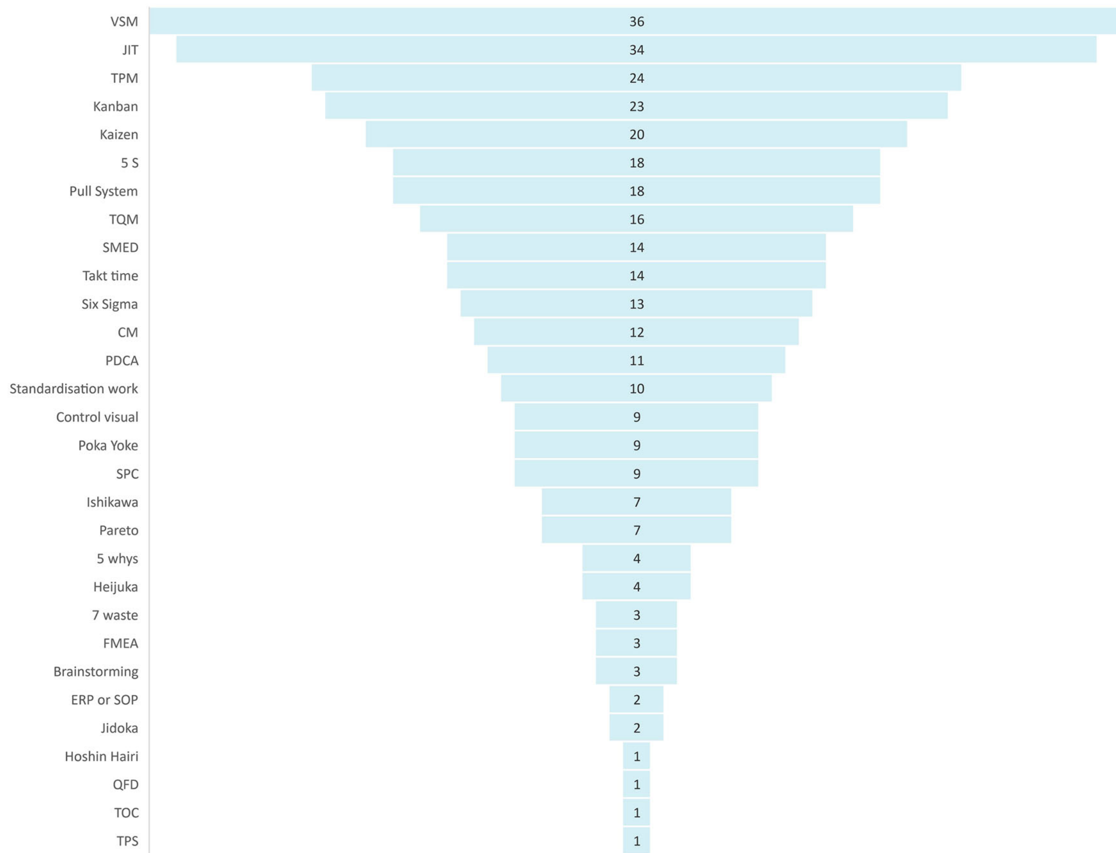

Figure 3. LM techniques identified in the selected articles.

applying VSM and JIT in his conceptual model of logistics strategies. Khalili, Ismail, and Karim (2017) consider LM tools, namely VSM, poka yoke, visual control, 5S, TPM, Kanban, standardisation work, SMED, FMEA, Kaizen and PDCA, which impact the improvement and potentiality of a quality management system.

In their six sigma application, Rabii, Naoufal, and Omar (2018) use some LM techniques and the DMAIC methodology. In the define phase, they employ a Pareto diagram; in the measure phase, they integrate the use of TPM; in the analysis phase, they resort to Ishikawa and 5S; in the improve phase, they use visual check, seven waste, SMED, poka yoke, 5S and TPM; in the control phase, they resort to SPC. Shrafat and Ismail (2019) consider that the commonest LM techniques are TPM, 5S and SPC. Baliga, Raut, and Kamble (2020) define, as part of LM dimensions, the techniques JIT, pull production system, SPC and TPM, which contribute to promote environmental practices in SCs. Cuesta et al. (2020) apply 5S by reducing production times and increasing production capacity in an industry that assembles televisions.

It is worth mentioning that the success of LM techniques is combined with other factors, such as human resources, organisational strategies, among others, and it is established to carry out improvement processes and to increase organisations' profitability. Some authors address the barriers involved when implementing the LM methodology, such as Kumar and Kumar (2017), who identify seven barriers (lack of resources, lack of management commitment, conflict with other systems, past experience of failure, employee's resistance, lack of knowledge and no direct financial gains) to study relations and give weights to LM barriers in Indian industries. Sindhwani et al. (2019) agree with five of the barriers identified by Kumar and Kumar (2017), and identify eight more barriers (improper communication, lack of planning of strategies, market competition, inadequate data collection, lack of mutual trust, volatile customer demand, poor layout and infrastructure, and lack of government support). It is worth noting that identifying LM barriers can help any organisation to successfully implement LM techniques (Sindhwani et al. 2019).

