Appendix 1: Detailed analysis of the literature set and industry case studies

In this appendix, we provide interested readers with the opportunity to obtain more detailed information on each individual article in our literature set, the solution methods used and specific highlights. But first, we provide an overview of all industry case studies conducted in the literature on multi-factory production planning and scheduling.

1. Industry case studies dealing with multi-factory production planning and scheduling

This concise section illustrates the change brought about by increasing globalization, market uncertainty and technological trends like Industry 4.0.

Gascon, Lefrançois, and Cloutier (1998) examined a multi-product stochastic setting for a hardwood flooring manufacturer in Canada and developed an optimization software for the case company. Azevedo and Sousa (2000) coordinated production plans of semiconductor manufacturing plants through a global procedure and several local capacity models. Gnoni et al. (2003) modeled the supply chain of a braking manufacturer for the automotive industry in Italy with multiple sites and products. Lot sizing and scheduling are solved using a hybrid model. Next, Miller and De Matta (2003) synchronized production and transportation scheduling in a multi-site setting in the pharmaceutical industry. The authors studied this industry again in De Matta and Miller (2004). Cicirello and Smith (2004) used a wasp-like multi-Agent system (MAS) approach to solve an assignment problem of trucks to paint booths in a General Motors plant paint shop. Garcia, Lozano, and Canca (2004) studied order scheduling with vehicle assignment in a no-wait setting in the ready-mixed concrete industry. Naso et al. (2007) also examined this industry and solved a combined production and distribution scheduling problem with exact time windows using a genetic algorithm (GA). Lin and Chen (2007) then studied the TFT-LCD industry and considered variable time buckets for three manufacturing stages: array, cell, and module. Almada-Lobo, Oliveira, and Carravilla (2008) examined the glass container industry where the colour of glass melted in furnaces in plants is the main constraint for production planning and scheduling. Setup times are high, so lot sizing and scheduling have to be integrated. Tsai and Wang (2009) proposed three-stage available-to-promise mechanisms in the TFT-LCD industry to increase profit by satisfying demands with as little due date variation as possible. Chen, Huang, and Lai (2009) examined collaborative production for the TFT-LCD industry using an MAS and an advanced planning and scheduling (APS) system that are interconnected and only share the necessary information for collaboration. Aissani et al. (2012) developed an MILP model and an MAS for a clothing company with various sites and subcontractors and significant transfer times between sites. Guo et al. (2013) examined the order scheduling problem of an apparel manufacturer in China in a multi-objective formulation including total completion time, order tardiness, and machine idle time. Next, H'Mida and Lopez (2013) studied an industrial problem of handling production under different constraints (including transportation in different modes) but did not disclose their case company. Cóccola et al. (2013) focused on chemical supply chains and solved an integrated production and transportation scheduling problem with batch plants and distribution centres. Chen (2014) analysed order fulfilment planning in TFT-LCD manufacturing and proposed multi-site assignment through mathematical programming and constraint-based simulation to schedule each single site shop floor. Textile manufacturing is the scope of Kerkhove and Vanhoucke (2014), with sequence-dependent changeover times, unrelated machines, release dates, and weighted lateness/tardiness objective. Liu, Chen, and Chou (2015) studied the distributed flexible jobshop scheduling problem in a case study with a fastener manufacturer in Taiwan. Guo et al. (2015) used data from an outerwear manufacturer in China for the multi-objective make-to-order setting they examined. More recently, Wang, Yang, and Yu (2018) proposed a lean-pull strategy using e-Kanban for semiconductor crystal ingot-pulling with various manufacturing sites and varying demands. Lei et al. (2019) studied distributed unrelated parallel machine scheduling in heterogeneous production networks based on a case study with a PVC pipe production company in China.

As these studies show, many industries benefit from geographically separated factories and different wage levels. However, the problem is also relevant to industries with multiple factories in the same region, as time-to-market has become so important that insufficient allocation to factories at the regional level can still have a major impact on meeting due dates and securing follow-up business.

2. Multi-factory single machine literature

Now, we present a detailed analysis of all articles, arranged according to the shop conditions (single machine, parallel machine, flowshop, jobshop, open shop). Table 1 and 2 indicate the nomenclature for the abbreviated optimization models and solution methods as well as abbreviated objective functions used in the tables and comments below.

Table 1. Nomenclature of optimization models and solution methods

ABC	Artificial bee colony algorithm	HS	Harmony search
ACO	Ant colony optimization	IA	Immune algorithm
ALNS	Adaptive large neighbourhood search	ICA	Imperialist competitive algorithm
B&B	Branch & Bound	ICG	Iterated cocktail greedy algorithm
BBO	Biography-based optimization	IGA	Iterated greedy algorithm
BSH	Backtracking search hyper-heuristic	ILS	Iterated local search
BSIG	Bounded-search iterated greedy alg.	KCA	Knowledge-based cooperative algorithm
BSO	Brain storm optimization algorithm	LPT	Largest processing time
CDS	Campbell-Dudek-Smith heuristic	LRPT	Largest remaining processing time
CMA	Competitive memetic algorithm	LS	Local search
CRO	Chemical reaction optimization	MA	Memetic algorithm
CP	Constraint programming	MAS	Multi-agent system
DDE	Discrete differential evolution alg.	MCS	Monte Carlo simulation
DEA	Differential evolution algorithm	MILP	Mixed-integer linear programming
DES	Discrete event simulation	MSSO	Memetic social spider optimization algorithm
EA	Evolutionary algorithm	NLP	Non-linear integer programming
EAS	Elitist ant system	NEH	Nawaz-Enscore-Ham heuristic
EDA	Estimation of distribution algorithm	NEH2	NEH, assigning job j to the factory with the lowest C_{max} after including job j
EDAMA	Estimation of distribution-based memetic algorithm	PSO	Particle swarm optimization
EM	Electromagnetism mechanism	RVNS	Reduced variable neighbourhood search
GA	Genetic algorithm	SA	Simulated annealing
GRASP	Greedy randomized adaptive search procedure	SPT	Shortest processing time
GVNS	General variable neighbourhood search	SS	Scatter search
HCS	Hybrid cuckoo search	TS	Tabu search
HIA	Hybrid immune algorithm	VNS	Variable neighbourhood search
HIGA	Hybrid iterated greedy algorithm	VND	Variable neighbourhood descent

Table 2. Problem characteristics / objective function

C_{max}	Makespan	M_{util}	Machine utilization (or workload)
$\sum C_j$	Total Completion time	M_{setup}	Setup times
$\sum T_j$	Total Tardiness	Service	Service level (or throughput)
$\sum E_j$	Total Earliness	Inv.	Inventory
T_{max}	Maximum Tardiness	TEC	Total energy consumption
E_{max}	Maximum Earliness	Cost	Cost
T_{avg}	Average Tardiness	Profit	Profit
$\sum T_j + \sum E_j$	Due Date (Tardiness & Earliness)		

Table 3. Overview and classification of multi-factory single machine literature

Author and year	Factory type	Demand	Network structure ser.	Network structure par.	Objective	Solution method	Transportation considered	Stochasticity	Experiments	Comments
Nigro et al. (2003)	het	st, det		√	Cost, Service	DES, MAS				Minimizing production costs and demand satisfaction (service level)
Garcia, Lozano, and Canca (2004)	hom	dyn, det		√	Profit	MILP, Exact, Heur.	√			Graph-based approach and min. cost flow heuristic
Naso et al. (2007)	hom	dyn, det		√	Cost + M_{util}	MILP, Hybrid GA	√		Concrete industry in Netherlands	GA for job assignment to factories, heuristic to schedule loading operations and truck routing
Tsai and Wang (2009)	het	st, det	√	√	Profit	MILP	√		TFT-LCD manufacturer in Taiwan	Three MILP models for ATP mechanism, opportunity cost considered
Chung, Chan, and Ip (2011)	het	st, det	√	√	$\sum T_j$	Hybrid GA			Electrical home appliance industry in China	Vertically partnered factories in collaboration, Hybrid GA with LS heuristic
Shah and Ierapetritou (2012)	hom	dyn, det		√	Cost	MILP, Exact				Augmented Lagrangean decomposition method
Chen (2014)	het	st, det	√		Profit	MILP, Simulation	√		TFT-LCD manufacturer in China	Allocation solved using CPLEX, Plant Simulation for single-site scheduling
Karimi and Davoudpour (2015)	het	st, det	√		Cost	Exact, Heur.	√			Serial network with batch transportation, B&B method
Feng et al. (2017)	het	st, det		√	Cost	MILP, NLP, Heur.	√			Lagrangean decomposition heuristic to solve the NLP model
Karimi and Davoudpour (2017a)	het	st, det	√		Cost	MILP, Time-indexed model, Heur.	√			LP-relaxation of a time-indexed formulation of the MILP
Karimi and Davoudpour (2017b)	het	st, det	√		Cost	MILP, ICA	√			Knowledge-based imperialist competitive algorithm
Marandi and Fatemi Ghomi (2019)	het	st, det	√	√	Cost	MILP, ICA	√			Integrated production-distribution problem in a network configuration

Nigro et al. (2003) considered a decentralized approach to production planning and scheduling in distributed networks with a MAS with the objective of minimizing production costs and increasing service level. Two coordination approaches are presented: a competitive and a cooperative strategy. The latter achieved lower costs in simulation experiments, but also higher production losses. Therefore, decisions for a strategy should be taken on a management level.

