Towards Energy Efficient Scheduling and Rescheduling for Dynamic Flexible Job Shop Problem

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Plan

1. Introduction
2. State of the art
3. Contributions
4. Case study
5. Experimental results
6. Conclusion and Future works

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Introduction

✍ Factories of the future (FoF) are key economic driver for the society.

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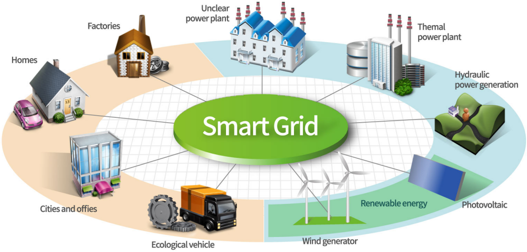
✍ Urgent need for sustainable development : balancing economic, environmental and social impacts.



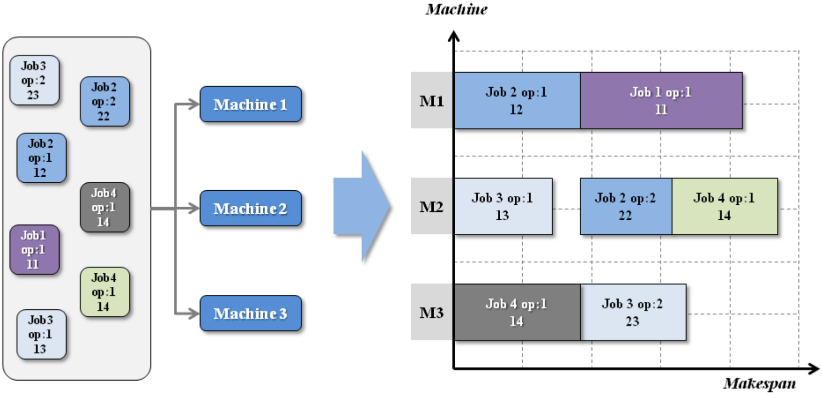
Green Manufacturing

✍ Energy aware production scheduling and rescheduling system : EAPSRS.

➽ One of the most studied problem : Flexible Job Shop Scheduling Problem (FJSSP)

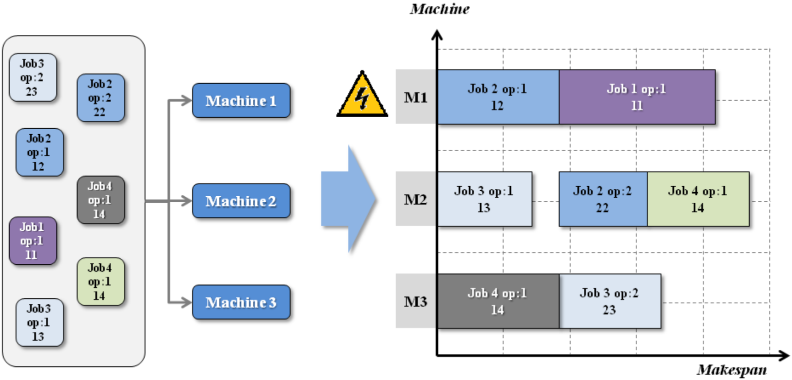
Introduction

- Flexible Job Shop Scheduling Problem

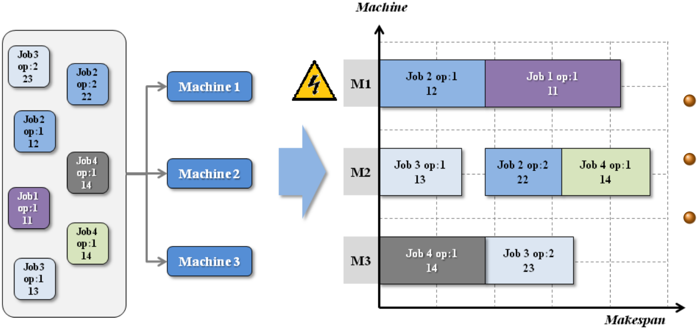


Introduction

- Disruptions affect the original schedule : random job arrival, machine breakdown,
- Rescheduling is needed.



Introduction



- Flexible Job Shop Scheduling Problem.
- Disruptions affect the original schedule.
- Rescheduling is needed

Green Manufacturing

✍ Reducing Energy consumption is an important issue in real-word Scheduling.

➼ Propose an energy efficient scheduling and rescheduling model for dynamic FJSP.

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State of the art

Static Scheduling (without perturbation)

- Centralized approaches : based on one decision entity
  ✍ GA :Kacem et al, 2002 ; Pezzellaa et al, 2008 ; Zhang et al, 2012.
  ✍ PSO : Venter et al, 2005 ; Jia et al, 2007 ; Jun et al, 2009
  ✍ Hybridation : Xia et al, 2005 ; Zhang et al, 2009 ; He et al.2015
- Distributed approaches : Distributed scheduling decisions
  ✍ Multi Agent System : Chen et al, 2004 ; Azzouz et al, 2012 ; Ennigrou et al, 2008 ; Henchiri et al,2013

Scheduling with energy optimization

✍ Raileanu et al.2017 : An agent-based approach for measuring real time energy consumption of resources for JSP.
✍ Gonzlez et al.2017 : Hybrid metaheuristic : GA + LS for JSP.
✍ He et al.2015 : An energy saving optimization method for FJSSP.