One of the main objectives of LM is reduction of waste, and some of the most representative ones are shown in Table 8: standby, which refers to idle times; non-utilised talent, which refers to the underutilised capabilities of human resources; inventory excess, which includes the quantities of inventory held in excess of target or required inventories; poor information management, which denotes mismanagement of information

Table 8. Types of LM waste.

Waste	Articles
Standby	25
Non-utilised talent	19
Inventory excess	16
Poor information management	13
Defects	11
Process errors	6
Poor supplier quality	6
Motion	5
Overproduction	5
Overprocessing	3

by decision makers, sometimes due to the information systems used or even lack of information and/or knowledge; defects, which are related to quality product/service failures; process errors, which implies inefficiencies occurring during processes, such as machine stoppages, material errors, among others; poor supplier quality, which represents the unreliability of supplies due to non-compliance with specifications in terms of delivery times, quantity and/or quality of supply; motion, unnecessary movements by workers or robots at their workstations; overproduction, which refers to the quantities of production carried out in excess of what is needed; and overprocessing, which adds more value to a product/service than the customer actually requires. It is worth noting that Alkaabi et al. (2019) and Jain and Ajmera (2019) address up to eight of the LM waste types identified in their articles. Appendix 9 details the types of LM waste considered by the reviewed articles.

3.2.4. Uncertainty factors

We now look at the main contributions and applications related to the modelling approaches used by the reviewed articles for the treatment of system and environmental types of uncertainty. In this section, only the reviewed articles using analytical optimisation and other analytical modelling approaches, artificial intelligence and simulation (Table 6), are considered to analyse objective functions, decision variables and parameters for modelling LM systems under uncertainty.

The main contributions of those studies that employ LM techniques to address the type of system uncertainty are: cycle time reduction, equipment availability and error correction. For example, Nallusamy and Saravanan (2018) study reducing the total cycle time in valve manufacturing by implementing Kaizen, VSM and motion study to meet customer demand. Gomero-Campos et al. (2020) address lowering the percentage of delay due to machine availability by applying LM techniques: 5S, SMED, focused improvement and Johnson method in a printing industry. Wasim et al. (2013) study the elimination of errors in the design stage using poka yoke and voice of customer incorporation with a method composed of a user interface, three lean enablers and knowledge-based engineering in several industrial sectors. In the system uncertainty context, we find that SC applications most frequently apply the VSM technique to improve efficiency. Accordingly, el Kihel et al. (2019) focus on the VSM-based methodology for the continuous improvement of the SC distribution process. Here Henríquez-Alvarado et al. (2019) highlight the time taken by workers in a fibreglass production plant to get used to the proposed model integrated by the VSM and 5S tools.

The main research contributions that address environment uncertainty focus on lean with uncertain demand, the practical application of LM techniques and the handling of dynamic environments. Lu, Yang, and Wang (2011) explore lean in glass display manufacturing with uncertain demand by knowing current and future state maps. Vinodh and Joy (2012) verify the positive influence of the environment on the application of LM techniques practices (TPM, SPC and housekeeping 5S) in several industries. Dubey and Singh (2015) identifies four groups of variables using the fuzzy MICMAC analysis in a dynamic environment. In this environment uncertainty context, the following limitations are identified: exhaustive modelling times, lack of tools to assess social dimensions and lack of statistical data validation. In this sense, Lu, Yang, and Wang (2011) indicate that their proposed methodology to manufacture liquid crystal displays requires a long modelling time, which becomes a barrier to adopt this model. Soni and Kodali (2016) mention that their study very specifically addresses lean SCs in the Indian manufacturing industry. The model applied by a confirmatory factor analysis does not reveal the interrelations between the identified lean SC management pillars and constructs. Dubey and Singh (2015) consider the rigidity of the ISM approach as a limitation for its time-consuming nature and the impossibility of easily including minority perspectives.

Regarding mixed environments of system and environment uncertainty, the work of Gürsoy and Soner Kara (2021) is noteworthy. They propose MILP for the SC network design problem composed of suppliers, manufacturers, distribution centres and retailers for JIT deliveries. McLeod, Stephens, and McWilliams (2016) apply an exploratory analysis and identify nine potential application factors for LM modelling among SMMs: (i) training; (ii) involved employees; (iii) supplier/customer feedback; (iv) production flow; (v) SC coordination; (vi) TPM; (vii) product development; (viii) pull production; and (ix) rapid changeover. McWilliams and Tetteh (2009) consider analytical models to determine labour requirements and the impact of demand variation on

