MIRACLE

Micro-Request-Based Aggregation, Forecasting and Scheduling of Energy Demand, Supply and Distribution

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1 Summary

Energy market deregulation and environmental sustainability increase the need for efficiency and flexibility of energy systems. New services are sougt to ensure reliable supply, utilize the renewable energy sources (RES), and balance the costs and benefits of the involved parties. In this context, the European FP7 project MIRACLE (Micro-Request-Based Aggregation, Forecasting and Scheduling of Energy Demand, Supply and Distribution) proposes a conceptual and infrastructural approach allowing electricity distributors to manage higher amounts of renewable energy and balance supply and demand. For this purpose, MIRACLE introduces the concept of micro-requests that allow consumers and producers to specify flexibilities of their energy profiles in terms of the energy amounts and their time shifts. Such micro-requests from numerous consumers and producers will enable fine-grained scheduling of consumption and production of electricity, and maintaining a system-wide balance between demand and supply.

Work Package 5 (WP5) of the MIRACLE project deals with scheduling and negotiation in the proposed approach. Based on the forecast of energy supply and demand, negotiation will take place to determine how and when consumption and production can be matched, and a schedule for production and consumption will be determined. The goals of WP5 are to specify a framework to schedule production and consumption for the forthcoming period, specify a negotiation framework, implement and integrate the two frameworks, and validate them on real data from the project trial cases.

This deliverable is a result of the WP5 preparatory phase and reports on the state-of-the-art in scheduling and negotiation approaches. Regarding scheduling, it first presents a common type of scheduling problems together with their properties, and introduces some characteristic aspects of the scheduling domain. It then focuses on scheduling in energy sector where it identifies particular problems: generation scheduling, unit commitment and economic dispatch. Finally, it reviews methods applied in solving scheduling problems in energy sector, including deterministic and meta-heuristic techniques, and with a special attention to the approaches for deregulated markets. The state-of-the art survey on negotiation approaches starts with an introduction to negotiations and two negotiation types: bilateral contracts and auctions. Energy exchange auctions are then described with the focus on hourly bids, block bids, pricing and trading phases. Examples of multi-agent negotiation systems are then presented, taken from related projects and the literature. The report concludes with comments related to further work on both scheduling and negotiation in MIRACLE.

2 State-of-the-art in scheduling

2.1 Introduction to scheduling

Scheduling is a process used in decision-making applications in various industries. For example, a standard scheduling problem is to allocate resources/machines to tasks/jobs. The allocation is not done randomly – its goal is to optimize one or more objectives by taking into account a set of constraints. Such optimization is performed over given time periods.

Scheduling can be classified in terms of a three-field classification $\alpha|\beta|\gamma$ where α denotes the machine environment, β job characteristics, and γ the optimality criterion [GLL+79].

2.1.1 Machine environment

The machine environment defines how the jobs are processed. This can be done in several ways [Bru07]:

(1) Each job is processed on a dedicated machine.
(2) Jobs are processed on parallel machines:
    a. Identical parallel machines – processing time for each job is the same on all machines.
    b. Uniform parallel machines – processing speed for all jobs is the same on a specific machine.
    c. Unrelated parallel machines – each machine processes a job with specific job-dependent speed.
(3) Jobs processed on multi-purpose machines with identical or uniform speeds.
(4) Jobs part of a multi-operation model, namely general shop, i.e., each job as a set of operations with defined precedence is processed on dedicated machines:
    a. Job shop: operations are processed sequentially on different machines.
        i. Job shop with machine repetition: a specific machine processes several operations.
        ii. Flow shop: constant number of operations per job and operations are processed in the same sequence:
            I. Open shop – there is no operation precedence.
            II. Permutation flow shop: order of job processing on a machine is always the same.

2.1.2 Job characteristics

The job characteristics are specified by the set β containing the following 6 elements [Bru07]:

- β_1: preemption or job splitting, e.g., a job can be stopped and resumed later;
- β_2: precedence relations between jobs presented as an acyclic directed graph;
- β_3: release dates;
- β_4: restrictions on the processing times or on the number of operations;
- β_5: job deadline;

- β_6 : jobs processed in batches, batch processing problems are: (1) p-batching problems – the last processed job defines the batch end; (2) s-batching problems – the sum of the processing times of batch jobs defines the batch end.

2.1.3 Optimality criterion

The optimality criterion is usually defined with the job finishing times that are associated with costs forming a cost function. Two types of total cost functions essentially exist: the bottleneck cost functions take into account only the maximum cost of all jobs, and the sum cost functions take into account the sum of all job costs.

Examples of the most commonly used cost functions are as follows.

- Makespan takes into consideration the maximal job finishing time.
- The total flow time takes into consideration the sum of job finishing times.
- The weighted (total) flow time takes into consideration the weighted sum of job finishing times.

However, the use of finishing time is not compulsory. It can be substituted by the due date introducing the following measures: lateness, earliness, tardiness, absolute deviation, squared deviation and unit penalty. Each of these measures can also be used as makespan, total sum and total weighted sum. In addition, linear combinations of these objective functions can also be used [Bru07].

2.1.4 Deterministic versus stochastic scheduling problems

Generally, scheduling problems can be deterministic or stochastic. Deterministic scheduling problems assume that job data are exactly known in advance. On the other hand, in stochastic scheduling problems job data are not exactly known in advance. For example, processing times, release dates and due dates may not be exactly known in advance, but only their distribution is known in advance. In such cases the data may become exactly known only when a job processing starts or even only when the job processing ends [Pin08].