State of the art

Dynamic Scheduling (with perturbation)

✍ Proactive approaches : offline, anticipation by taking into account knowledge of uncertainties
✍ Reactive approaches : Online, Priority Dispatching Rule, MAS.
✍ Hybrid approaches : Predictive reactive approaches FJSSP.

Rescheduling Methods

✍ Right shifting Rule (RSR)
✍ Viera el al.2003 : Affected Operation Rescheduling for FJP.
✍ Nouiri et al.2017 : A predictive reactive approach to solve FJSSP.

State of the art

Rescheduling Methods with energy optimization

✍ Salido et al.2016 : a new match-up technique and a genetic algorithm to solve JSSP.
✍ Zhang et al.2013 : new goal programming mathematical model to solve FJSSP.
✍ Nouiri et al.2018 : Green Rescheduling Method (GRM) to solve FJSSP.

The designed approaches for energy optimization

✍ May et al. 2015 : a 7-step methodology to develop firm-tailored energy-related KPIs.
✍ Giret et al.2017 : an engineering method to design sustainable intelligent manufacturing systems.
✍ Trentesaux et al.2016 : a set of key requirements when designing MAS/HMS architecture for future energy aware production scheduling systems.

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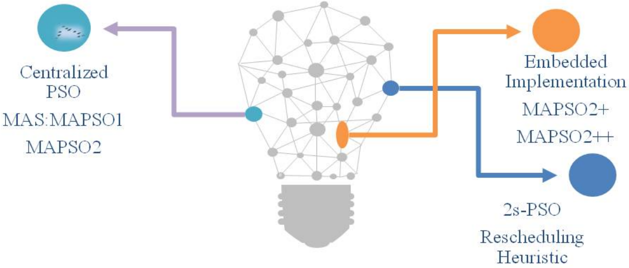
Contributions

➼ Propose a flexible system, able to make scheduling decisions and deal with unforeseen breakdowns.



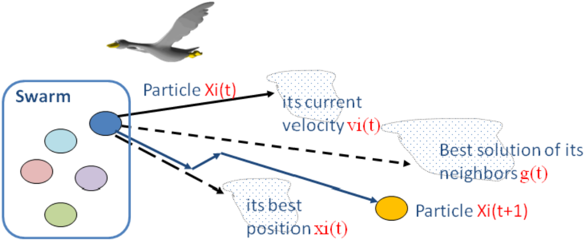
- Objective Function : minimize the makespan value
- Improve the robustness and the stability of the solution

Particle Swarm Optimization

- The meta-heuristic used : Particle Swarm Optimization

Principle of PSO algorithm

- Creation of initial swarm.
- Move these particles to find optimal solutions.
- Iterative search of the global optimum
- Output :**Gloal Solution** that optimizes an objective function.



Particle Swarm Optimization

- The meta-heuristic used : Particle Swarm Optimization

Initialization methods

✍ 30% Min Energy, 30% Randomly, 20% KacemApproach, 20% ModifiedApproach.

Objective function

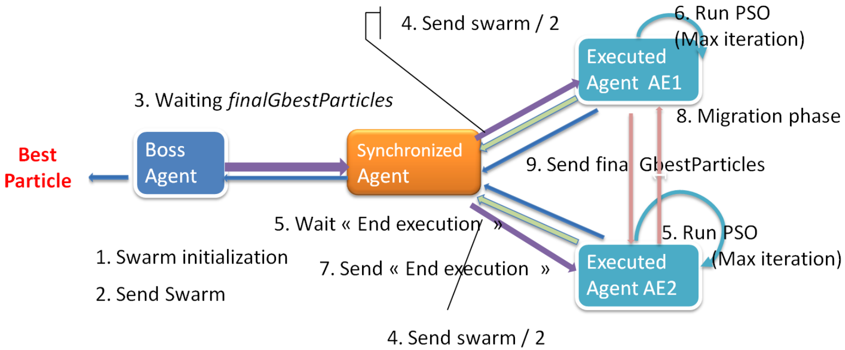
✍ minimize the makespan value

MAPSO2

✍ composed of Boss Agent, Synchronized Agent, n Executed Agent
✍ communication between agents
✍ Migration phase to diversify the search space