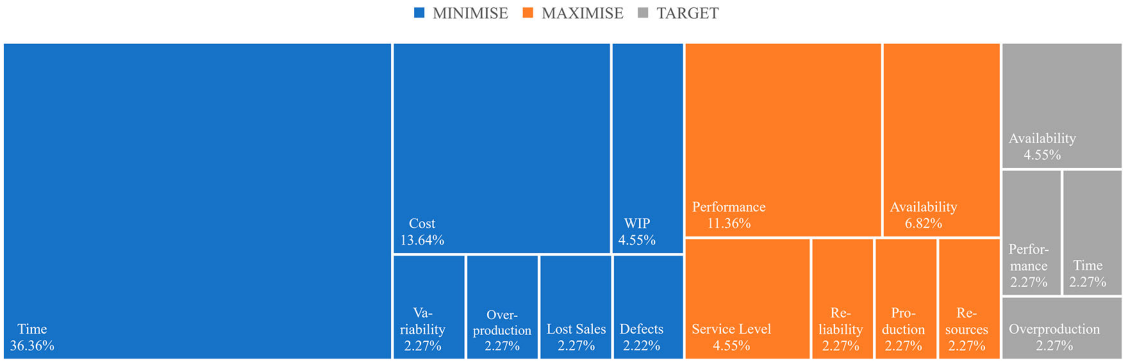

Figure 4. Decision variables and objective functions.

LM systems to gain insight into the behaviour of the CM system with U-shaped work cells and non-negligible times between subfamilies and to reduce manufacturing costs. The limitations identified in the mixed uncertainty context relate mainly to: the application of multi-agent systems (MAS) and the attributes associated with industrial dynamics and SCs. For example, Agarwal, Shankar, and Tiwari (2006) mention that the ANP methodology requires pairwise comparison matrices and, in addition, these values depend on decision makers' knowledge in the decision-making process. In another approach, McLeod, Stephens, and McWilliams (2016) identify that late data collection due to the busy schedules of the consulted SMM executives make it difficult to obtain valid results. They also consider that a strategy which focuses only on routine operational improvement is not economically viable in the long term.

For the analysis of parameters and decision variables that are affected mainly by uncertainty, the quantitative analytical modelling approaches of optimisation and others, artificial intelligence and simulation are considered. The parameters and decision variables that are identified mostly in the analytical modelling approaches in the uncertainty context are (in order of significance): time, cost, performance, availability of machines and/or equipment, service level and work in progress (WIP). There are other less representative variables, such as reliability, production, overproduction and resources, which are also considered in the reviewed models.

Thus time is the most representative decision variable (Figure 4) with 32.65%, which is related to takt time, lead time and manufacturing time. It is followed by the cost variable, which represents 18.37% and is oriented towards transport, production and logistics; the performance variable, with 18.36%, is related to the efficiency of production processes; the availability variable, which is related to machines or equipment, represents 6.12% when the objective is to maximise, and 2.04% when it is to maintain; the service level variable represents 4.08% and is related to customer satisfaction; the WIP variable represents 4.08% and is related to works in progress. The least representative variables are: defects, variability, reliability, lost sales, overproduction and resources. Appendix 10 shows the details of the decision variables analysed in each reviewed article.

The main type of uncertainty identified in the examined quantitative LM models is system uncertainty, followed by models containing variables that affect both the system and organisations' environment in a mixed way and, finally, fewer models address only environmental uncertainty (Figure 5). Hence system factors, such as production and personnel performance, maintenance policies, process barriers, service level, cycle time, among others, are identified as internal factors in organisations which affect manufacturing performance. These factors represent 79.8%. Environmental factors, such as uncertain demand, experts and suppliers' opinion, among others, represent 5.50% and refer to external factors that affect companies' manufacturing performance. Finally, some articles simultaneously address both system and environmental factors (mixed), which account for 14.14%.

Appendix 11 presents different modelling approaches with identified uncertainties. Within the systems uncertainty context, they are mostly modelled using DOE and applying other analytical modelling techniques. The uncertainty of cycle time is the most representative and can be modelled by applying: (i) Gaussian process metamodels; (ii) multilevel factorial DE and scenarios; (iii) MILP models; (iv) time Petri nets; (v) flexibility in SC with ANP; (vi) fuzzy set theory; and (vii) elitist genetic algorithm MH. Regarding the environment uncertainty, demand uncertainty is the most representative and can be modelled according to each of the scenarios proposed by the authors through: (i) EPQ model; (ii) multiobjective with fuzzy logic; (iii) experimentation in different scenarios; and (iv) probability distributions with different scenarios. Finally, in the system and environment (mixed) context, demand-machines uncertainty can be modelled by: (i) SD with continuous-time model and