2.1.5 Classes of schedules

Schedules can be classified regarding the allowed job sequences that limit the scheduler. Some examples of schedule classes are [Pin08]:

- Non-delay schedules: no machine is kept idle while an operation is waiting for processing.
- Active schedules: a subset of feasible nonpreemptive schedules that cannot be changed in such way that one operation finishes earlier and no operation finishes later.
- Semi-active schedules: a subset of feasible nonpreemptive schedules that cannot be changed in such way that no operation completes earlier without changing the processing order on any of the machines.

2.1.6 Solving scheduling problems

Scheduling problems can be solved in two ways. A problem can be directly solved without any change by using standard techniques, such as dynamic programming and branch-and-bound methods. On the other hand, some scheduling problems are similar to the well-known combinatorial optimization problems. Consequently, they can be transformed to such well-known problems, for example, linear programs, maximum flow problems, or transportation problems [Bru07].

2.2 Scheduling in energy sector

Scheduling in energy sector is usually used for assigning energy units to producers, consumers and transportation lines. For example, the unit commitment process determines which generating units will be used at each time point. This is done over a short time horizon by taking into consideration system capacity requirements and economic aspects. Another process is the economic dispatch process. It allocates system demand among the generating units in operation at any point in time. This is done depending on the relative efficiencies of the units in order to find the minimum-cost schedule over a short-time period [MK77].

2.2.1 Generation scheduling

Generation scheduling is a process that includes the unit commitment process and the economic dispatch process. It mainly depends on the energy industry organization. For example, if the energy industry is vertically integrated, generation scheduling is carried out by the utility system operator. Such operator has the knowledge of the system components, constraints and operating costs of generating units. It makes decisions on unit commitment in order to minimize the utility's generation cost. Besides, it has to satisfy several constraints, such as the load balance, system spinning reserve, ramp rate limits, fuel constraints, multiple emission requirements and minimum up and down time limits over a set of time periods. The process is called the security constrained unit commitment (SCUC). Besides the generalized cost minimization, it must also insure system transmission and voltage security including the occurrences of $n-1$ transmission contingencies. Therefore, the specific goals are: supplying load, maximizing security and minimizing cost. More precisely: supplying load is a hard constraint; maximizing security is achieved with the spinning reserve; cost minimization is done with the commitment of less expensive units and economic dispatch.

The energy industry was vertically integrated in the past, while today it is usually horizontally organized. This implies that the generation, transmission and distribution are unbundled. Energy industry organization differs from country to country. Nevertheless, all country markets include decentralized competitive bidding in auction markets for energy and reserves. Besides, market actors have access to the transmission that is the condition for acting. Their goal is to maximize their own profit. An actor can have and can consequently commit a generation unit. The commitment is associated with financial risks. Since the whole process is price-based, it is called price-based unit commitment (PBUC). As a consequence, satisfying load is no longer a hard constraint. The goal is only to maximize the profit. Besides, the security provision is also priced as an ancillary service. The system operator does not commit the load anymore. This is done by each energy supplier that is responsible for its own bidding decisions. The system operator has to maintain the energy system security. To do that, it has to take into account two types of contracts: bilateral contracts containing bids known a priory, and online contracts containing instantaneous bids depending on each actor's forecast of energy flow that is than traded on organized market. In summary, the market price is the driving force of the PBUC. It reflects the current state in the energy market. Besides, if transmission congestion occurs, the energy price may differ among different regions [Yam04].

2.2.2 Unit commitment & economic dispatch

The unit commitment process is a subprocess of the generation scheduling process. It defines when each unit is started, stopped and how much it generates in order to achieve the minimum-cost production and distribution. The load profile, i.e., the requested load for each hour of the day, is given in advance and it is a hard constraint. The load profile during one hour is constant. Besides, available units are also given, where each of them is described with several attributes, e.g., minimum and maximum loads and production price. The choice of a unit depends on several factors, e.g., cost, availability and current status. In summary, the unit commitment process has to take into account system and unit constraints and the cost function includes only the price.

The economic dispatch problem has similar formulation as the unit commitment problem. The main difference is that now the units are already selected. Consequently, only energy amount has to be scheduled on these units.

The unit commitment problem is a complex problem due to the large number of possible unit and system constraints. Specifically, unit constraints are the constraints affecting each unit individually, for example:

- maximal generating capacity,
- minimal stable generation,
- flexibility,
- minimal “up time”,
- minimal “down time”,
- ramp rate.

Unit flexibility is usually the most interesting constraint/feature. Units are either flexible or inflexible. When dealing with flexible units, their status and power output can be optimized. Some examples include:

- coal-fired units,
- oil-fired units,
- open cycle gas turbines,
- combined cycle gas turbines,
- hydro plants with storage.

On the other hand, when dealing with inflexible units, their power output cannot be adjusted for technical or commercial reasons and it is treated as given. Some examples are:

- nuclear plants,
- run-of-the-river hydro plants,
- renewable energy sources (RES), such as wind and solar energy,
- combined heat and power (CHP, cogeneration).

System constraints are the constraints that affect more than one unit, for example:

- load/generation balance,
- reserve generation capacity,
- crew constraints,
- emission constraints,
- network constraints.

