Engineering Applications of Artificial Intelligence 25 (2012) 359–375

Contents lists available at SciVerse ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Fuzzy scheduling with swarm intelligence-based knowledge acquisition for grid computing

S. García-Galán*, R.P. Prado, J.E. Muñoz Expósito

Telecommunication Engineering Department, University of Jaén, Alfonso X el Sabio, 28 Linares, Jaén, Spain

ARTICLE INFO

Article history:
Received 20 September 2010
Received in revised form
6 September 2011
Accepted 4 November 2011
Available online 26 November 2011

Keywords:
Grid scheduling
Fuzzy Rule-Based Systems
Swarm intelligence
Automatic learning

ABSTRACT

In spite of the existence of a large diversity in literature related to scheduling algorithms in computational grids, there are only a few efficiently dealing with the inherent uncertainty and dynamism of resources and applications of these systems. Further, the need to meet both users and providers QoS requirements, such as tardiness or resource utilization, calls for new adaptive scheduling strategies that consider current and future status of the grid. Fuzzy Rule-Based Systems (FRBSs) are knowledge based systems that are recently emerging as an alternative for the development of grid scheduling middleware. Their main strength resides in their adaptability to changes in environment and their ability to model vagueness. However, since their performance strongly depends on the quality of their acquired knowledge, new automatic learning strategies are pursued. In this work, a FRBS meta-scheduler for scheduling jobs in computational grids is suggested which incorporates a novel knowledge acquisition method based on Swarm Intelligence. Simulations results show that the fuzzy meta-scheduler improves six classical queued-based and scheduled-based approaches present in today's production systems and it is able to easily adapt to changes in the grid conditions.

1. Introduction

The recent advent of high-speed networks and the increasing need for new proficient infrastructures facing large-scale computational problems have prompted Grid computing as a promising platform (Foster and Kesselman, 2003). A computational grid is made up of a set of heterogeneous and geographically distributed resources sharing theirs capabilities with the aim of achieving a common goal. Resources may belong to different administrative domains considering their own access policies and security constraints, and their coordination and cooperation is considered critical for the harnessing of grids potential (Foster and Iamnitchi, 2003). In this sense, a major challenge is given by the efficient allocation of users jobs to resources or scheduling problem (Christodoulopoulos et al., 2009). It should be noted that resources within a grid environment are diverse and they can unpredictably join or leave the system. Moreover, jobs computational needs and requirements are unknown *a priori* (Kalantari and Akbari, 2009).

Scheduling problem in grids has proven to be NP-complete in its general form and a lot of research has been done to obtain efficient solutions (Garey and Johnson, 1979; Klusacek et al., 2008b). Queued-based techniques such as *EASY-Backfilling* (*EASY-BF*) or *Earliest Deadline First* (*EDF*), are extensively used in today's production systems (i.e. Condor, Thain et al., 2005 or Grid Service Broker, Venugopal et al., 2004) and their main advantage is given by its simplicity and short algorithms runtimes (Klusacek and Rudova, 2008). However, queue-based methods are not able to guarantee most of QoS demanding features such as job turnaround and start time or resources utilization since decisions are taken considering a current known state of the grid. On the other hand, scheduled-based methods such as *EGS* (*Earliest Gap*), allow a more accurate scheduling plan by the consideration of up-to-date grid state information (Klusacek, 2008). It must be underlined here that the grid available information is mostly imprecise due to the inner system dynamism and uncertainty. That is, an efficient scheduling strategy must also be able to faster react to environment changes. Thus, the new trends are focused on the development of so-called adaptive scheduling (Xhafa and Abraham, 2008, 2010). In this area, it is relevant to point out the role of Fuzzy Rule-Based Systems (FRBSs).

FRBSs are expert rule-based systems where Fuzzy Logic (FL) is employed as a way of representing the system knowledge and the interaction between variables (Cordón et al., 2001). These systems base theirs decisions on "IF-THEN" rules where antecedents and consequents represent fuzzy statements for the variables featuring the system state, and in this way, they are able to cope with complex problems where there exist vagueness and uncertainty. Hence, the reasoning strategy is founded on the definition of

* Corresponding author.
E-mail addresses: sgalan@ujaen.es (S. García-Galán), rperez@ujaen.es (R.P. Prado), jemunoz@ujaen.es (J.E. Muñoz Expósito).

0952-1976/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.engappai.2011.11.002

Knowledge Bases (KBs) that include the fuzzy rule semantics or fuzzy sets, Data Bases (DBs) and linguistic rules or expert knowledge, Rule-Bases (RBs). FRBSs have been successfully applied to a wide set of areas such as speech and music discrimination (Exposito et al., 2007) or ventilation systems (Alcalá et al., 2005) and they are proving to be an efficient alternative for adaptive scheduling (Franke et al., 2008; Prado et al., 2010c, 2009). However, as it can be inferred, the scheduling performance using FRBSs strongly depends on the quality of its knowledge and thus, with the learning strategy. Since the incorporation of an expert knowledge is not a feasible option in most areas of application of FRBSs, automatic strategies are needed. One of the most extended techniques for the evolution of RBs are Genetic Algorithms (GAs) (Garcia et al., 2009; Hoffmann et al., 2007). GAs are global optimization techniques providing quasi-optimal solutions in complex search spaces that make use of genetic operators such as selection and crossover for the searching of the best suited individuals. Specifically, there exist two successful approaches for rules learning with GAs, namely Pittsburgh (Smith, 1980) and Michigan approach (Booker et al., 1989; Carse et al., 1996). Whereas Pittsburgh approach considers a whole RB as an individual, within Michigan approach each fuzzy rule represents a candidate that competes to be included in the next generation. Both strategies are known to be able to find near optimal solutions. Nevertheless, given the dependence of FRBSs with the knowledge acquisition process, the design of faster and more accurate learning strategies is relevant.