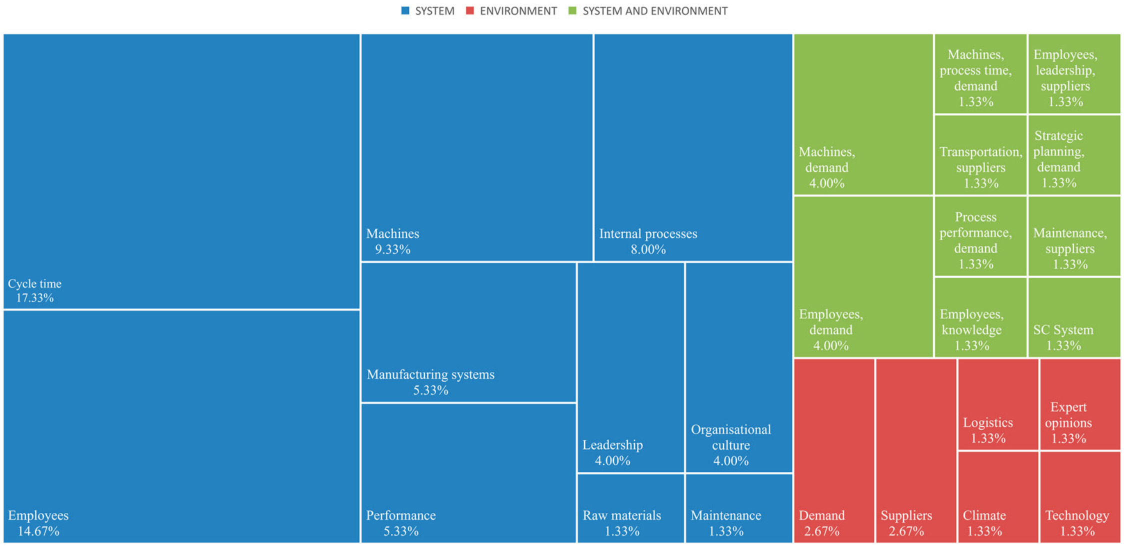

Figure 5. Factors of the identified uncertainty types.

with stochastic parameters; (ii) fuzzy logic based quantitative lean index; and (iii) MCDM, hybrid Taguchi, and TOPSIS.

4. Discussion

This paper analyses quantitative modelling approaches that address LM under uncertainty. The findings of the formulated research questions are discussed below.

RQ1. Categorisation of the selected articles

Figure 6 summarises the main results of the categorisation of the selected and reviewed articles.

These studies have been conducted in several sectors, such as automotive, healthcare, construction, agrifood and beverages, graphics, technology, retailing, logistics and maintenance. This work also identifies that most research is limited because it is applied to narrow settings, such as specific regions, countries, products or services.

The modelling approaches referred to in our review are grouped into four main groups: conceptual, analytical, artificial intelligence and simulation. Four subgroups are established for the analytical approach models: multivariate statistics, LM techniques, optimisation and other quantitative models. The simulation modelling approach is divided into two subgroups: simulation optimisation and simulation. This allows LM practitioners, academics and researchers to obtain a guide to existing models for possible applications in different types of product, process, service and mixed organisations.

The main techniques applied in the LM and uncertainty context according to the reviewed articles show that VSM is considered a technique of potential application because it allows the current and future states related to an organisation's processes to be known, and it also interacts with other LM techniques. The other techniques highlighted in the research articles for their usefulness are: JIT, TPM, Kanban, Kaizen, 5S, pull production, TQM, SMED, takt time, six sigma, CM, PDCA and standardisation work. It is worth mentioning that some authors relate several of these tools in their studies and categorise them according to common objectives.

The content of the reviewed research works largely addresses several factors, such as machines, employees, process barriers, service level, production capacity, WIP, raw material and transport, among others, in relation to system uncertainty. These factors can be adjusted with the application of some LM techniques, which can also involve staff at all levels and top management to improve the processes that directly affect manufacturing performance. It is worth mentioning that factors like demand, suppliers, expert opinion, among others, are considered relevant under environmental uncertainty, which poses a serious challenge due to the high percentage of uncertainty that it causes. Although these factors are not controllable by organisations, environmental variables are as important as system variables. Therefore, it is necessary to search for models or methods to integrate them because they affect such organisations' manufacturing performance.

Although environment uncertainty-type variables are difficult to control, such as uncertainties caused by meteorological aspects and natural disasters (Qiu 2011), some authors present methodologies that address them and seek their possible reduction. Likewise, market demand is the most difficult to control due to its wide variation, which significantly influences production times. Identifying, managing and reducing demand uncertainty require a lot of effort in an LM system (Lu, Yang, and