In addition to the constraints, the most important information of an energy system is the number of units. The unit commitment cannot be efficiently solved with a simple algorithm if the number of units is large, since the number of possible combinations is too large to check all of them.

The complexity of the unit commitment problem can be seen in the following example. If there are N units, 2^N possible states exist, where an example of a state is: first unit on, second unit off, etc. Besides, the time is partitioned into T intervals. Consequently, the units' states have to be defined for each time interval. One solution defines the state of each unit in each time interval. Consequently, the number of possible solutions is $(2^N)(2^N)...(2^N) = (2^N)^T$. Such large number of possible solutions implies that the unit commitment problem is very hard. Moreover, it is also a non-linear, non-convex and mixed-integer problem. Therefore, a suitable technique has to be implemented for solving it. The requirements for this technique are as follows [Kir10]:

- It has to find the solution close to the optimum.
- It must have low computing time.
- It must have the ability to model constraints.

The techniques used for solving the unit commitment problem can be grouped into [SZJ06]:

- deterministic techniques,
- meta-heuristic techniques,
- hybrid approaches based on deterministic and meta-heuristic techniques.

Examples of deterministic techniques are:

- extensive enumeration,
- priority list,
- dynamic programming,
- linear programming,
- Lagrangian relaxation,
- branch-and-bound.

Examples of meta-heuristic techniques are:

- expert systems,
- artificial neural networks,
- fuzzy logic,
- simulated annealing,
- genetic algorithms,
- evolutionary programming,
- tabu search.

2.2.3 Methods for solving energy scheduling problems

2.2.3.1 Extensive enumeration

This method checks all possible solutions and stores the result in a table. Since the whole search space is checked, the optimality is assured. Moreover, once the table is created, the future selection of the appropriate solution is fast. On the other hand, such method can be used only if the search space is small [SK98] [HJW71] [WW84].

2.2.3.2 Priority list

The priority list technique commits the units regarding their priorities. A prerequisite is to define the priorities. This can be done regarding the production costs. Another example is the priorities based on the production capacity, e.g., higher capacity implies higher priority. Besides, additional data can be taken into account if two units have equal capacity [Lee88]. When the priorities are defined, the algorithm uses them in order to create a schedule. Additionally, the constraints can be taken into consideration [BG75] [SK98].

An example of the priority list implementation commits units sequentially for each hour. When committing units for one hour, the power balance, security constraints and unit constraints have to be satisfied. After the units are committed for the whole day, a shut-down searching procedure decommits inefficient units in order to reduce the final cost [Yam04] [KSF+66].

Such method is fast since the result is calculated in one run using the described heuristic method. On the other hand, it is not efficient due to its simplicity and the straightforward approach. Its disadvantage is that unit commitment and economic dispatch are not considered together and some unit constrains are not considered appropriately [TT08]. In addition, the solutions obtained with this method are usually far away from the optimal solution [Yam04].

Several priority list based techniques have been developed that differ regarding the priority calculation, where priority is defined with, e.g., commitment utilization factor [Lee91] and classical economic index average full-load cost [Lee88] [Yam04].

2.2.3.3 Dynamic programming

Dynamic programming operates with time periods known as stages where each stage consists of states. Each state defines each unit state in the given stage. Consequently, the solution consists of exactly one state in each stage. When selecting the state at the next stage, a recursive relationship is used defining the optimal state for the next stage. This relationship is found using a backward procedure. It starts at the end of the time interval and defines the optimal state transition for each state in each stage until the initial stage is reached [Yam04].

The initial implementations did not handle the time dependency between stages since the states of the stages were selected independently through the stages [Low66]. In addition, certain unit constraints were not handled appropriately. These shortages were efficiently overcome with a procedure, presented in [PC76].

Dynamic programming searches the space of solutions organized in a decision tree containing only feasibly solutions. To find the optimal solution, the whole tree is searched. Such implementation is time consuming. To overcome this limitation, several approaches have been proposed. These approaches usually combine dynamic programming with priority list techniques. Examples are truncated dynamic programming and sequential dynamic programming.

Truncated dynamic programming approach [PSA81] searches only the efficient generating units by also taking into consideration the load demand. Other, inefficient units are not taken into consideration thus reducing the search time. Since the whole search space is not checked, this approach does not guarantee the optimal solution. A similar priority-based approach is the sequential dynamic programming approach [PSA81] which neither guarantees the optimal solution.

The solution space defined as a tree can be searched in two directions: forward and backward. Forward search starts at the initial stage and searches until it reaches the last stage. Afterwards, some corrections can are done backward. The backward search starts at the last stage. Such implementation is not preferable since it cannot be stopped in the middle because it may not have already found the initial stage. In contrast, the forward search always contains the initial stage and can be easily stopped in the middle if the computational resources have been completely used [Yam04].

The classical dynamic programming approach solves the problem as a whole. If the problem is large, partitioning it might be a more appropriate approach. Several approaches have been proposed that decompose the problem and solve it by parts [SPR87]. Basically, there exist two approaches: successive approximation that solves the subproblems sequentially, and hierarchical approach that solves the subproblems in parallel. For example, when the successive approximation is used, Dantzig-Wolfe decomposition can be used for the decomposition, and linear programming to solve the economic dispatch [WAB81].

