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Multi-objective energy-aware scheduling

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1 Introduction

Scheduling determines the way in which jobs are assigned to resources. Multiple resources, e.g. machines and human operators, are available for the problem under consideration. Jobs and resources are defined by various characteristics and constraints, required to match in feasible assignments. Manufacturing companies strive for good quality schedules, in terms of operational efficiency and custom-related objectives. Makespan and tardiness are two objectives often separately considered during single objective optimisation. These objectives are denoted as "business objectives" and show a latent correlation. For example, makespan optimisation may positively influence the total tardiness of the schedule.

In the last years, energy consumption has gained considerable attention as the cost (kWh) impacts the total production cost in energy-intensive sectors. Hence, the need for minimising energy consumption and, consequently, energy cost increases. (Van Den Dooren et al., 2015) define a methodology for addressing multi-machine scheduling problems with the focus on minimising energy consumption. Experiments were conducted on the ICON challenge benchmark datasets (O'Sullivan et al., 2014), providing both real and forecasted energy cost data. The energy cost is time dependent and is enforced by assigning a corresponding energy price to every time slot. The energy consumption depends on resource requirements during execution of the jobs.

To take into account both energy and business objectives, a multi-objective optimisation approach is needed. Multi-objective approaches have been researched thoroughly (Varadharajan and Rajendran, 2005; Pasupathy et al., 2006). The present work focuses on analysing the energy objective so as to determine a detailed and specific energy modelling approach. Additionally, alternative multi-objective approaches for combining business and energy objectives are firmly researched. The influence of both objectives are analysed. Experiments are conducted using the MOLA (Multi-Objective Late Acceptance) method (Vancroonenburg and Wauters, 2013).

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2 Approach

Energy cost reduction is a relatively new scheduling objective. Extensive research is needed in order to determine the objective's inherent characteristics. Subsequently, relations with business objectives can be defined, e.g. supportive or conflicting nature of the objectives. Previous research (Van Den Dooren et al., 2015) provided some insights and a methodology concerning energy consumption modelling. Multiple schedule characteristics influence energy consumption, e.g. machine states, electricity cost per time period. The introduced methodology implements a LAHC (Late Acceptance Hill Climbing, Burke and Bykov (2012)) approach with multiple neighbourhoods.

An extension to previous research is carried out by implementing the MOLA method. MOLA consists of LAHC with Pareto dominance evaluation. The method works as follows. New solutions are generated using neighbourhoods and are accepted based on the Pareto dominance relation (Drugan and Thierens, 2012). Current best, pairwise non-dominating, solutions are saved in the Pareto set. The new solution is compared, accepted and added to the Pareto set when its objective value dominates the objective value a few iterations ago. Thus, the dominating solution replaces the oldest solution in the set. When the method come to a halt after having reached its stop criteria, this method could provide the Pareto front, which defines the best solutions for specific objective settings. Figure 1 illustrates the MOLA methodology.

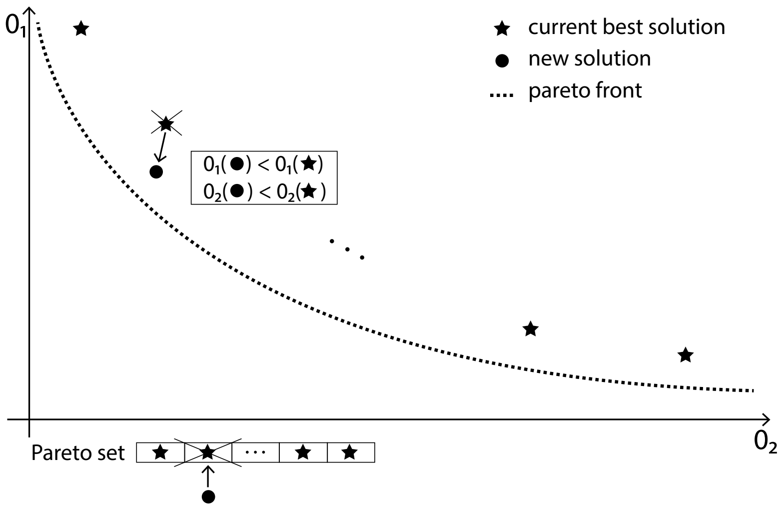

Fig. 1: MOLA methodology for a bi-objective example

3 Experimental Setup

3.1 Data

New datasets, based on the ICON benchmark sets (O'Sullivan et al., 2014), have been generated in order to investigate the effect of an energy cost objective being optimised simultaneously with business objectives. Real energy data, energy cost per time period, is provided within the ICON benchmark sets. However, the ICON benchmark instances contain restrictions, e.g. fixed time horizons, disabling possible business objectives. Thus, modifications to the general time restrictions are necessary: the time horizon is increased, and the jobs' time characteristics are modified. These changes enable incorporating business objectives such as makespan and tardiness. In addition to the academic datasets, real datasets have been collected in industry in order to enlarge the test environment and validate the developed optimisation approach.

3.2 Experiments

The experiments can be divided into three parts: objective function analysis, multi-objective optimisation and sensitivity analysis. They are performed using the MOLA method. The objectives are examined both individually and in combination. To this end, the Pareto objective approach is examined first. Secondly, lexicographical and weighted objective function tests are executed for different objective settings. A sensitivity analysis is provided by defining mutual objective influences, examining various objective settings, and comparing the aforementioned multi-objective approaches. Finally, a suggestion on how to approach multi-objective energy-related scheduling problems is given. The end results contain both the influence of problem specific characteristics and the effect of simultaneously optimizing different objectives.

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