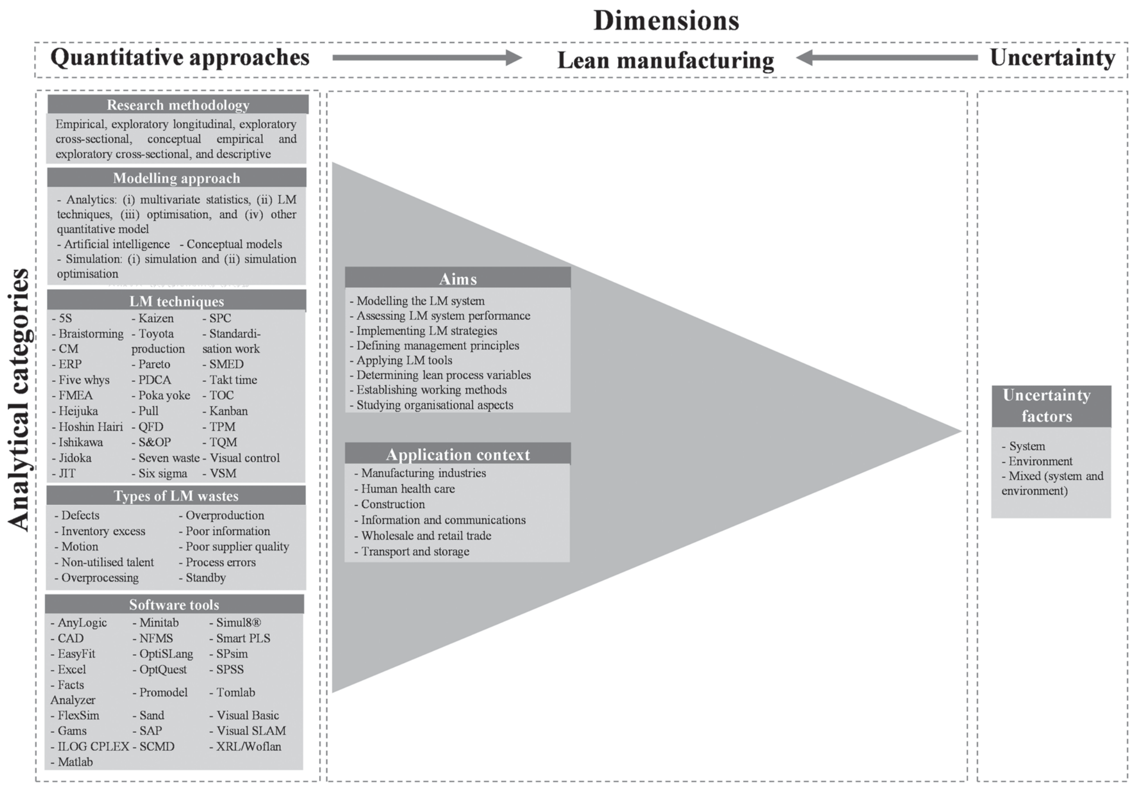

Figure 6. Results of analytical categories.

Wang 2011), and having to take into account that demand impacts a manufacturing system's delivery performance (McWilliams and Tetteh 2009); for example, there is one proposal to apply LPS to identify the uncertainties related to demand and, in this way, to propose solutions (Qiu 2011).

Of the contributions that involve a mixed environment with system and environment uncertainty we find: LM applications in SCs, exploratory factor analysis and analytical models for labour resource requirements. Thus we identify the pairs of demand uncertainty and machine uncertainty, and demand uncertainty and employee uncertainty, as the main ones addressed in the reviewed articles; although there are other sets of mixed uncertainties (see Figure 5).

In general, the quantitative research works that target LM under uncertainty offer multiple valuable contributions in terms of: (i) reducing cycle and waiting times; (ii) equipment availability; (iii) error correction; (iv) developing experimentation algorithms; (v) increasing throughput rates per experiment; (vi) applying resilience engineering; (vii) applying VSM; (viii) improving process performance; (ix) defining the lean index for Monte Carlo modelling; (x) implementing analytical models; (xi) improving the robustness of statistical models for manufacturing performance; (xii) fuzzy set theory applications to capture demand uncertainty; (xiii) reliability-focused optimal configuration; (xiv) uncertainty reduction; (xv) optimisation based on lean logistics; (xvi) model validation based on expert opinions; (xvii) facing a dynamic environment; (xviii) supporting LM practices; (xix) lean studies with uncertain demand; (xx) supplier evaluation and development; (xxi) supply base reduction; (xxii) supporting LSS processes; (xxiii) standardisation approaches; (xxiv) flexibility in SCs; (xxv) the process sustainability index; and (xxvi) improving organisational performance.

As negative effects of uncertainty are generally detrimental for manufacturing performance, immediate solutions must be sought to reduce their impact on production processes. Making the right decisions to narrow down the variation of different factors is becoming increasingly more challenging, but it is necessary to obtain tangible and operational benefits related to the reduction of defective products, and to improve manufacturing times, have equipment or machinery available, meet customer deliveries, have committed staff, and improve productivity, among others.

RQ2. Research gaps and future research on quantitative modelling approaches for LM under uncertainty

Here Figure 7 presents a conceptual framework for future LM quantitative modelling with uncertainty research.