In this work, we suggest the use of FRBSs for the design of a meta-scheduler for computational grids that incorporates a novel learning strategy inspired by Swarm Intelligence. To be precise, the learning strategy consists of the adaptation to rule representation of Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995). PSO was first introduced with the aim of simulating the birds movement within a flock and it has been widely applied to optimization of multidimensional discontinuous problems in several fields such as electromagnetics (Robinson and Rahmat-Samii, 2004) and wireless communications (Huang et al., 2009). Further, it has been used for scheduling in grids as a population-based heuristic in works such as (Liu et al., in press). A major advantage of PSO is the convergence control and simplicity. In contrast to genetic strategies, PSO requires a reduced number of fixing operators and convergence is driven by particles internal velocities updating, what notably decreases the number of required communications and computational effort. However, in the authors knowledge, PSO has not been applied for rules evolution in grids. Thus, *Knowledge Acquisition with a Swarm Intelligence Approach* (*KASIA*) is suggested in this work for the improvement fuzzy rule-based meta-schedulers performance in grid computing. KASIA was introduced in Prado et al. (2010b), where its efficiency as a general learning strategy for FRBSs and feasibility for its application to grid computing scheduling was shown. In this work, KASIA robustness as an expert knowledge acquisition strategy for grid computing environment is proved in terms of several optimization criteria. Furthermore, a wide range of classical scheduling strategies, including genetic fuzzy rule-based schedulers, are considered for comparison and many relevant grid performance indexes are used for its analysis.

The remainder of the paper is organized as follows. Section 2 presents an overview of scheduling strategies in grids and the existing learning strategies for FRBSs. The proposed meta-scheduler structure and general operation together with the definition of the knowledge acquisition method for expert grid computing schedulers, KASIA are introduced in Section 3. Section 4 focuses on simulations results of the proposed schema and it provides a comparison with traditional schemas. Finally, Section 5 concludes the paper.

2. Background

The capability of providing QoS is one of the striking aspects of grid scheduling. As stated in Xhafa and Abraham (2008), a grid is a *fully dynamic environment with uncertainties*, i.e., the grid state is subject to changes at any time and little assumption can be made in relation to future resources and jobs parameters. In grids machines actually running jobs may suddenly fall down or new machines appear, jobs execution time may be wrongly estimated in their submission or resources sharing policies may change with time (Foster and Kesselman, 2003). Hence, any acquired knowledge of the system state is inherently imprecise and guaranteeing certain levels of QoS in terms of time (i.e. *flow-time*, *tardiness*, *slowdown*, *average weighted response time, average weighted waiting time*), resource utilization (i.e *classic usage*, *weighted usage*) or jobs constraints (i.e. *jobs deadlines*) is a major challenge.

Most of today's production systems such as LSF (Xu, 2001), PBS (Nitzberg et al., 2003), Condor (Thain et al., 2005) and other grid meta-scheduling systems like Grid Service Broker (Venugopal et al., 2004) or GridWay (Huedo et al., 2005), found their planning on queue-based scheduling strategies. Queued-based scheduling have proved to be able to satisfy simple performance objectives in grids and they are consolidated as the de facto standard nowadays. However, at the advent of the growing demand for complex QoS performance criteria, such as the ones mentioned above, queued-based strategies have been forced to resort to other supporting techniques such as advanced reservation (Klusacek and Rudova, 2008). Nevertheless, queued-based schedulers are unable to cope with a large amount of reservations. Specifically, it is studied that the number of reservations overtaking a system established boundary leads to a resource usage detriment and the starvation of jobs with no reservation requirements. Hence, more flexible scheduling strategies are pursued. Adaptive scheduling techniques suggest the consideration of both current and future state of the grid in order to avoid and prevent performance degradation (Xhafa and Abraham, 2008). In this sense, scheduled-based techniques base their planning on the consideration of a ''known'' actual state of the grid environment and this way, allows a more accurate mapping of jobs and meeting of QoS requirements. The ''known'' actual state refers to available resources capabilities, jobs computational needs or even to the number of jobs. However, it is worthy highlighting here the grid state is imprecise by nature and that the advanced knowledge of these features is impossible, at least in a precise way. This uncertain state generally leads to schedule plans that do not correspond to real conditions. Notwithstanding, it is stated that a scheduling strategy aiming to provide a certain level of QoS has to consider a more or less accurate information of the grid state (Klusacek, 2008). From here it can be derived that techniques able to react to the environment changes and imprecisions may be convenient, since obtaining a precise knowledge of the system parameters is not a feasible option.

When dealing with uncertainty, the role of FL has to be underlined. FL is essentially based on the idea that the human reasoning is naturally approximate and it provides a methodology for the representation of this fuzzy or imprecise knowledge in situations where a certain degree of vagueness must be tolerated (Cordón et al., 2001). In this regard, FRBSs represent an extension of traditional rule-based systems that try to accommodate the classical engineering techniques precision and artificial intelligence interpretability and flexibility. FRBSs have been successfully applied to a wide range of fuzzy modeling, control and classification problems (Alcalá et al., 2005; Exposito et al., 2007) and they have recently attracted the researchers attention for their application to large-scale scheduling (Franke et al., 2008; Prado et al., 2009, 2010). One of the major advantages of FRBSs is