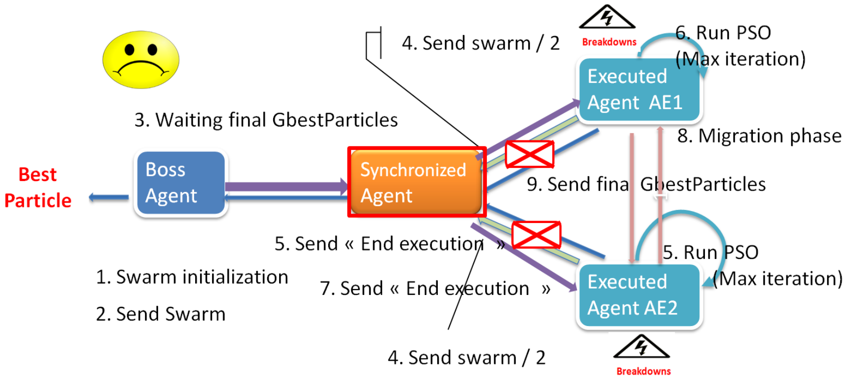
Multi agent Particle Swarm Optimization

- **MAPSO2**



Multi agent Particle Swarm Optimization

- **MAPSO2 drawbacks**



Multi agent Particle Swarm Optimization

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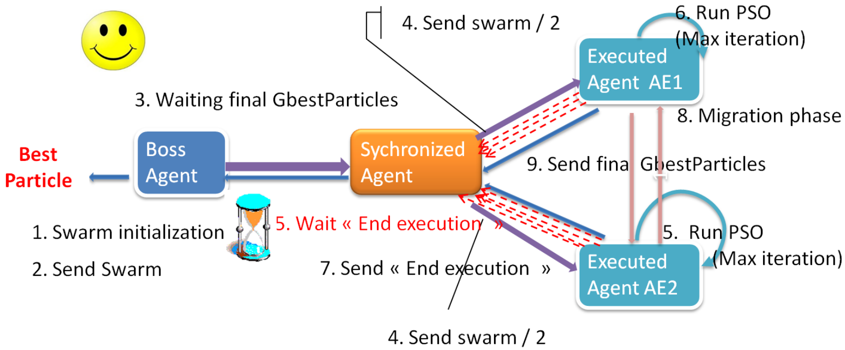
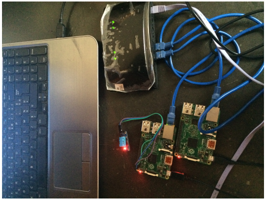
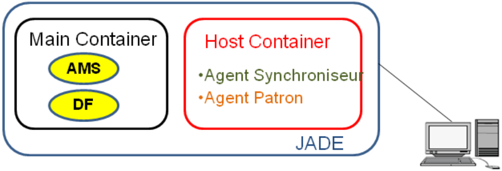


Embedded Implementation of PSO

- **Multi Agent Particle Swarm Optimization** : MAPSO2++





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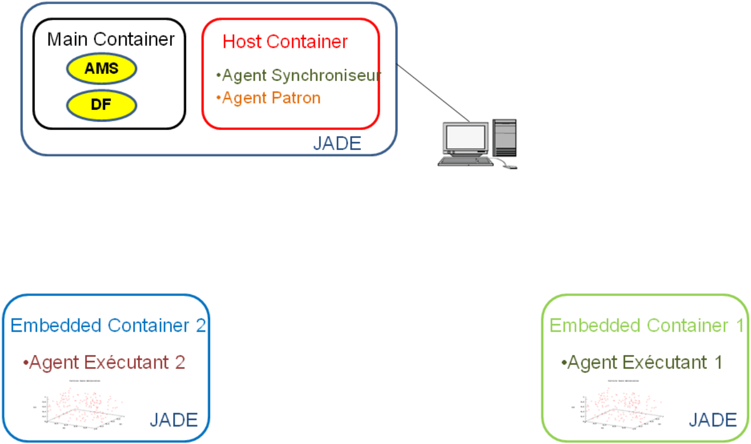

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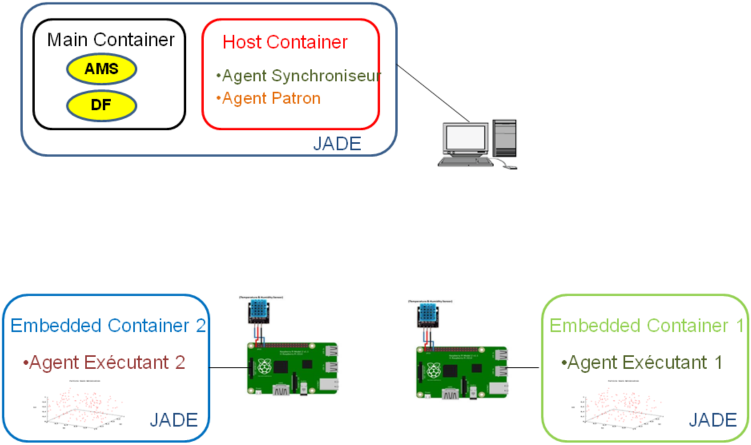