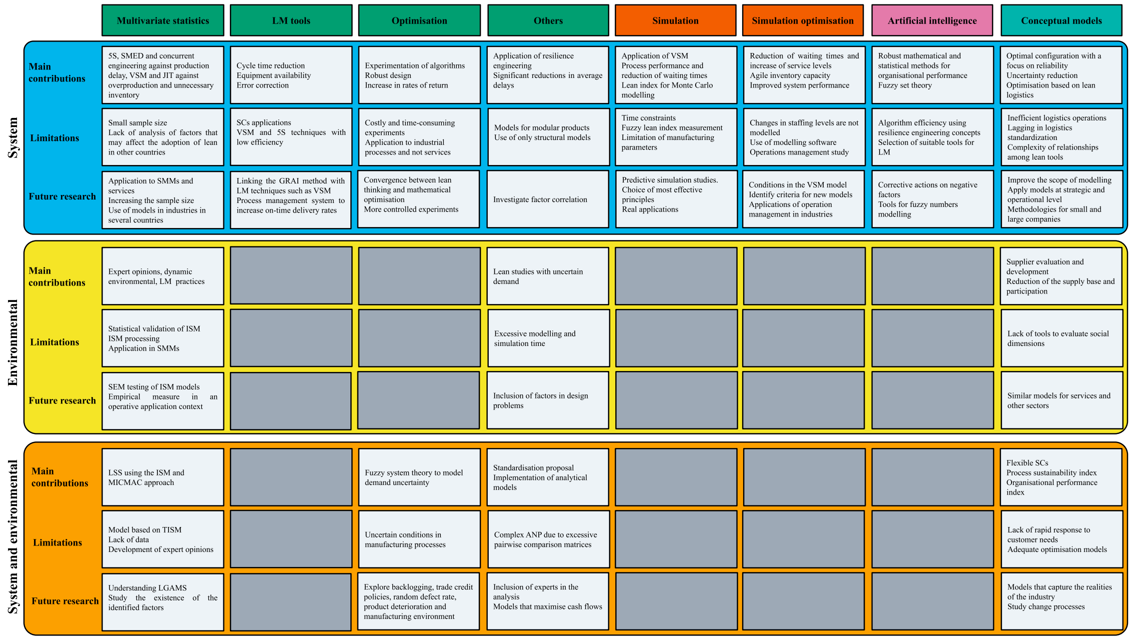

Figure 7. Conceptual framework for future LM quantitative modelling with uncertainty research.

The main challenges identified in the type of system uncertainty are related to linking method graphs with results and actions interrelated (GRAI) and the process management system to improve on-time delivery rates. el Kihel et al. (2019) consider linking the GRAI method to control a distribution system with VSM to observe the variables of actions and to link the supply chain operations reference (SCOR) model by also deciphering critical phases from the process analysis point of view. Nallusamy and Saravanan (2018) contemplate layout optimisation by involving all products and extending the operations of manufacturing components to effectively reduce lead times by means of additional tools, such as 5S, Kanban, line balancing, among others, as a future work. Gomero-Campos et al. (2020) mention that the development of a process management system can be considered to help to reduce activities and to increase on-time delivery rates.

The challenges identified in the type of environment uncertainty are: extending models to include detailed factors to cover design problems and to develop similar models for services and other sectors. Lu, Yang, and Wang (2011) contemplate extending the model to include the factors that address design issues and supplier considerations, and indicate that the smaller size of moving batches that are currently fixed should be investigated. Dubey and Singh (2015) also agree with Lu, Yang, and Wang (2011) about extending the proposed model, but by investigating lean implementation challenges in other manufacturing industries, such as automotive, furniture or other consumer goods. They also recommend using SEM to statistically test the model developed with ISM.

Regarding the mixed uncertainty context, the main identified challenge is to conduct further studies to confirm the existence of the factors that enable practical LM application in SMMs (McLeod, Stephens, and McWilliams 2016). Deif (2012) mentions that more dynamic LM issues, the impacts of other more complex pull policies on the performance of lean CM and the dynamic analysis should be extended to multistage production, and should be studied. The dynamic nature of demand and lean production require more research. McWilliams and Tetteh (2009) indicate the need for a simulation model of the manufacturing system to validate the analytical model that they propose, and they assess the system's dynamic behaviour. Tayyab, Sarkar, and Ullah (2018) mention that research should be extended towards several directions by considering controllable production rate, planned and partial backlog, trade credit policies, random defect rate, product deterioration and constrained manufacturing environment in the production system.

As a summary, Figure 7 shows that the main limitations of the reviewed research lie in the difficulty to apply and practically validate the proposed solutions in different real cases by considering mainly those aspects related to internal policies, the identification of variables between sectors that affect organisations, among others. Thus practically implementing the quantitative modelling approaches for LM under uncertainty proposed by the reviewed articles in different industries from several sectors to assess usability, efficiency, among others, is considered critical. Along with actually implementing the proposed solutions, Solke and Singh (2018) and

Gürsoy and Soner Kara (2021) generally recommend extending sample size to serve as a global guide for the cross-sectorial and cross-industry implementation of LM techniques in uncertainty contexts.

Thus the following research gaps were identified in this research paper in relation to uncertainty types and modelling approaches.

Research gaps in the system uncertainty context:

- Regarding the multivariate statistics approach: (i) small sample size (Yang et al. 2015; Tortorella et al. 2018); (ii) lack of analysis of the factors that may affect the adoption of lean in other countries (Tortorella et al. 2015; McLeod, Stephens, and McWilliams 2016; Kumar and Kumar 2016; Tajri and Cherkaoui 2016; Uriarte et al. 2016; Vasanthakumar, Vinodh, and Ramesh 2016; Ghobakhloo et al. 2018).
- In relation to LM tools: (i) SCs applications (Nguyen and Dafo 2016; el Kihel et al. 2019; Baliga, Raut, and Kamble 2020); (ii) VSM and 5S techniques with low efficiency (Zhao, Ye, and Gao 2012; Wang et al. 2015; Faisal 2018; Henríquez-Alvarado et al. 2019).
- Artificial intelligence: (i) algorithm efficiency using resilience engineering concepts (Siomina and Ahlinder 2008); (ii) selecting appropriate tools for LM (Houshmand and Jamshidnezhad 2006; Uriarte et al. 2016; Basu, Ghosh, and Dan 2018a).
- Conceptual models: (i) inefficient logistics operations (Wang 2015); (ii) lagging in logistics standardisation (Wang 2015); (iii) complexity of relations among lean tools (Vinodh and Joy 2012; Anvari, Zulkifli, and Yusuff 2013; Abbasian-Hosseini, Nikakhtar, and Ghoddousi 2014).
- Optimisation: (i) costly and time-consuming experiments (Li and Zhu 2008; Wasim et al. 2013; Bocanegra-Herrera and Orejuela-Cabrera 2017; Rabii, Naoufal, and Omar 2018); (ii) despite the existence of applications to industrial processes, applications to services are still lacking (Basu, Ghosh, and Dan 2018b; Hodge et al. 2011; Khalili, Ismail, and Karim 2017, 2018; Noha and Abderrazak 2019; Vinodh and Aravindraj 2012).
- Simulation: (i) time constraints (Shrafat and Ismail 2019); (ii) fuzzy lean index measurement (Oleghe and Salonitis 2016; Tayyab, Sarkar, and Ullah 2018); (iii) limitations of manufacturing parameters (Goldsby, Griffis, and Roath 2006; Meade, Kumar, and Houshyar 2006; Nagi, Chen, and Wan 2017; Basu, Ghosh, and Dan 2018b).
- Simulation optimisation: (i) changes in staffing levels not modelled (Camuffo and Gerli 2018; Ramadas and Satish 2018b); (ii) using modelling software (Vinodh and Joy 2012; Cuesta et al. 2020); (iii) operations management studies (Gomero-Campos et al. 2020).
- Other modelling approaches: (i) models for modular products (Alkaabi et al. 2019); (ii) using only structural models (Uriarte et al. 2018c; Wickramasinghe and Wickramasinghe 2018).

Research gaps in the environmental uncertainty context:

- In relation to the multivariate statistics approach: (i) statistical validation of ISM (Dubey and Singh 2015; Soni and Kodali 2016; Singh and Singru 2018; Sarhan et al. 2019); (ii) ISM processing (Chaple et al. 2018a); (iii) application in SMMs (Sharma, Dixit, and Qadri 2016; Solke and Singh 2018).
- Conceptual models: lack of tools to evaluate social dimensions (Machado and Pereira 2008; Azadeh et al. 2017).
- Other modelling approaches: (i) excessive modelling (Sharma, Dixit, and Qadri 2016 and Greinacher et al. 2020); (ii) simulation time (Ajaefobi and Weston 2007; Lu, Yang, and Wang 2011).

Research gaps in the mixed uncertainty context (system and environmental):

- In relation to the multivariate statistics approach: (i) model based on TISM (Chaple et al. 2018b; Sindhwani et al. 2019); (ii) lack of data (Besseris 2014; Zuniga, Moris, and Syberfeldt 2017; Sarhan et al. 2019; Shrafat and Ismail 2019); (iii) developing expert opinions (Mandujano et al. 2017; Zuniga, Moris, and Syberfeldt 2017; Pérez Vergara and Rojas López 2019).
- Conceptual models approach: (i) lack of a rapid response to customer needs (Mahfouz, Shea, and Arisha 2011ME; Wang et al. 2015; Nallusamy and Saravanan 2018); (ii) adequate optimisation models (Machado and Tavares 2008; Deif 2012).
- Optimisation: uncertain conditions in manufacturing processes (Dotoli et al. 2012; Jayamaha, Grigg, and Pallawala 2018).
- Other modelling approaches: complex ANP due to excessive pairwise comparison matrices (Agarwal, Shankar, and Tiwari 2006; Raval, Kant, and Shankar 2018).

These research gaps need to be filled in the future as follows.

Future research in the system uncertainty context:

- Multivariate statistics approach: (i) application to SMMs and services; (ii) increasing sample size; (iii) using models in industries in several countries.

- LM tools: (i) linking the GRAI method with LM techniques like VSM; (ii) process management system to increase on-time delivery rates.
- Artificial intelligence: (i) corrective actions for negative factors; (ii) tools for fuzzy numbers modelling.
- Conceptual models: (i) improving the scope of modelling; (ii) applying models at strategic and operational levels; (iii) methodologies for small and large companies.
- Optimisation approach: (i) convergence between lean thinking and mathematical optimisation; (ii) more controlled experiments.
- Simulation: (i) predictive simulation studies; (ii) choice of the most effective principles; (iii) real applications.
- Simulation optimisation approach: (i) conditions in the VSM model; (ii) identifying criteria for new models; (iii) operation management applications in industries.
- Others: investigate correlation factors to determine the success of the application of LM tools in the system uncertainty context.

Future research in the environmental uncertainty context:

- In relation to the multivariate statistics approach: (i) SEM testing of ISM models; and (ii) empirical measures in an operative application context.
- Conceptual models: similar models for services and other sectors.
- Others: including factors in design problems.