Garcia, Lozano, and Canca (2004) studied the scheduling of orders with subsequent vehicle assignment in a no-wait delivery setting in the ready-mixed concrete industry. They present an MILP model, an exact graph-based approach, and a minimum cost flow method as a heuristic for large instances to increase the overall profit.

Naso et al. (2007) also studied the production-distribution problem in the same industry but considered independent factories that work together in a centralized planning system. A hybrid GA with a constructive heuristic is proposed and tested against several real-life scheduling policies like shortest distance or shortest idle time.

Tsai and Wang (2009) studied an available-to-promise (ATP) problem with backlogs in the TFT-LCD industry and combined three MILP models to an ATP mechanism: Order assignment, ATP allocation, and ATP reallocation for unsatisfied orders. Opportunity costs for unused capacity lead to a system with more early completed orders in their experiments. This ensures free capacity for future orders, which is vital for industries with varying, short-term demands.

Chung, Chan, and Ip (2011) examined different collaboration strategies for supply chains with several layers and proposed a decentralized distributed planning model. A hybrid GA is used for scheduling in each factory, combined with an LS heuristic. The collaboration strategy provides improved flexibility to the system and is able to reduce tardiness efficiently.

Shah and Ierapetritou (2012) consider integrated planning and scheduling for multi-site, multi-product batch plants with transportation to distribution centres. A planning model based on discrete-time representation and a scheduling model based on continuous-time representation is solved using an augmented Lagrangean decomposition to minimize overall costs.

Chen (2014) designed a two-phase procedure for order fulfilment in the TFT-LCD industry that allocates orders to multiple factories first and then uses a constraint-based simulation system for scheduling in each factory. The approach showed promising results in heavy load settings. *CPLEX* was utilized for the allocation and *PlantSimulation* for single-site scheduling.

Karimi and Davoudpour (2015) studied a network with three single-machine factories in series, with batch transportation between each factory and to customer. A B&B method is applied in combination with a heuristic that provides an upper bound for the B&B search to determine the batch number, assignment of jobs to batches, and scheduling in each factory to minimize total tardiness and transportation costs.

Feng et al. (2017) study a coordinated production and transportation planning problem with heterogeneous vehicles. An MILP is formulated to minimize overall costs and solved using *CPLEX* for small instances. A non-linear programming model (NLP) is also proposed for large instances, with transportation costs being expressed as a discontinuous piecewise linear function. Lagrangean decomposition and relaxation are employed to solve the NLP model that performed well in computational experiments.

Karimi and Davoudpour (2017a) proposed a new integrated scheduling and transportation problem where stage-dependent holding costs are considered in a serial structure of factories. Each job needs processing in several factories and is transported with other jobs in batches. An MILP model and a time-indexed formulation are proposed. LP-relaxation is employed to compute a lower bound.

Karimi and Davoudpour (2017b) then proposed a knowledge-based ICA (KBICA) to minimize total tardiness and transportation costs for a similar problem.

Recently, Marandi and Fatemi Ghomi (2019) studied an integrated production and distribution problem in a network configuration with factory allocation, production scheduling, vehicle allocation, and routing decisions. They proposed an MILP model and an improved ICA to solve large instances, where jobs are stored in a central depot after production and then delivered to customer locations.

3. Multi-factory parallel machine literature

Table 4. Overview and classification of multi-factory parallel machine literature

Author and year	Factory type	Demand	Network structure ser.	Network structure par.	Objective	Solution method	Transportation considered	Stochasticity	Experiments	Comments
Gascon, Lefrançois, and Cloutier (1998)	hom	dyn, stoch	√		Inventory, Service	Heur., DES	√		Hardwood flooring factory (USA)	Scheduling software for case company
Sauer (1998)	hom	dyn, det	√		M_{util}, ∑Tj + ∑Ej, Cost	Heur., Fuzzy-logic approach, GA				No experiments
Guinet (2001)	het	st, det		√	∑Tj + ∑Ej, Cost	MIP, Heur.	√			Primal-dual heuristic vs. lower-bound heuristic
Cicirello and Smith (2004)	hom	dyn, stoch	√		Cost, C_{max}, Throughput	MAS		√	Automotive paint shop (USA)	Wasp-like agents for simulation
Chen and Pundoor (2006)	het	st, det		√	∑Cj, Cost	Dynamic programming, Heur.	√			Distribution cost considered
Almada-Lobo, Oliveira, and Carravilla (2008)	hom	st, det	√		Inventory, M_{setup}	MILP, VNS			Glass container industry in Portugal	No case study data for experiments included
Terrazas-Moreno and Grossmann (2011)	het	dyn, det		√	Profit	MILP, Exact	√		Chemical industry	bi-level decomposition (with spatial Lagrangean relaxation) and distribution
Behnamian and Fatemi Ghomi (2012)	het	dyn, det		√	C_{max}, ∑Cj	MILP, ICA, ε-constraint method	√			Transportation between *F* considered
Behnamian and Fatemi Ghomi (2013)	het	st, det		√	C_{max}	MILP, Heur., GA + LS				Modified largest processing time (MLPT) heuristic
Cóccola et al. (2013)	het	st, det		√	Cost	MILP, Exact	√		Chemical industry	Integrated production & distribution sched.

Author and year	**Factory type**	**Demand**	**Network structure**		**Objective**	**Solution method**	**Transportation considered**	**Stochasticity**	**Experiments**	**Comments**
			ser.	**par.**						
Behnamian (2014)	het	st, det		√	Cost + Profit	MILP, VNS + TS	√			Multi-objective, virtual production network
Kerkhove and Vanhoucke (2014)	het	st, det		√	Cost (Tj)	MIP, Constructive heuristic + hybrid meta-heuristic (GA + SA)	√		Knitted fabrics producer (Belgium)	Best constr. heuristics: *Min. Slack, EDD* for sequencing and *Min. transportation time* for machine assignment
Behnamian (2015)	het	st, det		√	Cost	MILP, Exact	√			Multi-Cut Benders Decomposition
Yazdani, Gohari, and Naderi (2015)	het	st, det		√	C_{max}, ∑Cj	MILP, ABC			Behnamian and Fatemi Ghomi (2013) instances	3 MILP models, improved MILP by Behnamian and Fatemi Ghomi (2013)
Behnamian (2016)	het	st, det		√	C_{max}	Graph-Colouring + PSO	√			Parallel job scheduling (more than one machine for a job is allowed)
Behnamian (2017a)	het	st, det		√	C_{max}	MILP, PSO	√			Anarchic PSO outperformed GA by Behnamian and Fatemi Ghomi (2013)
Behnamian (2017b)	het	st, det		√	Cost	MILP, Matheuristic	√		Behnamian and Fatemi Ghomi (2013) instances	Matheuristic combines an electromagnetism-like algorithm with a VNS and a relaxed mathematical model
Lei et al. (2019)	het	st, det		√	C_{max}	ICA			PVC pipe production in China	DPMSP consists of factory assignment, machine assignment, and scheduling decisions

Gascon, Lefrançois, and Cloutier (1998) developed a computer-assisted scheduling heuristic for a multi-item, multi-machine, and multi-site scheduling problem in a hardwood flooring factory to minimize inventory with a high service level in a dynamic, stochastic setting. The heuristic was tested in simulation experiments with data from the case company and reached satisfactory service levels for all tested demand patterns.

Sauer (1998) considered a combination of global scheduling and local adjustments to the global plan and developed a multi-site scheduling system (MUST) with different goals for both levels. Heuristics, fuzzy-logic, and a GA are employed to schedule the system. Unfortunately, experiments are missing in the paper.

Next, Guinet (2001) proposed a flow problem to minimize variable and fixed costs of production and an unrelated parallel machine problem to minimize earliness and tardiness of orders. A primal-dual heuristic approach is used to solve the problems and compared with a B&B algorithm.

An agent-based approach (based on wasp behaviour) for distributed factory coordination was presented by Cicirello and Smith (2004). In a case study with parallel multi-purpose machines in an automotive truck paint booth, the approach showed promising results under heavy workload, minimizing cost associated with setups.

Chen and Pundoor (2006) examined a supply chain with multiple factories and distribution centres, with static and deterministic orders and varying process times and costs. The authors proposed four problem variants, with different performance measures, which include both delivery lead time and total production and distribution costs. In addition to determining the optimal factory allocation for each order and the schedule for each factory, the heuristics presented in the paper have to compute a schedule for the delivery of completed orders as well.

Almada-Lobo, Oliveira, and Carravilla (2008) examined the glass industry and proposed a VNS algorithm to minimize the weighted sum of setup times, inventory levels, and the number of stockouts for the lot sizing and scheduling problem that was introduced as a MIP model. In a case study with four plants, the algorithm's performance showed a strong correlation with the quality of the initial solution, a weightable dynamic composite dispatching rule.

Expanding on a chemical background, Terrazas-Moreno and Grossmann (2011) developed an iterative bi-level decomposition approach. They proposed an MILP model for continuous multi-product factories with parallel lines, sequence-dependent changeover time and costs, and profit maximization objective.