Another technique used to increase the efficiency of dynamic programming implements vectorization and parallelizatio. Such implementation is especially appropriate for supercomputers where vector processors are used [MB94].

All data for the unit commitment problem may not be exactly known in advance. Consequently, the presented approaches have to be modified to take this fact account. For example, generation parameters and forecasted load may be uncertain. To cope with these uncertainties, fuzzy dynamic programming has been developed [SK98].

2.2.3.4 Linear programming

The initial implementation of linear programming was designed for scheduling thermal units [Gar62]. Later, several other linear programming approaches have been developed, for example a mixed-integer programming technique is presented in [MW68]. The unit commitment problem that takes into account also the reserve was solved with integer programming approach and presented in [Dil78]. These algorithms do not take advantage of the problem structure and therefore are not appropriate for solving large problems [Yam04]. The problem structure can be taken into account to reduce the solution search space. For example, it can reject the infeasible subsets of solutions [MW68].

Linear programming has been largely used in combination with other approaches. For example, in combination with dynamic programming the linear programming approach solves the economic dispatch. Besides, the information about the search space is passed to the dynamic programming in order to search the solution tree more efficiently [SK98] [TB00] [FBC95].

2.2.3.5 Lagrangian relaxation

Lagrangian relaxation is used for solving mixed-integer programming problems. The initial version, called linear programming relaxation, was used to found the lower bound in the branch-and-bound technique. Such relaxation usage made the search more efficient [MK77].

The main idea of the Lagrangian relaxation is the usage of a dual function. This function is the cost function that combines power balance and security constraints. This is done with two sets of Lagrangian multipliers. By forming this new cost function, additional constraints are added to the original optimization problem. After the dual cost function is defined, the reformulated problem, called the dual problem, is solved as follows. Firstly, the original or primal scheduling problem is solved. Afterwards, the dual problem is solved with dual function maximization by considering the additional constraints. Besides, the original constraints are relaxed. Such dual problem formulation allows decomposing the original problem into smaller subproblems containing the operation of only one generating unit where dual function is used to solve the problem as a whole. A subproblem is obtained by fixing the multiplier values. This is then solved by taking into consideration only the constraints defining the operation properties of one generating unit [Yam04] [KF09]. In order to fix the multiplier values, the dual problem has to be solved. This is usually done by maximizing the dual function with a subgradient method. This sequence of problem–subproblem optimization is done in several iterations [Fis81]. The search stops when the quality difference between the primal cost function and the dual function drops under the prescribed bound.

Lagrangian relaxation does not guarantee the optimal solution. The optimal solution as a combination of subproblem solutions is guaranteed only if the problem is convex. However, most problems are not convex. Therefore, the found solution is usually only the lower bound of the primal problem optimal solution. Nevertheless, the quality difference between the found solution and the optimal solution is usually less than 2% [Fis81].

The original implementation is time-complex. Therefore, several studies have been carried out as attempts to reduce it. For example, a method taking into consideration only the spinning reserve was developed. This can be done since the reserve requirements are achieved only after the load requirements are met. Consequently, the reserve requirements are used as the only goal. In addtion to the computation of the lower bound, also the upper bound is computed. The search stops when the relative difference between these bounds drops under the defined limit. Although the optimal solution is not guaranteed, the found solution usually differs from the optimal solution for less than 0.5% [MS87]. This method efficiently handles only the thermal units. If other units are present, e.g., fuel-constrained and hydro, the dispatch complexity increases since the number of constraints increases significantly. Consequently, the presented method does not perform well on such problems [Yam04].

The original cost function can be expanded by adding, i.e., relaxing constraints, such as load demand, emission control and system spinning reserve. Examples of such applications are presented in [MS87] [CW87]. After the cost function is formed, the achieved subproblems are solved with dynamic programming. The dual function values are always lower than the primal function values forming the duality gap as a measure of near-optimality [WSK+95] [SK98] [BZ00].

The original method does not handle the fuel-constrained units. To do that, an additional set of multipliers has to be added to the dual cost function. Consequently, the function complexity increases significantly [CW87]. In order to reduce this complexity, additional iteration loops have been added to the dual algorithm. Therefore, the solution is searched in more than two loops where in each loop a set of multipliers is fixed and another set of multipliers changes through the optimization process. The optimization process of one loop is done with a subgradient method. The loop sequence is as follows. Firstly, the fuel-constrained units are optimized and fixed. Afterwards, the thermal units are optimized and fixed. Finally, the dual function is optimized. Such decomposition significantly reduces the complexity [CW87]. Besides the presented implementation, additional loop have been added to the cost function. Such function expansion is especially useful when several combinations of constraints have to be taken into account [AIS+89].

Although the Lagrangian relaxation is largely used, it has an important drawback: it is very sensitive to the variation of Lagrangian multipliers. Consequently the search efficiency is lower and it may not found acceptable solutions [Yam04]. Besides, the convergence and the duality gap reduction may be unstable. In order to overcome such drawback, an augmented Lagrangian method has been developed. It adds quadratic demand penalty to the cost function. The consequence is the improved convergence and the reduced oscillations during the iterations [Fis81] [Yam04].

2.2.3.6 Branch-and-bound

The branch-and-bound approach firstly finds a lower bound of solutions and afterwards finds the near-optimal solution by taking into account the lower bound. The search is performed with the priority list approach. It efficiently models all time dependent constraints [CY83].