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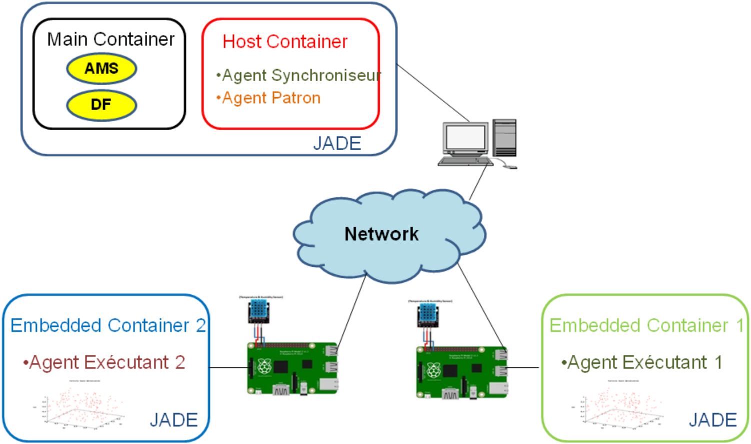
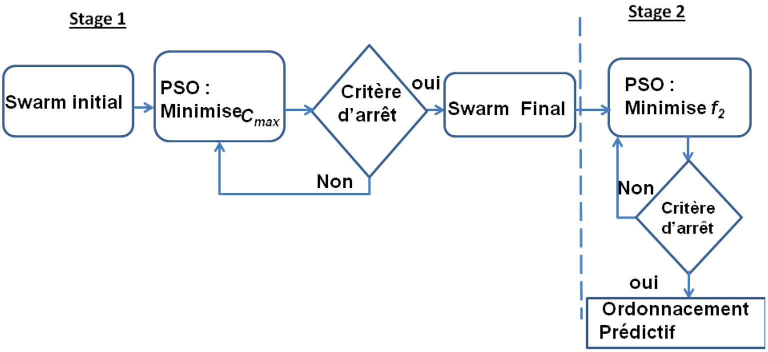
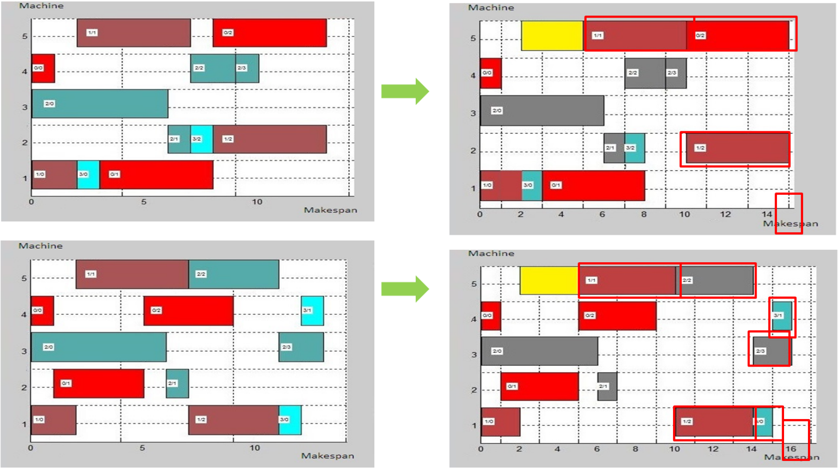


- **Predictive Reactive approach : 2 Stage PSO**
  - Integrate the probability of the breakdown to perturb the predictive solution
  - Evaluation of the solution with the robustness and the stability

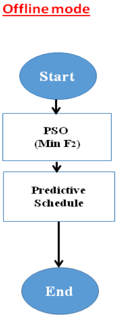


Predictive Reactive approach



- The Green Rescheduling Method.

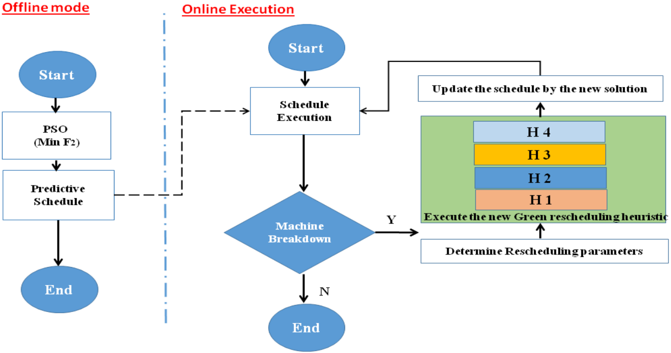
The flow chart of the proposed GRM



$$F_2 = \gamma min \frac{makespan}{summakespan} + (1 - \gamma) \frac{SumEnergy}{MaxEnergy}$$

✍ A new initialization method **"MinEnergy"** is added.

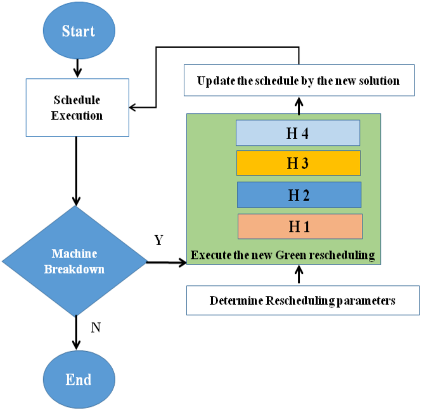
- The Green Rescheduling Method



$$F_2 = \gamma min \frac{makespan}{summakespan} + (1-\gamma)\frac{SumEnergy}{MaxEnergy}$$

✍ A new Green Rescheduling heuristic is proposed.