Behnamian and Fatemi Ghomi (2012) used a multi-agent approach to minimize the sum of completion and makespan in a virtual production network, where some factories are interested in the first and some in the second objective. Each job may be transported from an initial to another factory for processing. A ε-constraint approach and an ICA are proposed to solve the presented multi-objective MILP model.

Behnamian and Fatemi Ghomi (2013) developed a heuristic for a similar MILP model with makespan objective and proposed a GA combined with an LS technique. In small to medium test instances, the heuristic outperforms the GA, while in large instances the GA becomes efficient.

Cóccola et al. (2013) focused on batch plants in chemical engineering with subsequent distribution to customers or intermediate depots. The authors proposed an MILP model and an integrated approach to production and distribution that is compared with a separated production-cost or distribution-cost oriented approach and leads to significant cost savings in acceptable computation times.

Behnamian (2014) again focused on virtual production networks with self-interested factories. An MILP model to minimize total processing costs and maximize production profits is relaxed to a single objective with a weighted metric technique and solved through a hybrid VNS-TS method.

Kerkhove and Vanhoucke (2014) scheduled unrelated parallel machines for a textile manufacturer with a two-phase approach. A constructive heuristic is optimized by a hybrid meta-heuristic to minimize costs due to weighted earliness/tardiness. The authors observed a positive effect of increasing production locations as this improves responsiveness. There is also a trade-off between costs of manufacturing and benefits of low tardiness levels and fast responses as the number of machines in distant locations has a negative impact on the objective value due to long transportation time. The configuration of production networks is still an important strategic decision.

Behnamian (2015) used multi-cut Benders decomposition to generate an assignment problem and a series of single factory scheduling problems connected by Benders cuts. In experiments challenging the GA by Behnamian and Fatemi Ghomi (2013), the decomposition approach outperformed the GA but needed considerably more computation time.

Yazdani, Gohari, and Naderi (2015) improved the MILP model by Behnamian and Fatemi Ghomi (2013) for C_{max} and proposed two new models for $\sum Cj$. An ABC algorithm is modified to improve memory utilization, an LS is employed in each factory for diversification. In experiments with the model and GA by Behnamian and Fatemi Ghomi (2013) and a TS, MA, and GA from classic parallel machine scheduling, the ABC algorithm outperformed the other algorithms concerning the average optimality gap.

Behnamian (2016) then studied a multi-factory network with parallel machines and parallel job scheduling, meaning that jobs can be processed on more than one machine at a time. A graph colouring algorithm is combined with a discrete PSO (DPSO) that showed its strength on large instances and is robust against increasing job and factory numbers.

Behnamian (2017a) and Behnamian (2017b) developed two further algorithms for distributed parallel machine scheduling: An anarchic PSO algorithm to minimize C_{max} and a matheuristic to schedule jobs with the objective of minimising production costs.

Most recently, Lei et al. (2019) studied the distributed unrelated parallel machine scheduling (DPMSP) with C_{max} objective and developed a novel imperialist competitive algorithm with memory (MICA). MICA was compared with the GA by Behnamian and Fatemi Ghomi (2013) and a hybrid PSO and GA designed for classic PSMP. MICA outperforms both algorithms and swiftly converges to a decent solution.

4. Multi-factory flowshop literature

Table 5. Overview and classification of multi-factory flowshop literature

Author and year	**Factory type**	**Demand**	**Network structure**		**Objective**	**Solution method**	**Transportation considered**	**Stochasticity**	**Experiments**	**Comments**
			ser.	**par.**						
Azevedo and Sousa (2000)	het	st, det		√	E_{max}, T_{max}, Cost	MILP, SA	√		Semiconductor manufacturing	Global and local capacity models, Transport. considered
Gnoni et al. (2003)	het	dyn, stoch		√	Cost	MILP, DES			Automotive industry	Hybrid modelling: combining an MILP and a simulation model
Miller and De Matta (2003)	het	dyn, det		√	Cost	MILP	√		Pharmaceutical industry	Integrated production and transportation scheduling, single product
Lin and Chen (2007)	het	dyn, det		√	Cost	MILP	√		TFT-LCD manufacturing	Time scales with differing lengths for production planning (monthly/daily)
Chen et al. (2009)	hom	dyn, det		√	$\sum Tj + \sum Ej$, M_{util}, Inv.	MAS			TFT-LCD manufacturing	Multi-tier and multi-site production network
Xu et al. (2010)	het	st, det		√	C_{max}, Inv.	MILP, Heur.				Coordination heuristic
Naderi and Ruiz (2010)	hom	st, det		√	C_{max}	MILP, Heur.			Taillard (1993)	Generalized the DPFSP, six MILP models, 14 heuristics
Liu and Gao (2010)	hom	st, det		√	C_{max}	EM			Naderi and Ruiz (2010)	EM transformed to solve discrete optimization problem
Ruifeng and Subramaniam (2011)	het	st, det		√	Profit	Exact	√	√		Stochastic model of a single product tandem supply chain with intermediate buffers, machine maintenance considered
Gao and Chen (2011)	het	st, det		√	C_{max}	GA + LS			Naderi and Ruiz (2010), Taillard (1993)	Hybrid GA with specific mutation and crossover operators
Gao, Chen, and Deng (2013)	het	st, det		√	C_{max}	TS			Naderi and Ruiz (2010)	Sub-sequences of jobs swapped to generate new neighbourhoods
Lin, Ying, and Huang (2013)	het	st, det		√	C_{max}	IGA			Naderi and Ruiz (2010)	IGA with SA based acceptance criterion with sinking temperature parameter
Hatami, Ruiz, and Andrés-Romano (2013)	hom	st, det		√	C_{max}	MILP, Heur.				Distributed Assembly PFSP (DAPFSP) and 6 constr. heur. as well as 6 VND heur.

Author and year	**Factory type**	**Demand**	**Network structure**		**Objective**	**Solution method**	**Transportation considered**	**Stochasticity**	**Experiments**	**Comments**
			ser.	**par.**						
Wang et al. (2013)	hom	st, det		√	C_{max}	EDA			Naderi and Ruiz (2010)	EDA produces new populations implicitly, alg. not compared with other meta-heuristics
Xu et al. (2014)	hom	st, det		√	C_{max}	IA + LS			Naderi and Ruiz (2010)	Precedence operation crossover operator in IA
Naderi and Ruiz (2014)	hom	st, det		√	C_{max}	SS			Naderi and Ruiz (2010)	Evolutionary algorithm as a principled approach with diversification
Xiong et al. (2014)	hom	st, det		√	$\sum C_j$	VNS, Hybrid GA, Hybrid DEA				Distributed two-stage assembly flowshop scheduling problem (DTSAFSP)
Xiong and Xing (2014)	hom	st, det		√	C_{max}, $\sum C_j$	MIP, GA-RVNS				Combination of GA and VNS
Hatami, Ruiz, and Andrés-Romano (2015)	hom	st, det		√	C_{max}	Heur., VND, IGA				Sequence-dependent setup times, enhanced VND method
Fernandez-Viagas and Framinan (2015)	hom	st, det		√	C_{max}	BSIG			Naderi and Ruiz (2010)	Bounded-search iterated greedy algorithm
Li et al. (2015)	hom	st, det		√	C_{max}	GA			Hatami et al. (2013)	GA with LS after crossover
Deng, Wang, Shen, et al. (2016)	hom	st, det		√	C_{max}	HS				Distributed two-machine FSP
Lin and Ying (2016)	hom	st, det		√	C_{max}	MILP, ICG			Naderi and Ruiz (2010)	Distributed no-wait FSP
Deng et al. (2016)	hom	st, det		√	C_{max}	MILP, MA			Xiong & Xing (2014)	Ring-based neighbourhood structure, MA with competition and local intensification
Wang, Huang, and Qin (2016)	hom	st, det		√	C_{max}	EDA, GA		√		Machine breakdowns considered for the DPFSP for the first time, fuzzy-logic EDA
Wang, Wang, and Shen (2016)	hom	st, det		√	C_{max}	HCS			Naderi and Ruiz (2010)	Earliest completion factory rule to map individuals into feasible schedules
Li et al. (2016)	het	st, det		√	C_{max}	MILP, SA	√		Naderi and Ruiz (2010)	Transport. from raw material origin to factories, vehicle capacity constraints
Ji et al. (2016)	hom	st, stoch		√	C_{max}	PSO + SA		√	Hatami et al. (2013)	Stochastic no-wait DAPFSP, alg. with hypothesis test