Originally, this approach was used for solving the unit commitment problem containing only the thermal units. The lower bound was found with a simple rule. This bound limited/reduced the search space thus improving the efficiency [CW93].

The most important mechanism of this approach is the reduction of the search space with the determination of the lower bound. Such bound can be found in several ways. For example, we already mentioned that the Lagrangian relaxation technique can be used for lower bound determination [SK98]. Afterwards, this algorithm performs the depth-first search through the tree of solutions in order to find the optimal solution. An advantage of this method is that it can take into account stochastic properties of the problem [SK98].

The main drawback of the branch-and-bound approach is the time complexity. This is due to the iterative process of search space reduction and priority list search. In addition to this, the upper bound computation is time expensive and cannot be efficiently incorporated into the algorithm.

2.2.3.7 Expert systems

Expert systems do not find the solutions like other approaches. They are only used to help the system operator when the existing solutions have to be improved. In order to do that, expert systems contain the knowledge about the energy domain. This is usually extracted from the system operators' behavior, existing unit commitment problems and the rules presented by the experts [MSW88]. To reduce the required communication between the expert system and the operator, the knowledge is coded only once and permanently stored in the knowledge base.

Expert systems can also be used in combination with other methods. For example, combined with the truncated dynamic programming approach, the expert system can be used as a pre- or post- processor. In addition, pattern matching techniques can be used [BS97] [MBZ+97].

2.2.3.8 Artificial neural networks

Artificial neural networks (ANN) efficiently handle inequality constraints with sigmoid characteristic. Consequently, they are suitable for solving the unit commitment problem. In addition, the ANN can also handle the stochastic problem features [SK98] [VS04]. Another important ANN feature is that it learns from past activities and constructs an internal representation of the energy processes. This can be done by storing the typical load curves and corresponding (near-) optimal solutions into the database. Such data can then be used to construct the neural network [SWY92].

Examples of the ANN usage are as follows. When the ramp rate constraints are modeled, the algorithm proposed in [WS93] can be used. For solving both unit commitment and economic dispatch the algorithm was proposed in [KSB95]. It can model stochastic system and unit features. For example, load demand is modeled with normal Gaussian random variables. The solution is composed of independent Markov processes for each unit. The original ANN is augmented to handle both integer and continuous data [WM97].

2.2.3.9 Fuzzy logic

When uncertainty has to be taken into account, most approaches are not able to solve problems efficiently. In such cases, the fuzzy logic can be used to handle the uncertainty. An example of uncertain demand and thermal units' usage is presented in [TS90]. Since the uncertainty always involves some risk, the risk has to be analyzed. An example of risk analysis is presented in [ZBL+94]. It analyzes the unit failure risk when the committed capacity is insufficient. The efficiency of fuzzy logic usage has been explored in [MK95]. It demonstrated that for some types of problems fuzzy logic and other stochastic approaches are more suitable than deterministic approaches [Yam04].

2.2.3.10 Simulated annealing

Simulated annealing is a meta-heuristic optimization technique searching for the optimal solution in several steps. In one step, a new solution is randomly selected from the current solution neighborhood. The better solution of the current two solutions is stored. The neighborhood width is inversely proportional to the quality of the current solution [MAS98].

The advantages of this approach are that it can be used to solve large-scale problems and easily handles constraints. However, the convergence may not be fast and therefore the approach may not be efficient. To overcome this limitation, parallel simulated annealing can be used that stores and improves more than one solution simultaneously, thus improving the convergence [SK98] [ZG90].

2.2.3.11 Genetic algorithms

Genetic algorithms (GA) are stochastic search techniques. When searching for the optimal solution, they simulate the evolution and the Darwinian survival of the fittest principle. The solutions are coded as chromosomes, consisting of genes, similar to what is known from genetics. When applied to the unit commitment problem, a genetic algorithm consists of initialization, economic dispatch calculation, cost calculation, selection and variation of candidate solutions, using the crossover and mutation operators [DM94] [VS02].

The advantages of GA are that they are widely applicable and require no problem-specific information for search. Besides, constraints are easily handled during the search thus pruning the search space [SK98]. On the other hand, the classical implementation usually does not find (near-)optimal solutions. Consequently, the main algorithm has to be improved by adding problem specific operators [KBP96]. An example of problem specific mutation operators is presented in [MS96]. Another drawback is that the optimality is not guaranteed [SK98].

Besides the described classical implementation, numerous variations of the original algorithm exist. An example is a different constraint handling approach. It can be done by incorporating constraints into the fitness/cost function as penalty terms. This is a very suitable approach when the number of constraints is large and consequently the search space is a complex surface. Such implementation outperforms the classical GA approach as demonstrated in [PKB98].

Several approaches combine genetic algorithms with other methods, resulting in hybrid techniques. Examples are the combinations with simulated annealing and fuzzy logic [SZJ06]. Another example is the GA combined with knowledge-based methods. Initial population of solutions is found using problem-specific knowledge and not randomly initialized. Furthermore, using this knowledge, search is performed more efficiently as well [ABD+01] [CLL00].

For speeding-up the GA, parallelization may be involved. This can be easily achieved since the algorithm operates on a population of solutions. Consequently, a parallel implementation significantly reduces the search time. Some examples are presented in [YYH97] [Yam04].