- Using Routing flexibilty



- Is composed by four heuristics.
- Each heuristic search to assign the operations either
  - Randomly (H1)
  - Minimum Earliest Method (H2)
  - Less machining energy (H3)
  - Less non-machining energy (H4)

Algorithm 1 :Green Rescheduling Method

Input parameters :	the prechedule p, machine failed m_b, start time of breakdown st, duration of repair procedure d.
Step 1 :	Extract *subparticle* that contains the directly and indirectly affected.
Step 2 :	Construction *newsubparticles* by **specific method**.
Step 3 :	Construction of *swarm* that contains all particles with the new assignments.
Step 4 :	Re-Evaluate the fitness value F2 of all particles of *SwarmReschedule*.
Step 5 :	**Output :** Select best particle with lowest value of Bi-objective function.

The energy Model

- The energy Model : proposed in He et al.2015.

$$E = E_w + E_m$$

  - E_w : the non-machining idle energy of machines ;

$$E_w = P_0 * t_w$$

    - P_0 : the machine idle power ;
    - t_w : the idle wait time for before processing the new operation.

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  - E_m : the machining energy of operations.

$$E_m = E_s + E_c$$

    - E_s : the idle energy during job setup ;
    - E_c : the cutting energy.

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$$E_m = E_s + E_c$$

    - E_s : the idle energy during job setup ;
    - E_c : the cutting energy.

$$✍ F_3 = min \sum_{i=1}^{N} \sum_{j=1}^{j_n} \sum_{m=1}^{M} E_{ijm} + \sum_{m=1}^{M} P_{0m} * t_{wm}$$

Rescheduling performance measures

- Makespan Efficiency : the percentage change in makespan of the reschedule compared to the original schedule.

$$\eta = 1 - \frac{M_{new} - M_0}{M_0} * 100$$

  - M_{new} : the makespan of the repaired schedule using GRM ;

Rescheduling performance measures

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  - M_{new} : the makespan of the repaired schedule using GRM ;
  - M_0 : the makespan of the original schedule.
- Energy Efficiency : the percentage change in energy consumed of the repaired schedule compared to the original schedule.

$$\lambda = 1 - \frac{E_{new} - E_0}{E_0} * 100$$

  - E_{new} : the energy consumption of the repaired schedule using GRM ;

Rescheduling performance measures

- **Makespan Efficiency :** the percentage change in makespan of the reschedule compared to the original schedule.

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  - M_0 : the makespan of the original schedule.

- **Energy Efficiency :** the percentage change in energy consumed of the repaired schedule compared to the original schedule.

$$\lambda = 1 - \frac{E_{new} - E_0}{E_0} * 100$$

  - E_{new} : the energy consumption of the repaired schedule using GRM ;
  - E_0 : the initial energy consumption of the original schedule.

Experimental results

- Scenario 1 : Energy consumption Optimization

  ✍ The weighting parameter γ is equal to 0.

Scheduling Method	Total Energy (W h)	Makespan (min)
Our GRM	**1495,44**	45.5
He et al.2015	1668.72	42.7

Interpretation

➠ The GRM provides solution with the lowest total energy 1495,44 W h.

➠ 98.33% of the total energy consumption was associated with machining and only 1.67% was spent on machine idling

➠ The percentage of total energy saving is 11.58%.

Experimental results

- Scenario 2 : Makespan Optimization

  ✍ The weighting parameter γ is equal to 1.

Scheduling Method	Total Energy (W h)	Makespan (min)
Our GRM	**1931,63**	35.3
	1724.36	35.3
He et al.2015	2137,95	35.3

Interpretation

➠ The GRM provides 10,68% total energy saving.

➠ The GRM provide better percentage of total energy saving (23,98%) when swarmsize=2000, Maxiteration =1500.

Experimental results

- Scenario 3 : tradeoff between energy consumption Optimization and makespan
  ✍ The weighting parameter γ is equal to 0.6 and 0.3

Scheduling Method	Total Energy (W h)	Makespan (min)
Our GRM	1746.85	**38.1**
	1626.11	44.3
He et al.2015	1672.02	40.1

Interpretation

➠ The GRM finds the best solution in terms of makespan value (38.1) ➠ An improvement of the total energy consumption (3%).
➠ when makespan 44.3 is tolerated, there would be 18.78% energy saving.

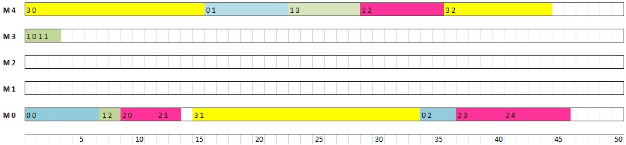
Experimental results

- Performance Evaluation of the rescheduling

Illustrate the effectiveness of the reactive part of the GRM.

✍ How disruption is to be generated ?

A machine with a heavy workload is more likely to breakdown.