Author and year	Factory type	Demand	Network structure		Objective	Solution method	Transportation considered	Stochasticity	Experiments	Comments
			ser.	par.						
Lin and Zhang (2016)	hom	st, det		√	C_{max}	BBO			Hatami et al. (2013)	BBO with path relinking, insertion- based and a novel local search method
Companys and Ribas (2016)	hom	st, det		√	C_{max}	Meta-heur.				Distributed blocking FSP (DBFSP) introduced
Wang and Wang (2016)	hom	st, det		√	C_{max}	EDA + MA			Hatami et al. (2013)	Balanced global exploration and local exploitation, combination of EDA-based search and LS operators
Rifai, Nguyen, and Dawal (2016)	hom	st, det		√	$C_{max,}$ T_{avg}, Cost	MILP, ALNS				Re-entrant DPFSP, multi-objective problem formulation
Ying et al. (2017)	hom	st, det		√	C_{max}	IGA			Naderi and Ruiz (2010)	Distributed no-idle PFSP
Ribas, Companys, and Tort-Martorell (2017)	hom	st, det		√	C_{max}	MILP, ILS, IGA			Taillard (1993)	Sequencing rules include SPT, LPT, CDS, NEH, PF, HPF2
Shao, Pi, and Shao (2017a)	hom	st, det		√	C_{max}	Hybrid IGA			Naderi and Ruiz (2010)	Acceptance criterion from SA with a constant temperature value
Komaki and Malakooti (2017)	hom	st, det		√	C_{max}	GVNS			Naderi and Ruiz (2010)	GVNS as a VNS plus shaking and LS procedure
Shao, Pi, and Shao (2017b)	hom	st, det		√	C_{max}	Hybrid IGAs			Naderi and Ruiz (2010)	Four new neighbourhood structures proposed: Critical swap and insert, single/multi
Bargaoui, Driss, and Ghédira (2017a)	hom	st, det		√	C_{max}	CRO			Naderi and Ruiz (2010)	CRO works by the laws of thermodynamics
Gonzalez-Neira et al. (2017)	hom	st, det		√	C_{max}	Heur., MCS		√	Hatami et al. (2013)	Simheuristic approach, stochastic processing times
Bargaoui, Driss, and Ghédira (2017b)	hom	st, det		√	C_{max}	CRO, MAS			Naderi and Ruiz (2010)	Agents in MAS behave independently and cooperatively
Dempster, Li, and Drake (2017)	hom	st, det		√	C_{max}	DEA			Deng et al. (2016)	Vector indicating the jobs to factories assignment. After assignment, the factory sequence is computed using Johnson´s rule (Johnson 1954).
Lin, Wang, and Li (2017)	hom	st, det		√	C_{max}	BSH			Hatami et al. (2013)	BSH as hyper-heuristic and a set of low-level heuristics
Ying and Lin (2017)	hom	st, det		√	C_{max}	MILP, HIGA			Naderi and Ruiz (2010)	HIGA with operators from TS and SA

Author and year	Factory type	Demand	Network structure		Objective	Solution method	Transportation considered	Stochasticity	Experiments	Comments
			ser.	par.						
Zhang, Xing, and Cao (2018a)	hom	st, det		√	C_{max}	Discrete DEA			Naderi and Ruiz (2010)	Four constructive heuristics implemented: SPT, LPT, Large-small, and NEH
Wang and Wang (2018)	hom	st, det		√	C_{max}, TEC	KCA				DPFSP in sustainable manufacturing
Zhang and Xing (2018)	hom	st, det		√	∑Cj	MSSO				MSSO inspired by the cooperative behaviour of social spider colonies, self-adaptive diversification strategy
Zhang, Xing, and Cao (2018b)	hom	st, det		√	C_{max}	MILP, Heur., Hybrid VNS, Hybrid PSO			Hatami et al. (2013)	DAPFSP with several assembly machines
Hatami et al. (2018)	hom	st, det		√	C_{max} (st/det), C_{max} percentile	ILS, MCS		√	Taillard (1993)	Simheuristic approach, DFSP with stochastic processing times
Fernandez-Viagas, Perez-Gonzalez, and Framinan (2018)	hom	st, det		√	∑Cj	MILP, Heur., EA			Naderi and Ruiz (2010)	18 constructive heuristics proposed based on the NEH method
Ying and Lin (2018)	hom	st, det		√	C_{max}	MILP, Self-tuning IGA			Oğuz et al. (2004)	Distributed hybrid FSP with multiprocessor tasks
Pan, Gao, Wang, et al. (2019)	hom	st, det		√	∑Cj	Constructive heuristics, meta-heur.			Naderi and Ruiz (2010)	LR, NEH, and a hybrid constructive heuristics and discrete ABC, SS, IGA and ILS as meta-heuristics
Ruiz, Pan, and Naderi (2019)	hom	st, det		√	C_{max}	IGA			Naderi and Ruiz (2010)	Two-stage IG method
Hao et al. (2019)	hom	st, det		√	C_{max}	BSO				Hybrid FSP with multiple parallel machines in each factory
Pan, Gao, Xin-Yu, et al. (2019)	hom	st, det		√	C_{max}	MILP, Heur., VNS, IGA			Hatami et al. (2013)	DAPFSP with a single assembly machine in each factory, Heur. based on NEH

Azevedo and Sousa (2000) investigated order allocation in the semiconductor industry in a multi-stage flexible flowshop. The authors proposed an MILP and used a two-stage model consisting of a global network planning process and a set of local capacity models. A SA and a constructive heuristic are presented.

Gnoni et al. (2003) integrated an MILP model with a DES model to solve a lot sizing and scheduling problem in an automotive case company in two settings: local optimization (LOS) and global optimization (GOS). The GOS outperforms the LOS if sites share penalties and benefits.

Miller and De Matta (2003) developed an MILP model for single product integrated production and transportation scheduling when an intermediate plant supplies a finishing plant. A case study was conducted with a company from the pharmaceutical industry.

Lin and Chen (2007) proposed a planning model capable of simultaneously considering different time buckets (monthly and daily) for TFT-LCD manufacturing. The model was solved using deterministic input parameters and two factories at each manufacturing stage. Considering multiple time buckets can be vital when different stages of the network have to be coordinated.

Chen, Huang, and Lai (2009) developed a distributed MAS system for TFT-LCD production, where each factory is using an APS system. Results suggest that collaborative networks reach promising solutions and generate organizational competitiveness while allowing rapid reconfiguration. Xu, Sand, and Engell (2010) examined flexible flowshops with intermediate storage and proposed a coordination method. The method saved computation time and performed well when compared with a centralized approach and decentralized push or pull approaches on case study data.

4.1 Distributed Permutation Flowshop Scheduling Problem (DPFSP)

Naderi and Ruiz (2010) proposed a new version of flowshop scheduling problems in multi-factory networks called the *Distributed Permutation Flowshop Scheduling Problem (DPFSP).* In the DPFSP, n jobs have to be processed in f identical factories. The set M of m machines is equal in each factory. The processing times $P_{j,i}$, $j \in N$, $i \in M$ are assumed to be identical, and all operations of a job have to be performed in the same factory. Two decisions are necessary: Job assignment to factories and job scheduling at each factory. Following the Graham et al. (1979) three field notation, the DPFSP can be denoted as $DF|prmu|C_{max}$. The total number of solutions for the DPFSP reduces from $f_1(n,f) = \binom{n+F-1}{F-1} n!$ to $f_2(n,f) = \binom{n-1}{F-1} n!$ when the following theorem is considered: *In at least one optimal solution of the DPFSP with makespan* *criterion, each factory has at least one job (if n > F).* For n = 10 jobs and F = 3 factories, the number of solutions can then be reduced from 239.5 million to 130 million. Naderi and Ruiz (2010) developed six alternative MILP models with a decreasing number of constraints, similar to an optimization approach. Then several heuristics from the permutation flowshop scheduling literature (SPT, LPT, Johnson's algorithm (Johnson 1954), CDS, Palmer's algorithm (Palmer 1965), NEH (Nawaz, Enscore, and Ham 1983), and VND) are selected to sequence jobs at each factory and complemented by two rules for rule-based subsequent allocation to factories. The first rule assigns job j to the factory with the lowest current C_{max}, not including j, while the second rule chooses the factory with the lowest C_{max} after including job j. For small instances, the heuristics and especially the VND came in close range to the optimum solution. The second allocation rule shows better overall results with a small computational penalty. On larger instances the VND (a) algorithm with the first allocation rule performed best, opening the research field for more sophisticated meta-heuristics and local searches.

Liu and Gao (2010) were the first to re-examine the DPFSP. They proposed an electromagnetism-like mechanism heuristic (EM) with an embedded VNS-based LS which improved 151 of the 720 best known solutions on the test instances of Naderi and Ruiz (2010). Naderi and Ruiz (2014) later showed that the average performance of the EM heuristic was inferior to the VND (a) in all scenarios.

Gao and Chen (2011) proposed a hybrid GA with specific mutation and crossover operators. In each iteration, an LS is performed on the best and a randomly selected solution. The best solutions of Naderi and Ruiz (2010) are improved by 2.22 % on average, although the algorithm takes about 250 times the computation time of the VND (a) method.

Gao, Chen, and Deng (2013) then employed a TS that extends the LS methods from Gao and Chen (2011). Only the exchange of sub-sequences of jobs are recorded in the tabu list, and the TS outperforms the hybrid GA of Gao and Chen (2011) and the heuristics of Naderi and Ruiz (2010).

Next, Lin, Ying, and Huang (2013) developed an IGA for the DPFSP inspired by the work of Ruiz and Stützle (2007). The approach with a sinking temperature parameter from SA is compared with Naderi and Ruiz (2010) and Gao, Chen, and Deng (2013) heuristics. It obtains 334 new best solutions for the 720 instances.

Wang et al. (2013) then proposed an estimation of distribution algorithm (EDA), a population-based optimization algorithm. EDA produces new populations implicitly rather than using mutation operators as GA. Four LS methods are applied to the best individual in each iteration. The EDA outperformed the heuristic solutions provided by Naderi and Ruiz (2010) but needs significant longer CPU times and has not been compared with other sophisticated algorithms or meta-heuristics for the DPFSP.

