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Algorithm based on particle swarm applied to electrical load scheduling in an industrial setting

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ABSTRACT

In this work we propose the development of a novel particle swarm-based heuristic to solve a discrete mathematical problem. Such a problem is present in allocating electrical loads throughout the day in an industrial setting. Data on the total installed load and energy demand throughout the day at 15-min intervals were collected in five industrial facilities. The loads were randomly distributed and the developed algorithm was applied to balance and optimize the energy demand throughout the day. The performance of the proposed algorithm was compared to a standard binary Particle Swarm Optimization and a mathematical model, which was also implemented to solve the problem. Our results demonstrate that the proposed algorithm is more efficient for all the considered scenarios, regardless of the amount of loads and constraints applied.

1. Introduction

Demand response (DR) can be defined as changes in the normal patterns of consumption at the end customer as well as in response to changes in the price of electricity over time. In addition, DR can also be defined as a form of incentive designed to induce a lower use of electricity in periods of higher prices due to, for instance, climatic factors, and when the generation of the system is compromised [1]. DR includes all changes in electricity consumption patterns by end-use customers that are designed to change instantaneous demand level or total electricity consumption [2].

A demand response can be achieved by three general actions [1]. Each of these actions involves costs and actions taken by the customer. First, customers can reduce energy consumption during peak periods when prices are high without changing their consumption pattern during other periods. This option involves a temporary loss of comfort. This response is achieved, for example, when the thermostat settings of heaters or air conditioners are temporarily changed [3,4].

Second, customers may respond to high electricity prices in the period, shifting some of their peak-demand operations to off-peak periods. The residential customer in this case will not suffer any loss and will incur no cost. However, this will not be the case if an industrial customer decides to reschedule some activities, as the costs of rescheduling to compensate for lost services should be considered.

The third type of customer response is the use of local generation on customer property [5,6]. Customers who generate part of their energy consumed may experience no or very little change in their electricity usage pattern. However, electricity usage patterns will change significantly and demand will appear to be lower.

In this paper, we implemented a novel tool to optimize scheduling of loads considering local power generation. This tool is called Particle Swarm Optimization (PSO) and is based on a metaheuristic aimed at solving unrestricted nonlinear optimization problems.

A recent research [7] suggests a method based on Binary PSO to solve the load scheduling problem with flexible and non-flexible loads, in addition to have Maximum Demand constraint. We implemented the algorithm proposed in Ref. [7] as benchmark to compare with the algorithm we proposed in this work. Other approaches using methods of analysis and computational intelligence for the allocation of flexible loads are reported in the literature. For instance, the Mixed Integer Non-linear Optimization used for the solution of restricted Demand Response problem was proposed in

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Ref. [8]. Another strategy, which is a type of Machine Learning (Automata), is also used to solve optimization problems and has been applied to the Demand Side Management [9]. A decentralization-based heuristic was proposed and implemented in Ref. [10] and is also an approximation approach based on Q-learning. A heuristic based evolutionary algorithm presented in Ref. [11] uses load allocation technique for Demand Response. In Ref. [12], an analytical approach of Mixed Integer Linear Programming is used to program smart devices. Various other methods were also presented in the literature, such as the one by Ref. [13]. In their work, particles were encoded as binary sequences and velocities (v) as a set of probabilities, while [25] implemented a particle cloud algorithm for the N-queens problem. In the work presented in Ref. [25], the velocity was also implemented as a vector of probabilities, but with some peculiarities, for example, the higher the velocity value associated with the dimension x, the more likely it was for the exchange to occur in x.

Due to various operational constraints, load allocation is a complex optimization problem. In Ref. [14], the authors used the heuristic of Particle Swarm Optimization to reduce uninterruptible loads. This algorithm provides a certain limitation on the flexibility in programming and restrictions on the different loads. Better programming approach is needed for real-time implementation of this heuristic. One type of model-free reinforcement learning technique known as Q learning is applied to load scheduling [15]. The real-time control strategy, including Half-hour rolling-ahead optimization and the real-control strategy team are designed to find the best solution for Demand Response [16]. In Ref. [17], a heuristic approach to combinatorial optimization problem solution is presented to allocate the loads in different timestamps.