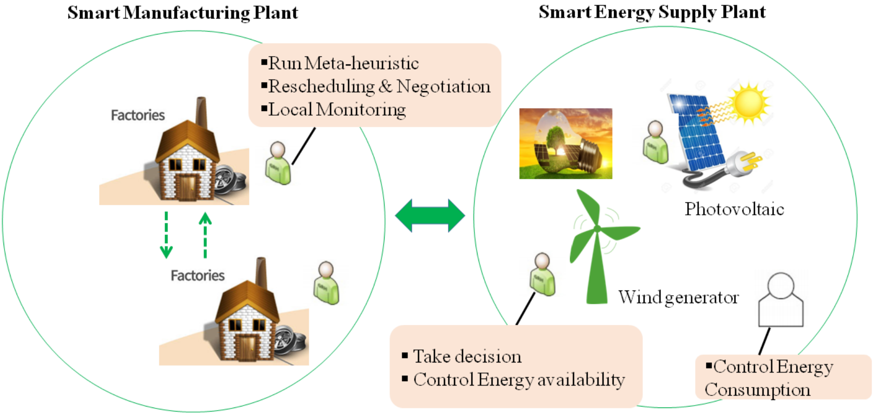


Interpretation

➠ The GRM finds the best solution in terms of makespan value (38.1) ➠ The GRM provides better results compared to RSR.
➠ **The energy efficiency** is improved from 85.80% to 91.32%.
➠ **The makespan efficiency** is improved from 93.82% to 100%.

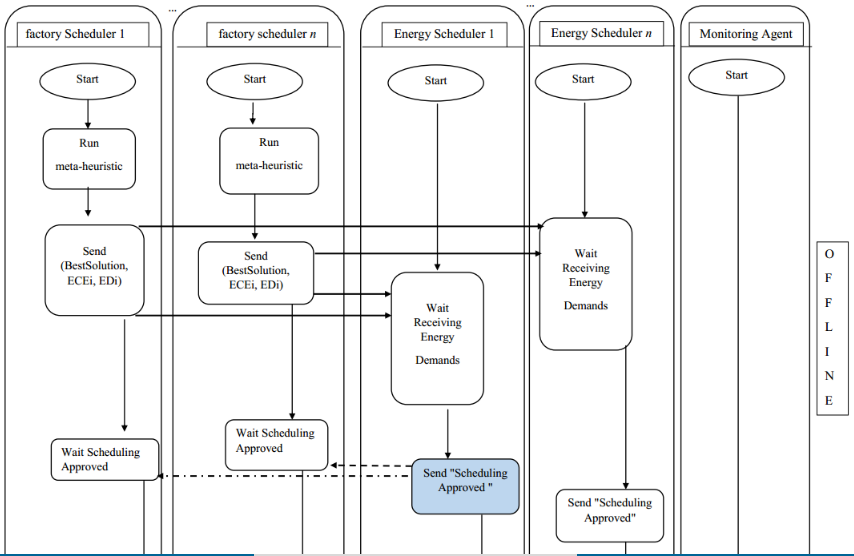
Global MA architecture for energy aware production

- MA-EAPSRS :



Global MA architecture for energy aware production

- The predictive part of MA-EAPSRS :



Global MA architecture for energy aware production

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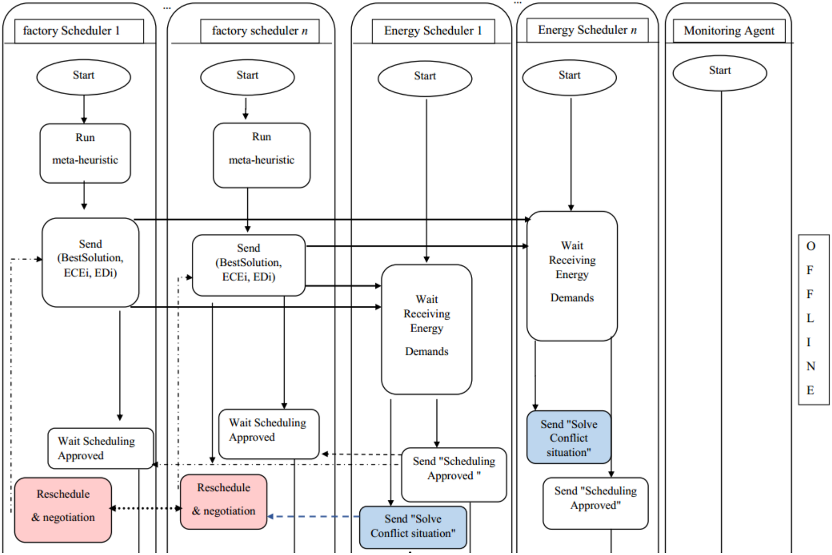
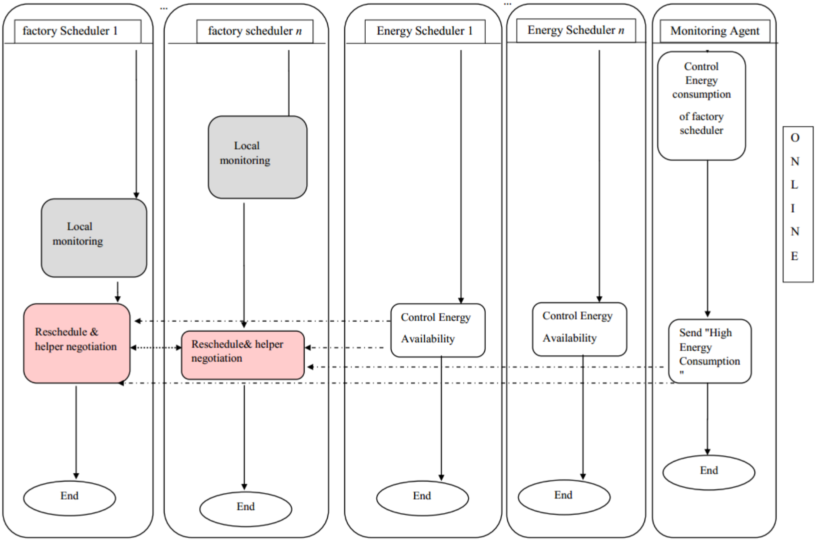