Xu et al. (2014) developed a hybrid immune algorithm (HIA), imitating the human immune system, which also considers local search operators. Out of the 720 large-sized instances of Naderi and Ruiz (2010), the HIA was able to obtain 585 new best solutions but required drastically longer CPU times.

Next, Naderi and Ruiz (2014) developed a scatter search (SS) meta-heuristic. The SS heuristic profits greatly from the inherently controlled diversification and outperformed eleven methods from literature in extensive computational experiments. All 720 original best known solutions from Naderi and Ruiz (2010) were improved. Only in instances with F = 7 factories did the IGA algorithm of Lin, Ying, and Huang (2013) obtain a better solution.

Fernandez-Viagas and Framinan (2015) compared existing heuristics for the DPFSP and proposed a bounded-search iterated greedy algorithm (BSIG) to reduce the search space and improve the solutions. Three LS methods are applied to the initial solution and after destruction and construction to improve the solution, followed by a simulated annealing phase. The BSIG outperformed IGA, TS, and EDA algorithms from literature, but has not been compared with the SS of Naderi and Ruiz (2014).

Wang, Huang, and Qin (2016) were the first to take uncertainties into account as they consider machine breakdowns through DES and proposed a fuzzy-logic based hybrid EDA. The algorithm was compared with several hybrid algorithms from literature but none of the specific algorithms designed for the DPFSP.

Next, Wang, Wang, and Shen (2016) proposed a hybrid discrete cuckoo search (HCS) that is inspired by the brood parasitic behaviour of some cuckoo species or the Lévy flight behaviour of birds. 644 of the 720 test instances of Naderi and Ruiz (2010) were improved, while the HCS was on average 1.86% better than the best known values.

Li et al. (2016) added transportation times and vehicle capacity constraints to the DPFSP and proposed an MILP and a heuristic with an SA-based LS. The performance of the heuristic was not compared to other existing algorithms.

Re-entrant line configurations faced in industries like semiconductor manufacturing are studied by Rifai, Nguyen, and Dawal (2016). The authors explicitly allow a factory to be left empty. In their multi-objective formulation (C_{max}, T_{avg}, and total production costs are minimized), an adaptive large neighbourhood search is utilized. Experiments followed Naderi and Ruiz's (2010) instances, which were extended to include re-entrant layers.

Bargaoui, Driss, and Ghédira (2017a) proposed a CRO meta-heuristic. Compared with VND(a), NEH2, and BSIG algorithms, it indicated competitive results for small-instance problems and outperformed the BSIG on large instances.

Bargaoui, Driss, and Ghédira (2017b) then develop an MAS that is connected with a CRO heuristic. The MAS allows independent entities to cooperate in distributed networks. The algorithm is compared with NEH2, IGA, and HCS, which are all outperformed.

Wang and Wang (2018) addressed the DPFSP in light of sustainable manufacturing and consider C_{max} and TEC. The authors proposed a KCA to generate efficient solutions and consider different processing speeds for every machine. Power consumption increases with increasing machine speed. The algorithm is tested against a GA and a competitive memetic algorithm from literature, which are outperformed.

Fernandez-Viagas, Perez-Gonzalez, and Framinan (2018) investigate the $DF|prmu|\sum Cj$ to minimize total flow time. This objective also aims at stabilizing the use of resources and reducing the inventory of running processes, which are important measures for distributed manufacturing environments. Three theorems are proposed for lower bounds for the problem. 18 constructive heuristics based on the NEH mechanism are presented by combining two different representations, six assignment rules, and the theorems. Additionally, an EA is proposed that outperforms efficient meta-heuristics from literature, namely BSIG, IGA, and SS. The constructive heuristics are significantly outperformed by the EA as well.

Pan, Gao, Wang, et al. (2019) studied a similar problem and proposed three constructive and four meta-heuristics. The meta-heuristics were compared with BSIG, IGA, and SS as in Fernandez-Viagas, Perez-Gonzalez, and Framinan (2018) plus their EA. The ILS meta-heuristics performed best in terms of ARPI values and also achieved 379 of the 720 best known instances. The trajectory-based meta-heuristics outperformed the population-based meta-heuristics significantly for the DPFSP with $\sum$Cj.

Ruiz, Pan, and Naderi (2019) proposed a modified IG method, which is applied for a proportion of the CPU time in its original form. The remaining time is devoted exclusively to the C_{max} generating factory. Three variants are tested against HIA, SS, and BSIG, outperforming them all. The variant with mixed CPU distribution is 3% to 5% better than the variant without distribution when 5% of the CPU time is dedicated to the second stage (improving the C_{max} factory).

4.2 Distributed Blocking Flowshop Scheduling Problem (DBFSP)

Companys and Ribas (2016) introduced the distributed blocking flowshop scheduling problem (DBFSP), denoted as $DF|block|C_{max}$. There are no buffers between consecutive flowshop machines, meaning a job cannot leave the current machine if the next scheduled machine is busy. 33 constructive procedures are tested by the authors to analyse their behaviour. A new allocation method that divides the job sequences into F fractions and assigns similar loads to the factories is introduced. Then the sequence in each factory is improved with insertion from NEH2 by Naderi and Ruiz (2010). The new allocation method works well for the blocking constraint but increases the CPU time significantly. The two best performing heuristics were originally designed for the blocking flowshop scheduling problem. The algorithms specifically designed for the DPFSP become competitive with increasing numbers of factories.

Ribas, Companys, and Tort-Martorell (2017) presented an MILP for the DBFSP. Ten different sequencing rules are utilized with two heuristics: an iterated LS and an IGA with perturbation, improvement, reassignment, and permutation phases. Computational experiments on the Taillard (1993) benchmarks showed that the proposed IGA outperformed BSIG and SS.

Ying and Lin (2017) also presented an MILP model and three hybrid IGAs (HIGA) that extend the IG algorithm with some operators from TS and SA. On single factory benchmarks from Taillard (1993), the HIG1 algorithm with a variable Tabu List performed best.

Zhang, Xing, and Cao (2018) proposed a discrete differential evolution (DDE) algorithm for the DBFSP, outperforming BSIG, SS, and HIG1. DDE performs best, followed by SS, HIG1, and BSIG.

4.3 Distributed Assembly Permutation Flowshop Scheduling Problem (DAPFSP)

The distributed assembly permutation flowshop scheduling problem (DAPFSP) was first presented by Hatami, Ruiz, and Andrés-Romano (2013). It considers two stages: f identical factories with m machines and n jobs to schedule and a single factory that assembles all jobs with one assembly machine. A product consists of n jobs and assembly can only start when all jobs that belong to the product are completed in the factories in stage one. Three decisions have to be made: factory assignment, job scheduling, and product scheduling. The authors presented an MILP model to minimize the makespan, three constructive heuristics for job scheduling, and VND variants.

Hatami, Ruiz, and Andrés-Romano (2015) then added sequence-dependent setup times to the model, enhanced the VND method, and included an IGA. Both VND and IG methods outperform the simple constructive heuristics but need longer computational time.

Li et al. (2015) applied a GA with a local search after crossover, focusing on jobs for the same product. Compared with the algorithms of Hatami, Ruiz, and Andrés-Romano (2013) on their test instances, the GA with local search outperformed the other GAs and the comparison heuristics from literature.

Ji et al. (2016) introduced the stochastic no-wait distributed assembly flowshop as a new variant of the DAPFSP. Processing and assembly times are modelled as uncertain and the no-wait constraint is introduced for the processing stage. A combination of PSO with SA (PSOSAHT) optimizes C_{max} in the proposed model. 180 instances from Hatami, Ruiz, and Andrés-Romano (2013) were solved with uniformly distributed processing and assembly times.

A BBO algorithm was proposed by Lin and Zhang (2016). Each product containing several jobs is assigned to the factory with the earliest completion time after completing the job. The BBO obtained 91 new best solutions with significantly longer CPU times.

Wang and Wang (2016) developed an estimation of distribution-based memetic algorithm (EDAMA). The EDAMA outperformed the heuristics of Hatami, Ruiz, and Andrés-Romano (2013) but was not compared to other meta-heuristics.

Gonzalez-Neira et al. (2017) studied a stochastic DAPFSP considering processing and assembly times as random variables. They combine biased randomization with an extension of the greedy randomized adaptive search procedure (GRASP) as a simheuristic that iteratively generates solutions for the deterministic version of the problem. The approach performed comparably to the BBO by Lin and Zhang (2016) but within shorter computing times. Lin,

Wang and Li (2017) constructed a hyper-heuristic approach based on backtracking search algorithm (BSH). The method performed well compared with the heuristics of Hatami, Ruiz, and Andrés-Romano (2013), EDAMA, and BBO. Although there is no statistical difference between BBO and BSH, the later requires less computation time.

Pan, Gao, Xin-Yu, et al. (2019) consider a slightly different problem, although they also call it DAPFSP. Instead of a single assembly machine in the system, each factory has its own individual assembly machine. M production machines form the first production stage in each factory. The authors present an MILP model, three constructive heuristics (based on NEH), two VNS, and an IGA. Computational experiments with the benchmark instances by Hatami, Ruiz, and Andrés-Romano (2013) show that the IG algorithm outperforms algorithms like BBO, BSH, and others.