Future research in the mixed uncertainty context (system and environmental):

- Multivariate statistics approach: (i) understanding how to integrate lean, green and agile paradigms into manufacturing systems (LGAMS); (ii) studying the existence of the identified factors.
- Conceptual models: (i) models that capture the realities of industry; (ii) studying change processes.
- Optimisation: exploring backlogging, trade credit policies, random defect rate, product deterioration and manufacturing environment.
- Other approach identified: (i) including experts in analyses; (ii) models that maximise cash flows.

5. Theoretical and managerial implications

Here theoretical implications focus on proposing analytical categories (Figure 6) and a conceptual framework (Figure 7) for future research on developing quantitative approaches for LM in an uncertain context to advance with theories, modelling approaches and applications on the topic, as inspired by Durach, Kembro, and Wieland (2017; 2021). Thus a new understanding is provided of the quantitative approaches of design of experiments, structural equation modelling, interpretive structural modelling, discrete events simulation, intuitive and pragmatic approaches, system dynamics, metaheuristics, fuzzy logic, hybrid simulation, analytical models, workflow, conceptual models, cost models, multiple criteria decision-making and/or multi-objective models, among others.

The managerial implications of this research work aim to provide a categorisation of the analysis of quantitative approaches for LM modelling under uncertainty to guide future research by academics and practitioners to develop new conceptual and analytic models that support LM practices and implementations under system, environment or mixed uncertainties. The incorporation of quantitative models for LM under uncertainty would increase manufacturing performance, and would be useful for application contexts like manufacturing, and other application areas like health, construction, information and communication, wholesale and retail, transport and storage, where quantitative approaches are also underresearched and poorly applied (Table 4). The factors herein mentioned can foster training and knowledge acquisition for manufacturing managers to utilise quantitative approaches when applying LM tools in uncertain contexts.

6. Conclusions

In order to provide new findings about quantitative methods for the optimisation and simulation of LM problems under uncertainty, the present research focuses on reviewing the literature to identify existing approaches. To this end, after exploring the literature review, we analysed the thematic and content of the reviewed articles, the research methodology, the applied modelling approaches, the most representative parameters and decision variables of the addressed approaches, the LM techniques, types of waste, software tools, types of uncertainty and factors that cause it. The main contributions, limitations and future research lines of the 99 selected research articles were also analysed.

The main scientific reviewed research works related to quantitative models for decision making in LM environments under uncertainty have been conducted mostly in the USA, India, the UK, China and Germany. The main aims pursued by the reviewed research works are: modelling the LM system and validating its application, evaluating the performance of an LM system, proposing and implementing LM strategies, defining management principles, applying LM techniques, determining lean process variables, establishing working methods, studying organisational aspects, among others. The most prominent application sector that comes over in the reviewed scientific articles is, and as expected, manufacturing, concretely the automotive and aerospace sectors, followed by the health, construction, agrifood and beverages, graphics, technology, retailing, logistics and maintenance sectors, which are also addressed, albeit to a lesser extent, by the reviewed research. Most articles focus on the empirical methodology, which represents 59.6% of the articles, followed by the cross-sectional exploratory methodology, with 15.15%. The most representative modelling approach is the analytical one, which deals with multivariate statistics, models using LM techniques and other quantitative models. It is followed by the second most representative approach, which is based on simulation modelling.

Although the number and diversity of LM techniques are considerable, the most widely used one in our literature review is VSM, followed by JIT. The main objective of LM techniques is to reduce waste, and the most frequently addressed aims in the reviewed articles are: waste standby, non-utilised talent, inventory excess, poor information management and defects. LM techniques are supported by several software tools to facilitate the decision-making process. From an analytical viewpoint, SPSS is the most widespread one. From a simulation point of view, Arena is the most representative software tool in the LM under uncertainty context.

The most representative objective function in LM under uncertainty in analytical modelling approaches pursues to minimise the time variable (takt time, lead time, manufacturing time), followed by the cost variable (transport, production and logistics costs). It should be noted that the type of uncertainty that is most commonly addressed is system uncertainty because it encompasses the internal factors for the domain of any organisation.

It should be highlighted that this literature review has some limitations. The consulted databases are Scopus and WoS, which are constantly being updated and the provided data correspond to those obtained at the time when the research was conducted. Despite following a systematic search process, some valuable papers could have been overlooked for this review. For instance, we avoided papers belonging to specific areas like physics, astronomy, toxicology, or other research fields, which would require more specific reviews. In any case, some limitations that appeared while conducting this study are actually an opportunity for new research lines and forthcoming works. Hence the proposed conceptual framework could serve as a guide to perform future studies related to quantitative modelling for LM under uncertainty. A forthcoming work is oriented to the development of a new conceptual model for LM under uncertainty where a multidimensional analysis for operations management will be provided. This conceptual model will be the basis for new quantitative models (analytical, simulation, artificial intelligence) to address LM, lean logistics and lean industry 4.0 (Hines et al. 2023). These new models will contribute to advance in theory and practice related to sustainable and resilient production systems.

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No potential conflict of interest was reported by the author(s).

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Data availability statement

The authors confirm that the data supporting the findings of this study are available in the article and in Appendices provided within a supplementary file.

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