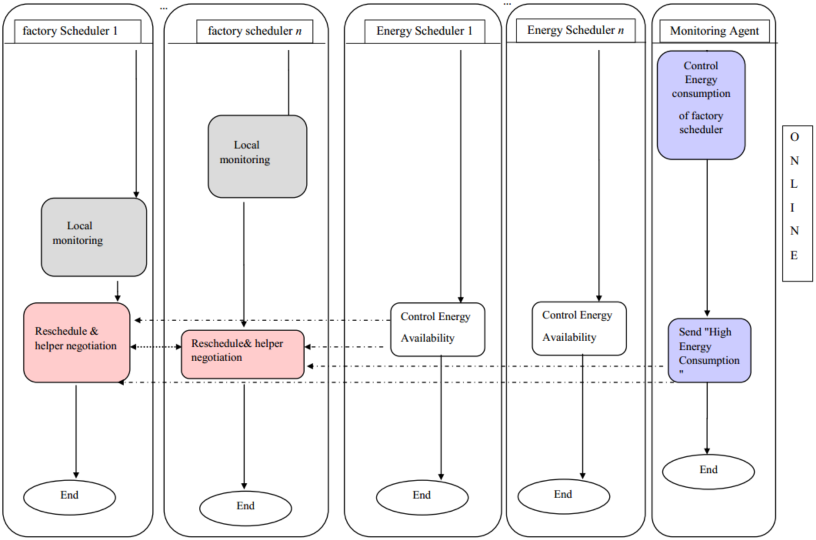
Global MA architecture for energy aware production

- The reactive part of MA-EAPSRS :



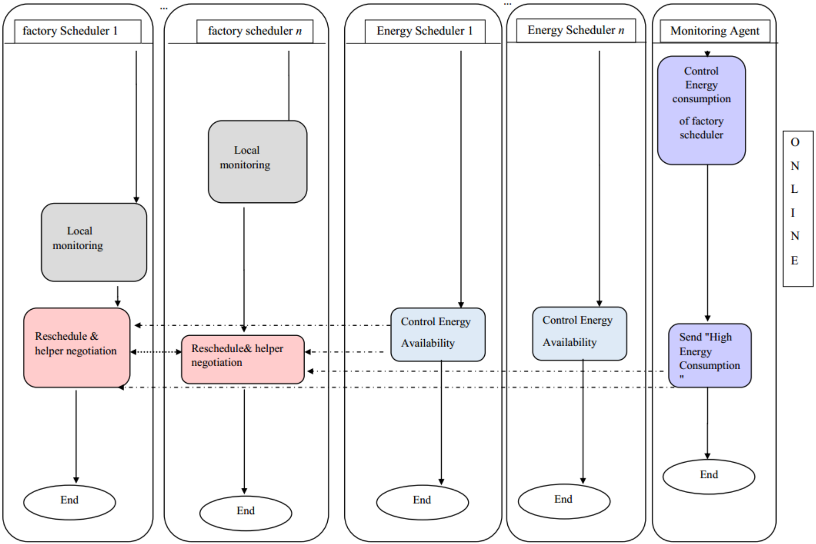
Global MA architecture for energy aware production

- The reactive part of MA-EAPSRS :



Global MA architecture for energy aware production

- The reactive part of MA-EAPSRS :



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Case study

Assumptions

✍ A case study addressing an energy aware flexible job shop scheduling problem.

✍ The smart multi agent system is composed of :

- two factory scheduler agents ;
- one energy scheduler agent ;
- a monitoring agent.

✍ The two manufacturing plants are homogeneous.

✍ There is only one energy provider of <u>one</u> type of renewable energy.

Case study

- The meta-heuristic used : Particle Swarm Optimization

Initialization methods

✍ 30% Min Energy, 30% Randomly, 20% KacemApproach, 20% ModifiedApproach.

Objective function

$$F_1 = \gamma min \frac{makespan}{summakespan} + (1 - \gamma) \frac{SumEnergy}{MaxEnergy}$$

The energy Model

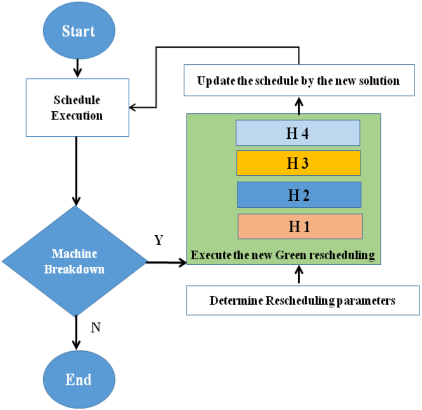
$$E = E_w + E_m$$

- E_w : the non-machining idle energy of machines ;
- E_m : the machining energy of operations.