4.4 Distributed Two-stage Assembly Flowshop Scheduling Problem (DTSAFSP)

The next problem is related to the DAPFSP and was first presented by Xiong et al. (2014): The two-stages (processing and assembly) for each job are located in a single factory which is chosen from the set of multiple factories. Each factory has an identical set of machines for processing and one assembly machine. Common objectives are total completion time as well as makespan and a combination of both. Xiong et al. (2014) considered sequence-independent setup times and generated an initial solution through an extended SPT heuristic. A VNS is employed in the solution neighbourhood and a reduced VNS-based method is employed for LS. The hybrid GA combined with an RVNS algorithm (HGA-RVNS) performed best, emphasizing the impact of the LS on the solution quality.

Xiong and Xing (2014) proposed a combination of a GA with VNS (GA-RVNS) to minimize the weighted sum of makespan and mean completion time. The GA-RVNS was compared with a GA without an LS and a standard VNS. The standard VNS is only outperformed with larger-size instances.

Deng et al. (2016) then presented an MILP model with setup times and a competitive memetic algorithm (CMA) which outperformed the VNS and GA-RVNS methods by Xiong and Xing (2014) for large instances.

Zhang and Xing (2018) focused on total completion time and developed an MSSO with an LS and self-adaptive restart strategy. Experiments with the heuristics from Xiong et al. (2014) show the superior performance of the MSSO. Unfortunately, the MSSO was not compared with the CMA by Deng et al. (2016) that also outperformed the algorithms by Xiong et al. (2014).

4.5 Distributed No-wait Flowshop Scheduling Problem (DNFSP)

In many industries (e.g. chemical or food) there are jobs that do not allow any in-process waiting between consecutive machines and are often assembled in a flowshop manner. The corresponding problem can be transferred to the distributed multi-factory case, where the problem is called distributed no-wait flowshop scheduling problem (DNFSP). Lin and Ying (2016) proposed an iterated cocktail greedy (ICG) algorithm for their MILP formulation of the $DFm|prmu,nwt|C_{max}$ problem. The solution representation is similar to Naderi and Ruiz (2010), as the NEH2 rule is used to assign each job to a suitable factory. Four different self-tuning mechanisms are utilized, though the best performing algorithm (ICG4) was not tested any further.

Next, Shao, Pi, and Shao (2017a) proposed a HIGA, where the acceptance criterion from SA is adopted with a constant temperature T. Compared with ICG by Lin and Ying (2016) and

BSIG by Fernandez-Viagas and Framinan (2013), the HIGA outperforms the algorithms with the Naderi and Ruiz (2010) instances.

Komaki and Malakooti (2017) proposed a general VNS (GVNS) and present an MILP model. The GVNS as an extension of classical VNS uses random and deterministic search. Compared with simple VNS variants, the GVNS outperforms the other meta-heuristics.

Extending their previous article, Shao, Pi, and Shao (2017b) designed four new neighbourhood structures based on factory assignment and job sequence adjustment. The HIGA is combined with a VND (IG_VND) which outperformed several algorithms from DPFSP literature and reached 483 of 720 best known solutions from Naderi and Ruiz (2010) instances.

4.6 Distributed Two-machine Flowshop Scheduling Problem (DTMFSP)

In the distributed two-machine flow-shop scheduling problem (DTMFSP) there are n jobs that have to be processed in f factories with two machines each. Deng, Wang, Shen, et al. (2016) introduced the problem and proposed a harmony search algorithm that uses the Johnson algorithm (Johnson 1954) to sequence jobs in each factory. Compared with a standard harmony search and the best-known harmony search from literature, the proposed IHS performed best. No data regarding the overall best solution or computation times were provided.

Next, Dempster, Li, and Drake (2017) used a DEA for the DTMFSP. Compared with the three harmony searches from Deng et al. (2016) on their test instances, the DEA performed well on small- and medium-sized instances ($F \leq 5$), whereas the IHS method by Deng et al. (2016) outperformed it with large instances ($F \geq 6$).

4.7 Other variants of the DPFSP

Hao et al. (2019) studied a hybrid flowshop problem with several parallel machines in each factory. After presenting an MILP model, the authors introduced a hybrid BSO to minimize C_{max}. NEH is extended in a distributed version (DNEH) that assigns jobs to factories randomly. The hybrid BSO algorithm performed best on random test instances.

Especially in industries with high setup costs and times, a no-idle constraint makes scheduling more complex. Rather than idling a machine, the start of processing for certain jobs is postponed to receive a feasible schedule. Ying et al. (2017) studied the distributed type of this problem ($DFm|prmu,no\text{-}idle|C_{max}$). The authors proposed an MILP model and an iterated reference greedy algorithm to solve it. Experiments with test instances from Naderi and Ruiz (2010) revealed that IRG is worse than the IGA of Pan and Ruiz (2014), but CPU time is significantly better. In large-instances with $2 \leq F \leq 7$ factories and up to 500 jobs, the proposed algorithm is superior to IGPR.

Zhang, Xing, and Cao (2018b) considered flexible assembly machines and sequence-independent setup times in the problem DFSP-FAST. Four successive decisions are required: assigning jobs to factories, sequencing jobs, assigning products to assembly machines and sequencing products on assembly machines. A constructive heuristic, a hybrid VNS, and a hybrid PSO algorithm are compared on Hatami et al. (2013) instances regarding C_{max}, average makespan, and standard deviation. The hybrid PSO algorithm outperformed the other two on large instances but also requires the most computational effort.

Ying and Lin (2018) consider the DFHSP with multi-processor tasks in which several identical parallel machines are connected in series on one or more processing stages. All jobs follow the same sequence of operations, and each job has to be processed simultaneously by multiple parallel machines. The authors present an MILP formulation and a self-tuning iterated greedy (SIG) algorithm. The problem is denoted as $DFFc|size_{ij},p_{ijk} = p_{ij}|C_{max}$. After assignment to factories and determining the permutation list at the first workcenter of each factory, the sequence for remaining workcenters is derived using a decoding rule. For 570 benchmark instances with multiple factories, the SIG algorithm was able to obtain 504 best solutions

5. Multi-factory jobshop literature

Table 6. Overview and classification of multi-factory jobshop literature

Author and year	Factory type	Demand	Network structure ser.	Network structure par.	Objective	Solution method	Transportation considered	Stochasticity	Experiments	Comments
Bok, Grossmann, and Park (2000)	het	dyn, det		√	Profit	MILP, Exact	√			Bi-level decomposition algorithm, transportation between sites considered
Thoney et al. (2002)	hom	st, det	√		T_{max}	Heur.	√			Transportation between sites considered
Moon, Kim, and Hur (2002)	het	dyn, det		√	$\sum T_j$	Binary integer programming model, GA	√			Transportation inter- and intra-site considered
Jia et al. (2003)	hom	st, det	√		C_{max} + Cost	GA				GA solves the classical JSP for small instances as well
Karageorgos et al. (2003)	het	dyn, det		√	$\sum C_j$ + Cost	MAS	√		Virtual Enterprise case study	Transportation inter- and intra-site considered
de Matta and Miller (2004)	het	dyn, det	√		Cost	MILP, Exact	√		Pharmaceutical industry in the USA	B&B with linear inequalities, production and inter-site transportation considered
Chan, Chung, and Chan (2005)	hom	st, det		√	C_{max}	GA			Jia et al. (2003)	DFJSP
Moon and Seo (2005a)	hom	st, det		√	C_{max}	MIP, GA	√			Transportation inter- and intra-site and setup times considered
Moon and Seo (2005b)	het	st, det		√	$C_{max} + M_{util}$	MIP, GA	√			Lot splitting to balance workload is considered
Chan, Chung, and Chan (2006)	het	st, det		√	C_{max}	MILP, GA	√			GA is nearly the same as in Chan, Chung, and Chan (2005)
Moon et al. (2006)	het	st, det		√	C_{max}	MILP, Hybrid GA	√		Moon et al. (2004)	DFJSP, GA with LS hybridization, Transportation intra-site considered
Chan et al. (2006)	het	st, det		√	C_{max}	MILP, GA	√	√		DFJSP, Transportation to customers and machine maintenance considered
Lau et al. (2006)	het	st, det		√	Cost	MILP, MAS	√			Transportation inter-site considered, Modified CNP for MAS approach