The authors in Ref. [18] published one of the most recent studies in the area of discrete PSO, where they describe the development of an algorithm based on set theories and possibilities. The main feature of the algorithm, called "Set-based PSO" (S-PSO), is how the velocity was implemented. In S-PSO, the velocity is defined as a set of possibilities. The authors describe a binary sequence as E, which represents a solution to the problem. To update the velocity the traditional equation of the classical algorithm is applied, but using elementary set theory to implement the subtraction between the two positions. Additionally, specific rules were used for the multiplication between the coefficients and the positions of the particles.

In this proposed study, the problem to be solved with the PSO meta-heuristic is that of the even daily distribution of electric loads (equipment) in an industrial setting, taking into consideration the times that specific loads will be used. Several researchers have proposed solutions to specific industries. Our contribution, which is novel, is the solution to the loads allocation problem in a general way applicable to any industry. Moreover, our proposed solution is of relatively easy implementation and provide good results. The goal is to not exceed the energy demand contracted by the supplier, and that the contract with the utility company is not oversized, thus reducing the fixed costs for the industry.

The proposed velocity calculation is specific to the characteristics of the problem, which produces the search space for the optimized solution making it more efficient under normal execution conditions. It is salutary to say that constructive algorithms and the local search ones are considered of great importance for efficiently solving combinatorial problems. Therefore, this manuscript shows a PSO using hybridization techniques in order to corroborate with [19], and to show that obtaining good solutions in binary combinatorial optimization problems is possible. The implementation of the algorithm was performed in JAVA language and the simulations conducted under the same computer hardware configurations.

The rest of the paper is organized as follows: In Section 2 the structure of the algorithm is presented and divided into sections for ease of understanding, and provides a step-by-step explanation of the proposed meta-heuristic approach. In Section 3, the practical results are illustrated in graphs and tables explaining its nuances, and confirming the efficiency of the proposed method over others. Finally, in Section 4 the most relevant results are listed. Future and current work under development by the authors are also presented.

1.1. Problem formulation

The model that is being proposed aims to simulate the allocation of loads according to their time constraints without extrapolating the determined maximum limit. We sought to formulate the model in the most general way possible, in order to approximate the theoretical results with the experimental data of previous researches.

It is pertinent to point out that the problem of load balancing is a combinatorial optimization problem whose decision variables are binary. The importance of the model is that it is guaranteed that contracted demand will not be exceeded under any circumstance, however, due to its restrictions, solutions are not always found.

The proposed model is mathematically formulated based on parameters of the model, objective function and constraints. The details of each item can be seen in the following sections.

1.2. Parameters

Parameter	Description
L	Number of loads
T	Number of time steps
P_i	Power of the ith load
D_i	Hours of utilization of the ith load
K_j	Power capacity in the jth time step
$F_{i,j}$	Fixed load

These variables are used in the composition of the objective function and in the constraints imposed on the model.

1.3. Objective function

The main objective of the problem is to minimize the total power demand in the determined moments of time given that the maximum demand is not exceeded and that the loads with fixed drive are guaranteed.

$$\text{Minimize} \sum_{i=1}^{L} \sum_{j=1}^{T} X_{ij} P_i \tag{1}$$

$$X_{i,j} = \begin{cases} 1, & \text{if the } j^{\text{th}} \text{ duty is in the solution} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

The objective function represented in Equation (1) minimizes the demand at each instant of time and the decision variable exposed in Equation (2) that composes the objective function is represented by the value 1 in case the load must be activated at that time instant or 0 otherwise. The decision variable follows criteria established in the constraints.

1.4. Constraints

Usually, the constraints imposed in the system description have a linear relationship (equality or inequality) developed to influence