Case study

- The Rescheduling Method used :

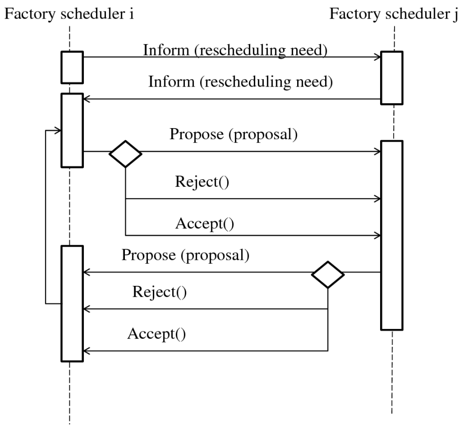
  Green Rescheduling Method proposed in Nouiri et al.2018



- Is composed by four heuristics.
- Each heuristic search to assign the operations either
  - Randomly
  - Minimum Earliest Method
  - Less machining energy
  - Less non-machining energy

Case study

- The negotiation protocol : is a key form of interactions.
- It is a cooperative negotiation.
- Find an agreement of the value of the weighting parameter.



- Send proposal : "new value of γ.
- If no agreement : γ is reduced by a value α.
- Favour the reduction of energy consumption.

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Experimental results

- MA-EAPSRS's results of first scenario
  - ✍ Using the same weighting parameter γ equals to 0.9.
  - ✍ Sum of energy Demands $ED_i < 4000\,Wh$.

Factory scheduler 1			Factory Scheduler 2			Energy scheduler's message
γ	Makespan	Energy consumption	γ	Makespan	Energy consumption	
0.9	35.3	2777.19	0.9	35.3	2899.61	Solve Conflict situation
0.8	35.3	2599.52	0.8	37.4	1852.43	Solve Conflict situation
0.7	35.3	2599.52	0.7	37.4	1852.43	Solve Conflict situation
0.6	39.9	1806.15	0.6	37.4	1852.43	Scheduling Approved

Interpretation

- ➠ Negotiation phase to find an agreement of the value of weighting parameter.
- ➠ The Energy agent sends a scheduling approved message when γ equals 0.6.

Experimental results

- MA-EAPSRS's results of second scenario
  - ✍ Using different γ values choosing randomly between 1 and 0.7.
  - ✍ Sum of energy Demands $ED_i < 4000\,Wh$.

Factory scheduler 1			Factory Scheduler 2			Energy scheduler's message
γ	Makespan	Energy consumption	γ	Makespan	Energy consumption	
1	35.3	2555.27	0.7	37.4	1852.43	Solve Conflict situation
0.6	38.1	1806.15	0.6	46.0	1697.299	Scheduling approved

Interpretation

➠ The predicted schedule of FS 1 has a high energy consumption compared to the FS 2.

➠ The first proposol of FS 1 "Rescheduling with γ equals to 0.9" is rejected by FS 2.

➠ The FS 2 sends another one " Rescheduling with γ equals to 0.6 which is accepted by FS 1.

➠ The Energy agent sends a scheduling approved message when γ equals 0.6.

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Conclusion and Future works

- Conclusion
  - the proposed MAPSO2 and its embedded implementation
  - The proposed 2s PSO
  - Green Rescheduling Method(GRM) was proposed
  - Find a feasible schedule that minimizes both makespan and energy consumption
  - Multi agent agent approach to solve energy aware production scheduling and rescheduling systems : MA-EAPSRS.
    - Hybrid approach combining the predictive and the reactive phase.
    - Takes into account sustainability in both parts.
    - Generic, suitable to smart grid infrastructure.
    - Can be applied to different real manufacturing problems.
  - A case study was presented.

Conclusion and Future works

- Interesting direction for future researches
- Develop an integrated hyper rescheduling method with different heuristics in a distributed way with a reconfiguration system to switch from one to another according to the state of the system.
- Integrate the "MA-EAPSRS" architecture on physically distributed system composed of embedded systems while using internet of thing (IoT).

Publications

- ## International Journal
  - **Nouiri, M.**, Bekrar, A., Jemai, A., Trentesaux D., Ammari, A. C, Niar, S (2017). Two Stage Particle Swarm Optimization to solve the flexible job predictive scheduling problem considering possible machine breakdowns.**Computers and Industrial Engineering**. V (112), pp 595-606.
  - **Nouiri, M.**, Bekrar, A., Jemai, A., Niar, S., Ammari, A. C (2015). An effective and distributed particle swarm optimization to solve flexible job shop scheduling problem. **Journal of Intelligent Manufacturing**, 29(3), pp 603-615.
- ## International Conferences
  - **Nouiri, M.**, Trentesaux D., Bekrar, A., Giret, A., Salido, M.A., (2018). Cooperation between smart manufacturing scheduling systems and energy providers : a multi agent perspective. SOHOMA, 11-12 June, Bergamo Italy.
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