Author and year	**Factory type**	**Demand**	**Network structure**		**Objective**	**Solution method**	**Transportation considered**	**Stochasticity**	**Experiments**	**Comments**
			ser.	**par.**						
Jia et al. (2007)	hom	st, det		√	C_{max}, $\sum T_j$, Cost	GA + Gantt Chart				DFJSP, Gantt chart for chromosome fitness evaluation
Chan and Chung (2007)	het	st, det		√	C_{max}	MILP, GA	√	√		similar to Chan et al. (2006)
Chan, Kumar, and Mishra (2008)	het	dyn, det		√	$\sum T_j$	MILP, PSO	√		Moon, Kim, and Hur (2002)	Cooperative multiple PSO, Transportation inter- and intra-site considered
Chung, Chan, and Chan (2009)	het	st, det		√	C_{max}	MILP, GA	√	√	Chan et al. (2006)	GA with new mutation operator
Chung et al. (2009)	het	st, det		√	C_{max}	MILP, GA	√	√		Perfect and imperfect maintenance scenarios
Kopanos and Puigjaner (2009)	het	dyn, det		√	Cost	MILP	√			Transp. of raw material from suppliers to plants and inter-site considered, solved with CPLEX
Chung et al. (2010)	het	dyn, det	√	√	C_{max}	MILP, GA	√		Moon et al. (2006)	Assembly operation at the last factory
De Giovanni and Pezzella (2010)	het	st, det		√	C_{max}	GA	√		Chan et al. (2006); Chan, Chung, and Chan (2006) and Jia et al. (2003)	DFJSP, Transport between raw material facility and factories considered
Lou, Ong, and Nee (2010)	het	dyn, det		√	C_{max}	MAS				Virtual jobshop, self-interested machines
Lawrynowicz (2011)	het	st, det		√	C_{max}	GA	√			Transport intra-site considered, re-entrant processing
Aissani et al. (2012)	het	dyn, det		√	C_{max}	MILP, MAS	√		Clothing company	DFJSP, Agents with reinforcement learning to react to dynamic conditions
Chan et al. (2013)	het	st, det		√	C_{max}	MILP, TS+SA	√			HTSSA as a combination of SA and TS to overcome local optima when executing the SA procedure
Guo et al. (2013)	het	st, det		√	M_{util}, $\sum T_j$, $\sum C_j$	MILP, GA + Sim.	√		Apparel manufac-turer in China	Pareto optimization of multiple objectives, Sim. for evaluation
H'Mida and Lopez (2013)	het	st, det	√	√	$\sum C_j$	CP	√		Case company (undisclosed)	Integrated production and transportation scheduling, constraint satisfaction problem (CSP)
Lim, Tan, and Leung (2013)	het	st, det		√	Cost	MAS, GA	√			Transfer of WIP considered, batch production
Ziaee (2014)	het	st, det		√	C_{max}	Heur.			De Giovanni and Pezzella (2010)	DFJSP, Considered factors include C_{max} for operations, idle times, total processing time of

Author and year	Factory type	Demand	Network structure		Objective	Solution method	Transportation considered	Stochasticity	Experiments	Comments
			ser.	par.						
										operations, weighted processing time of machines and mean processing time of jobs
Archimede et al. (2014)	het	st, det		√	$\sum T_j$	MAS				Shared resource scheduling, simple case study
Naderi and Azab (2014)	hom	st, det		√	C_{max}	MILP, Heur.			Taillard (1993)	Operation-sequence and operation-position based MILP models, 3 constructive and 3 greedy heuristics
Liu, Chen, and Chou (2015)	het	st, det		√	C_{max}	GA			Fastener manufac-turer in Taiwan, De Giovanni and Pezzella (2010)	GA applies crossover and mutation to machine selection, factory assignment and job operation assignment
Naderi and Azab (2015)	hom	st, det		√	C_{max}	MILP, SA			Taillard (1993)	SA enhanced with LS for further diversification capability
Sun, Chung, and Chan (2015)	het	st, det	√	√	Cost	MIP, Heur., GA	√			DJSP with distribution (inland or maritime), due-date based cut-off heuristic, 2-level fuzzy guided GA
Lu et al. (2015)	het	st, det		√	C_{max}	GA	√		De Giovanni and Pezzella (2010)	DFJSP, new encoding scheme proposed, Transportation from raw material origin to factories
Guo et al. (2015)	het	dyn, stoch		√	$\sum T_j + \sum C_j + M_{util}$	MILP, Harmony Search meta-heuristic, MCS	√	√	Outerwear MTO manufacturer in China	Deterministic problem solved first, Pareto optimal solutions then employed in MCS to evaluate performance under stochastic surroundings
Chang and Liu (2017)	het	st, det		√	C_{max}	Hybrid GA	√		Chan, Chung, and Chan (2005), Chan et al. (2006), De Giovanni and Pezzella (2010)	DFJSP, Transportation from raw material origin to factories
Wu et al. (2017)	het	st, det		√	C_{max}	GA	√		Chan, Chung, and Chan (2005), Chang and Liu (2017), De Giovanni and	Examination of different chromosome representations on the performance of a GA

Author and year	**Factory type**	**Demand**	**Network structure**		**Objective**	**Solution method**	**Transportation considered**	**Stochasticity**	**Experiments**	**Comments**
			ser.	**par.**						
									Pezzella (2010), Lu et al. (2015)	
Chaouch, Driss, and Ghedira (2017a)	hom	st, det		√	C_{max}	ACO			Taillard (1993)	Elitist ACO, no LS: performed poorly on medium and large instances
Chaouch, Driss, and Ghedira (2017b)	hom	st, det		√	C_{max}	ACO			Taillard (1993)	Modified ACO with LS
Marzouki, Driss, and Ghedira (2018)	het	st, det		√	C_{max}	MAS, TS				Supervisor, factory and scheduler agents; TS to optimize each machine schedule
Wang, Yang, and Yu (2018)	hom	dyn, stoch		√	Service + $\sum C_j$ + Cost + Profit + M_{util}	Lean-pull e-Kanban system	√		Semiconductor manufacturer in Taiwan	Priority classes for orders, with distribution to customers

Bok, Grossmann, and Park (2000) were the first to study a distributed jobshop setting. They formulated an MILP model for a short-term planning model in the continuous chemical process industry. The operating profit of the network is maximized by a bi-level decomposition algorithm that provides upper and lower bounds for the original problem.

Thoney et al. (2002) focused on production networks with batch processing and inter-factory transport. They proposed a heuristic to sequence n jobs on m machines with maximum tardiness as an objective. Multiple scenarios are considered and computed with the EDD dispatching rule.

Moon, Kim, and Hur (2002) examined integrated process planning and scheduling and proposed a GA to solve a binary integer programming model to minimize total tardiness of jobs. Machines at each plant are unequal and have different processing times for each operation, providing several options for job routing and machine selection.

Jia et al. (2003) then developed a modified GA (MGA) to minimize Cmax and production costs. Mutation is repeated twice to change the selected factory and re-arrange operation sequence. In experiments, the algorithm performed well for small instances of the classic JSP and the distributed JSP.

Karageorgos et al. (2003) developed an agent-based approach for virtual enterprises with external logistic services. A modified contract net protocol (CNP) processes orders by a wholesaler that calls for proposals from virtual enterprises. The approach leads to promising results in dynamically changing networks while requiring a high communication load.

De Matta and Miller (2004) proposed an MILP model and a B&B method for a production and transportation setting with two sequential plants and a mode-choice decision for transportation between the plants.

Then, Chan, Chung, and Chan (2005) studied the distributed flexible jobshop scheduling problem (DFJSP). In the DFJSP, each factory or manufacturing cell (Wu et al. 2017) has multiple machines and a set of jobs that are to be scheduled and completely processed in one factory. Each operation has different efficiencies on different machines, and not all machines are able to process each operation. The route each job takes depends on the operation requirements, available machines, and their efficiencies. The DFJSP requires three decisions: job assignment to factories, operation to machine assignment, and operation sequencing for each machine.

Chan, Chung, and Chan (2005) used an adaptive GA as an extension of the GA by Jia et al. (2003). Dominated genes and adaptive evolution make the GA competitive for medium and large instances when compared with simple heuristics like FIFO or SPT and a standard GA.

Moon and Seo (2005a) also applied a GA, but for integrated process planning and scheduling. Alternative operation sequences and machines for jobs with precedence constraints are considered in the MIP model.

In their next contribution, Moon and Seo (2005b) took lot splitting into account to balance the workload in the multi-objective MIP. An adaptive weight approach is used to obtain a set of Pareto solutions for the problem.

Chan, Chung, and Chan (2006) then examined the DFJSP again and proposed a slightly different GA with dominant genes, one-point crossover, and mutation (swap/exchange of jobs). The approach outperformed the GA approach by Jia et al. (2003).

Moon et al. (2006) presented an MILP model and a hybrid GA for a Cmax minimization problem with variable transfer batches, alternative sequences for orders, and alternative resources for operations.

Chan et al. (2006) used the dominant gene GA presented earlier and modified the DFJSP to take maintenance into account. If a machine reaches a certain age M, maintenance has to be carried out after the current job operation and the machine becomes unavailable. The objective is minimization of Cmax (completion time plus travel distance from factory to customer).

Lau et al. (2006) developed an agent-based approach for a supply chain with incomplete information. The agents do not know the capacity or current operations of other contractors. CNP is therefore modified to allow a simultaneous selection of contractors and information sharing to improve existing, feasible solutions.

Jia et al. (2007) integrated the GA of Jia et al. (2003) and a Gantt Chart mapping. Objectives are minimized C_{max}, $\sum Tj$, or production costs. For small and medium instances, the approach worked efficiently and reduced computation time in comparison to the GA alone.

The next contribution from Chan and Chung (2007) is similar to Chan et al. (2006), details can be found in the table above.

Chan, Kumar, and Mishra (2008) examined multi-factory supply chains that build upon coordination, cooperation, and synchronization. The authors developed a PSO algorithm to minimize $\sum Tj$, which was tested against the GA of Moon, Kim, and Hur (2002) on their test instances and outperformed this approach.