2.2.3.12 Evolutionary programming

Evolutionary programming (EP) is an evolutionary computation technique similar to genetic algorithms. It essentially employs the mutaion and selection operators to perform serach for good solutions. An example of its appplication includes solving the economic dispatch problem [YYH96]. A version of EP, known as cooperative EP, has also been developed for solving complex instances of the unit commitment problem [CW02].

2.2.3.13 Tabu search

Tabu search is a search method designed for solving combinatorial optimization problems. It belongs to the family of local search optimization techniques and is famous for maintaining the tabu list, i.e. the list of prohibited moves in the search space, that prevent returning to the already visited points in the search space. It easily handles constraints and improves promising solutions with local search [BS96].

Tabu search has also been used in combination with other approaches. For example, it has been used in combination with the dynamic programming to schedule hydrothermal units [BS96]. Another example is the combination of tabu search and priority list for unit commitment reported in [Yam04].

2.2.3.14 Methods for deregulated markets

Following the trend of electricity market deregulation, the scheduling metods need to be adjusted to handle new market properties. Such updated methods have to solve a problems similar to the PBUC problem where the main difficulty is the electricity price, which is not predetermined anymore. It is defined on the market by the supply/demand economic laws. Usually the hourly price is highly volatile [Yam04]. We briefly present some examples of used techniques.

Probabilistic techniques are suitable for modeling real-world problems. An example of unit commitment in interconnected generating systems with a probabilistic technique is presented in [CB90]. It models the requested load that is not defined in advance but it constantly changes. Another approach has been developed that models price-based ramp rates on hourly basis. It is used for price-based dynamic dispatch and unit commitment [LLL94].

Although the goal PBUC is price optimization, some SCUC goals and requirements need to be achieved as well. For example, the transmission constraints and reserve requirements do not change. A particular algorithm for solving the SCUC problem was presented in [CBC99]. This algorithm has additional features, including the capability of price optimization, that extend its applicability to the PBUC problem.

The requested load is not given in advance anymore but changes constantly. Consequently, the load profile has to be forecasted. The past forecast can be compared to the actual load profile and differences can be observed. The goal is to minimize such differences in the future. An approach for such difference minimization is described in [PMK00]. It forecasts lower load profile than the conventional forecasting and is used if the conventional forecasting performs poorly. Additionaly, it increases the reserve in order to reduce the consequences of forecasting errors.

When solving the PBUC problem, information about the future price can be very useful. An approach to future price forecasting is presented in [VM00a]. It applies the Monte Carlo procedure to forecast the production cost that is used to make future decisions. It takes into consideration the stochastic nature of the unit production.

Besides the system operator aspects of the PBUC problem, the production unit aspects must also be handled, where the key aspect is the bidding strategy. An example is described in [KSG00]. The bids depend on ramp rate, power balance and spinning reserve. The algorithm also observes the consequences of different bids on the market and suggests how to bid to maximize the profit.

Another method that considers both profit and operating constraints is presented in [VM00b]. Here unit commitment is modeled as a stochastic optimization problem. It is solved through decomposition where the solution is found for each unit individually. Besides, the price probability distribution is calculated. It takes into account the load uncertainty and the unit availability. A similar approach considering both fuel and electricity prices is discussed in [TKW00].

An algorithm based on linear programming for thermal unit commitment [AC00] focuses on the energy selling aspects. The goal is to increase the energy selling profit. Two types of energy selling are covered, i.e., energy for the market and energy for the spinning reserve.

Lagrangian relaxation has been used for solving the PBUC problem, too. An example is presented in [VM01]. Another example of profit-based optimization takes into consideration both power and reserve energy [AHK+02].

The main limitation of the majority of the presented methods is that they are price-oriented, and consequently, focus on the producer aspects. Even though the system requirements and other constraints are considered, the focus remains on the price. However, to handle the energy system as a whole appropriately, enhanced approaches are needed. Initial case studies from the literature include dealing with concepts, such as the equilibrium of auction markets with unit commitment [GM02], and multi-period auction for a pool-based electricity market system [ACG+02].

3 State-of-the-art in negotiation

3.1 Bilateral contracts and auctions

3.1.1 Negotiation

Negotiation is a form of social interaction where groups of more than two agents can freely come together and agree on a deal between them. If it involves two parties, it is referred to as bilateral negotiation, and if it involves more than two parties, it is called multilateral negotiation. An example of bilateral negotiation is where Swedish utilities trade with German utilities through the Baltic cable without using predefined market protocols. There are also two types of negotiations depending on the number of issues: single-issue negotiation or multi-issue negotiation.

Effective negotiation normally involves two stages [LBS+03]:

- pre-negotiation is intended for carefully preparing and planning for negotiation, particularly, agreeing on an appropriate negotiation protocol and defining the rules governing the interaction;
- negotiation is the central process of moving toward agreement usually by an iterative exchange of offers and counter-offers.

Negotiation protocol defines the following elements:

- states of the agents,
- actions of the agents depending on the current state,
- events that cause states to change.

Negotiation protocol also defines branching points where negotiators have to make decisions according to their strategies.

Energy resources can be accessed in two major ways:

- by establishing bilateral contracts,
- by bidding at the energy exchange using power auctions (power pools).

These two types of negotiation are discussed in the following sections.