Chung, Chan, and Chan (2009) optimized the LS ability of the GA from Chan et al. (2006) and presented a modified GA that executes mutation for a fixed percentage of the sum of operations. Mutation changes the production priority of operations, and maintenance is considered again.

Again considering maintenance, Chung et al. (2009) used a double tier GA to schedule operations in two settings: perfect and imperfect maintenance. Perfect means that the machine is assumed ‘as good as new’ after maintenance, while imperfect means that machines revert to a less-deteriorated condition after maintenance.

Simultaneous lot-sizing and scheduling in batch industries was the scope of Kopanos and Puigjaner (2009). They proposed an MILP to minimize total costs under constraints such as production and storage capacities, crossover, sequence-dependent setup time, and backlog.

Chung et al. (2010) focused on a multi-factory production in series with multiple factories at each stage and assembly operations in the last factory of each order. There are predefined transportation lot sizes and job batch sizes. The GA was tested against the GA by Moon et al. (2006) on their data set and outperformed this meta-heuristic, although no indication was given whether the optimal solution was reached in any instance.

De Giovanni and Pezzella (2010) studied the DFJSP aiming at minimizing total completion time of all jobs by applying a GA. The authors improved the MGA by Jia et al. (2003) and extended its capabilities to flexible distributed manufacturing. One-point and two-point crossover is used in the algorithm’s inner loop to generate new individuals. The IGA algorithm was tested in several experiments with data sets from Chan et al. (2006), Chan, Chung, and Chan (2006), and Jia et al. (2003) and the IGA reached or improved the best solution for all instances.

Lou, Ong, and Nee (2010) considered a virtual job shop with self-interested machines working together in a network and use an MAS for scheduling and coordination in this dynamic environment. Machine agents in the factories bid on received task information (first-price-sealed-bid). A task agent evaluates obtained bids and selects favourable machines to form a virtual shop to reduce the costs. Conflicts with other tasks or virtual shops are handled through negotiation and coordination procedures.

Lawrynowicz (2011) studied a local supply network based on transportation and jobs that may need processing on certain machines more than once (re-entrant). The production schedule in each factory and a transport schedule is determined through a GA.

Aissani et al. (2012) examined the DFJSP in a multi-site clothing company with transfer times between sites. They proposed an MILP model and a MAS with intelligent agents that learn through reinforcement. In computational experiments, the MAS was able to quickly react to disturbances (e.g. a factory shutdown).

A hybrid search (HTSSA) of TS and SA was proposed by Chan et al. (2013) for the DFJSP. After a random initial solution, the steps of SA are executed with an integrated tabu list to cover solutions that have been checked.

Guo et al. (2013) modelled and solved a multi-objective order scheduling problem with a GA and a production process simulator. Assignment by the GA is succeeded by the simulator to determine start times of each process step and evaluate the solution quality. Orders can be split to reduce waiting times.

Integrating production and transportation scheduling was modelled by H'Mida and Lopez (2013) as a constraint satisfaction problem (CSP). The authors extended the packing problem to transportation scheduling as the transportation between sites is modelled through cumulative and packing global constraints.

Lim, Tan, and Leung (2013) use an MAS to integrate process planning and scheduling with a currency-based bidding mechanism and a GA. Orders, jobs, machines, and transportation are represented by agents. The GA tunes the currency value to an optimized value in each iteration to obtain better solutions.

Ziaee (2014) developed a constructive heuristic for the DFJSP that considers several factors to minimize Cmax. Compared with the IGA of De Giovanni and Pezzella (2010) on their test cases, the heuristic achieved good solutions quickly.

Archimede et al. (2014) proposed a framework with multiple agents that cooperate indirectly to minimize total tardiness of all orders. Virtual customer and producer agents collaborate to derive a global schedule, with rescheduling if new orders occur.

Naderi and Azab (2014) then presented two MILP models for the DJSP to minimize C_{max}. They applied three well-known heuristics (SPT, LPT, and LRPT) and three greedy heuristics (GH1-GH3). GH3 outperformed the other methods in experiments, which indicates that job-factory assignment is of major importance. GH3 assigns jobs to facilities with the lowest makespan after sequencing the job operations.

Liu, Chen, and Chou (2015) proposed a simple encoding and evolutionary combination method to improve the performance of GA in DFJSP. Tests with De Giovanni and Pezzella (2010) were promising as were case studies with a fastener manufacturer.

Naderi and Azab (2015) then presented a new encoding scheme for the DJSP MILP model and applied an SA algorithm enhanced with an LS. In experiments, the SA outperformed GH3 and the GA by Jia et al. (2007).

Sun, Chung, and Chan (2015) studied the DJSP with distribution using inland and maritime transportation. An MIP was presented to minimize operating costs and solved using a heuristic and a fuzzy guided GA.

Lu et al. (2015) suggested a new encoding scheme for the DFJSP and a GA (GA_JS). The decoding of the chromosome involves three heuristic rules. GA_JS outperformed the IGA from De Giovanni and Pezzella (2010) on their 2 to 4-factory instances.

Next, Guo et al. (2015) presented an MILP model for a multi-objective make-to-order DJSP observed in an outerwear manufacturer in China. A harmony search-based Pareto optimization heuristic is utilized to solve the problem with stochastic constraints like incoming orders, processing times, and daily capacity of plants.

Chang and Liu (2017) presented a hybrid GA (HGA) and a new encoding mechanism for the DFJSP. A tournament approach selects preferred individuals, and uniform crossover and precedence-preserving order-based operators are used for machine selection and operation assignment.

Wu et al. (2017) examined the different chromosome representations in GAs in the DFJSP literature and proposed a new chromosome representation. The chromosome models only the operation-sequencing decision, all other decisions are decoded by heuristic rules. This enables the GA to move to a globally efficient solution and balanced workloads. The proposed GA_OP outperformed existing GAs for the DFJSP.

Chaouch, Driss, and Ghedira (2017a) applied an elitist ant system (EAS) to the DJSP to equilibrate the workload among factories using NEH heuristic to assign jobs to factories. The EAS algorithm could only cope with existing algorithms on smaller instances as no LS is implemented for large instances. The same authors then modified their ACO (Chaouch, Driss, and Ghedira (2017b) and applied an LS for exploration (MACO). The approach outperformed the EAS greatly but was not compared to other algorithms.

Recently, Marzouki, Driss, and Ghedira (2018) developed an MAS for the DFJSP with a TS and supervisor, factory, and scheduler agents. The approach outperformed the GA by Chan, Chung, and Chan (2006) on instances with two factories.

Wang, Yang, and Yu (2018) then developed a lean-pull strategy for a specific DJSP in the semiconductor industry to allocate demand to factories and distribute to customers.

6. Multi-factory open shop literature

Table 7. Overview and classification of multi-factory open shop literature

Author and year	Factory type	Demand	Network structure ser.	par.	Objective	Solution method	Transportation considered	Stoch-asticity	Exp.	Comments
Jia et al. (2002)	hom	st, det		√	C_{max}, Cost	GA, MAS				Web-based Java applet
Li and Ou (2007)	het	st, det		√	Cost	Heuristics	√			Costs: Sum of delivery and customer waiting costs

Jia et al. (2002) developed a web-based GA to ease communication and coordination between geographically dispersed factories. Different modules are integrated into the web-based system, including a multi-agent system for coordination with the factories. Agents from each factory communicate process times and availability to a main scheduling agent that collects data and enables the GA to find an optimized schedule.

Li and Ou (2007) studied a combined production and distribution problem in an open shop setting where products are delivered in batches to their respective distribution centres, bundled with associated products, and delivered to the customer. The task therefore is to assign and schedule the operations, select an appropriate batch size as well as a time slot to deliver the jobs in time to the distribution centre. The authors proposed three heuristics that outperform a hierarchical approach for medium to large instances.

7. Further interesting literature (not included in this review)

There are several other interesting contributions regarding the various planning functions and phases of multi-factory production that did not meet our inclusion criteria but will be briefly presented here. These contributions deal with aggregate multi-factory production planning, coordination between factories in production networks, integrated production-distribution problems or other functions.

One of the first studies on integrated production-distribution problems in multi-factory environments stems from Cohen and Lee (1988), who broke down the strategic model into four submodules representing different sections of the supply chain. In the years that followed, further important publications on this topic were published (Wilkinson et al. 1996; Moattar Husseini et al. 2009; Gharaei and Jolai 2018; Marandi and Fatemi Ghomi 2019). Z.-L. Chen (2010) also included a short section on integrated production and distribution planning in a multi-factory case in his review.

Multi-factory lot sizing problems were studied by (Sambasivan and Schmidt 2002; Sambasivan and Yahya 2005; Nascimento and Toledo 2009; Nascimento, Resende, and Toledo 2010).

Other authors used multi-agent architectures to coordinate production in multiple factories (G. Lin and Solberg 1992; J. Liu and Sycara 1997; Shen 2002; T. P. Lu, Chang, and Yih 2005; Rolón, Canavesio, and Martínez 2009; Renna and Argoneto 2010; Giordani, Lujak, and Martinelli 2013; He, Zhang, and Li 2014;).

In a recent empirical study, Olhager and Feldmann (2018) study the decision-making structure in multi-factory networks and the distribution of authority between the network and the plant level. The authors call for more empirical work on the consideration of multiple plants simultaneously, which affects the planning stage and could make approaches from this review significant for application in practice.

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