3.1.2 Bilateral contracts

Bilateral contracts are normally used between large producers and consumers. The main drawbacks of bilateral contracts [WKZ01] [BSM+97] is that the agreed prices can be higher than the average prices from power auctions (day-ahead, hour-ahead or real-time). To sign a bilateral contract, participants have to pay some broker fees, and the process of negotiation and financial settlements is time-consuming. However, they are financially safer for the market participants because they can hedge against high price volatilities, and the contracted amount of electricity is more reliable than that from the energy exchange.

3.1.3 Types of auctions and energy contracts

Auction is a process where one or more bidders agree with the auctioneer to buy one or more goods or services at a certain price [Wur01]. Auction is a highly structured form of negotiation between several agents while bilateral and multilateral negotiations are fairly unstructured processes. (With the arrival of Internet and electronic commerce, the differences between auction and negotiation have blurred.) The key idea behind acutions is that the price is unknown. It contrasts with the conventional sales process where the price is known: the buyer simply decides if the item is worth its price and buys it if the price is less than its own valuation. The general objective of the auction is actually to settle this price. For a seller it is an opportunity to increase the revenue relative to a fixed-price sale, while for the bidders it is an opportunity to obtain the good for a lower amount than their valuation.

There exist the following types of auctions depending on how they are organized [HJL03]:

- English Auction: Bidders place their bids openly, each bid being always higher than the last one until no more bids are placed. The participant that places the highest (i.e., last) bid wins the auction and pays the price offered in this last bid. There are two variations: (i) it is possible to set a buy-out price which, when reached, automatically terminates the auction, (ii) it is possible to set a reserve price (public or not) under which the commodity cannot be sold.
- Dutch Auction: The auctioneer starts with a high price which is decreased gradually until somebody is willing to pay the announced amount. In this case only one bid can be placed and therefore this auction is quick.
- First-Price Sealed-Bid: It is a sealed auction where participants do not know the bid amounts by the rest. They just submit their bids and the good goes to the highest one.
- Vickrey Auction: Vickrey auction is an English auction with an additional feature that the price paid by the winner is that of the second highest bid rather than the first highest bid.
- Continuous Double Auction (CDA): Here buyers and sellers are allowed to continuously update their bids or asks at any time in the trading process.

Auctions can also be classified according to the number of buyers and sellers:

- Forward Auctions: One seller (the auctioneer) and many buyers. It is the most widened format.
- Reverse Auctions: One buyer and many sellers. The buyer places an ask by initiating the auction and then the sellers offer their services or goods.
- Exchanges: Many buyers and sellers can trade simultaneously.

The main purpose of energy exchange is to organize energy transactions among qualified participants. Normally an energy exchange provides the following types of energy markets:

- day-ahead market (auctions),
- intraday market (continuous negotiation),
- financial markets (futures).

Energy transactions carried out on energy exchange are standardized contracts of the following two main types:

- hourly contracts on power,
- block contracts on power.

3.2 Energy auctions on Energy Exchange

3.2.1 Hourly bids

Exchanges work differently for energy because of the characteristic properties of this resource which influence how the price is set. In particular, during most time periods, the generation price is set by the operating costs of the most expensive generating unit which is needed to meet the demand. Therefore, this price is referred to as the marginal cost of production. Such a situation is due to the fact that suppliers do not want to sell energy cheaper than the most expensive unit producing energy at a given time (because consumers are ready to pay this price). Conversely, consumers do not want to pay more than the cost of the most expensive unit producing energy, since other suppliers are ready to provide cheaper energy. Accordingly, when prices are set to marginal costs, the market is clear.

In deregulated (free) markets, prices are set using trading on daily auctions. Energy producers submit bids, and the bidders with the lowest price are chosen to supply electricity to the grid. In such auctions, the same price for energy is set for all producers (it is the price submitted by the highest active bidder). An efficient and flexible approach to setting the price consists in bidding with demand/supply functions [DJ03] where a bidder submits a function which represents the cost of the units to be bought or sold (cost of electricity in the case of energy exchanges). Then the buyer can accept parts of different bids so that this approach provides a rather flexible method for expressing complex pricing policies. Such demand/supply functions reflect the cost of electricity generation and buyers can get energy simultaneously from several producers.

According to [EEX10], hourly bid is defined as follows (Figure 1):

Hourly bid is an offer with continuous price quotations between a minimum and a maximum price. Trading participant specifies which quantity of electricity in MWh he wishes to buy (positive quantity of electricity) or to sell (negative quantity of electricity at a given price in EUR in MWh during the delivery hour concerned in the form of a function which is linear in part.

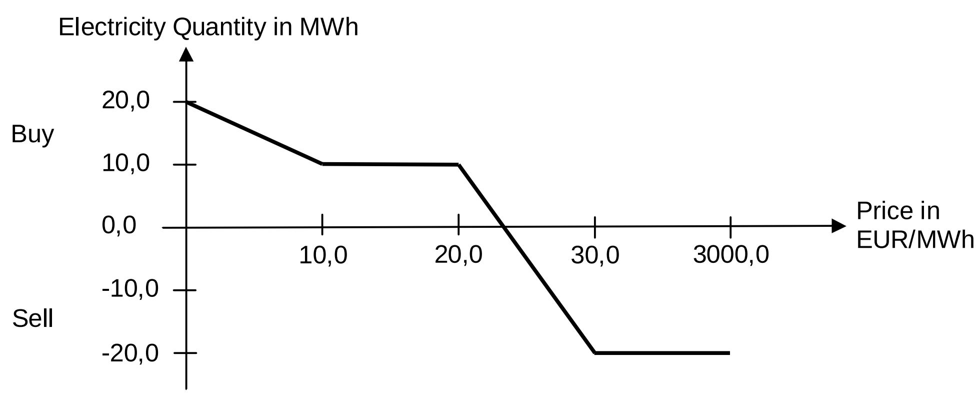

Figure 1: Hourly bid

Thus an hourly bid is a set of price-quantity pairs for each hour and price area. Hourly bids are entered, changed, deleted and retrieved in the form of easily comprehensible tables (Table 1) for all 24-hour contracts of a delivery day and a place of delivery (TSO). Each line of the table represents one of the 24 delivery hours of the delivery day and the place of delivery (TSO) concerned. The top line of the table contains price specifications in EUR per MWh. A cell within the table contains the quantity of electricity in MWh for the respective delivery hour of the line and for the respective price specification of the column.

Hour	*Price entry in EUR/MWh*					
	0,00	10,00	20,00	30,00	50,00	3000,00
01	20,0	10,0	10,0	-20,0		-20,0
02	10,0					10,0
03	-20,0					-20,0

Table 1: Tabular representation of a hourly bid

It is not necessary to enter an electricity quantity into each cell. An empty cell indicates that there is no pair of values regarding the price specification of the column for the specific hourly bid concerned.

An hourly bid always refers to an hour contract on electricity, which involves three parameters: delivery day, delivery hour and place of delivery (TSO zone). Accordingly, a trading participant can enter precisely one hourly bid by specifying one given delivery hour of a delivery day for each place of delivery (TSO). It is possible to enter several hourly bids with the same delivery day and delivery hour for one place of delivery (TSO), but for that purpose it is necessary to have several trading accounts. In other words, one trading account can be used to enter only one bid with equal parameters.

Another important property of hourly bids (for a price-dependent order) is that different quantities of electricity can be executed depending on the exchange price. In the case of price-independent order (with the constant curve), the same quantity of electricity independent of the exchange price will be bought by the trading participant.

3.2.2 Block bids

Block bid is defined as follows [EEX10]:

<u>Block bid</u> is used for the procurement or for the sale of any block deliveries of electricity which are specific to the respective hour (such as, for example, base load or off-peak deliveries) by means of trading of hour contracts and it is, hence, a combination of up to 24 partial orders for hour contracts for electricity. A block bid can either be a buy order (all partial orders are purchase orders) or a sales order (all partial orders are sales orders). Either all partial orders of a block bid are carried out jointly or all of these partial orders jointly are not carried out.

Thus block bid aggregates several hours and gives the opportunity to set the “all or nothing” condition and a fixed price-volume parameter for all the hours within this block. There are special versions of block bids. A linked block bid establishes dependencies between several block bids so that the acceptance of one block bid (daughter block) is dependent on the acceptance of another block bid (mother block). There is a possibility to sell energy for a single hour with a fixed price-volume where the hour is not specified. The chosen hour is the one with the highest price (if it is higher than the price of the bid). Such bids are referred to as flexible hour bids.

The following requirements have to be satisfied by all partial orders for hour contracts within a block bid:

- Each partial order refers to one hour.
- One block consists of 2-24 partial orders belonging to one delivery day and place (TSO).
- All partial orders specify the same quantity of electricity (for Germany maximum 500 MWh).

A price-dependent block bids is given a price specification (limit) which is made in EUR per MWh. Such a bid is executed at the average value of the exchange prices of all the hour contracts of the bid if this average is equal to or better than the limit.

Block bids are entered, changed, deleted and retrieved in the form of an easily comprehensible table (Table 2) which is specified for one day of delivery and one place of delivery (TSO). The top line of the table enumerates the delivery hours. Accordingly, each line of the table represents a block bid with a price specification (limit) for the respective delivery day and place of delivery (TSO) concerned. Each column of the table represents an hour contract.

A cell of the table then contains the electricity quantity in MWh for the respective delivery hour of the column and for the respective price specification (limit) of the line. Positive quantities of electricity represent purchases while negative quantities of electricity represent sales. It is not necessary to enter a quantity of electricity in each cell. An empty cell means that the corresponding hour contract is not assigned to the block bid.

	Delivery Hour													
Price Limit	1	2	3	4	5	6	7	8	9	10	11	...	23	24
20,0	5,0	5,0	5,0	5,0	5,0	5,0	5,0	5,0				...		5,0
3000,0									7,5	7,5	7,5	...	7,5	

Table 2: Tabular representation of a block bid

If the limit is not specified then such a bid is referred to as price-independent block bid and it is always executed at the average of the exchange prices of all the hour contracts in the bid. The price specification (limit) for buy orders has to correspond to the maximum price of hourly bids (EUR 3,000 per MWh) and for sales orders it has to correspond to the minimum price of hourly bids (EUR 0 per MWh).

3.2.3 Pricing

Market area is defined as follows [EEX10]:

Market area is a number of places of delivery (TSO zones) with the same price for electricity established at energy auction. Each place of delivery (TSO zone) is assigned to one market area and this composition of market areas is determined in advance. In some special cases like sudden system congestion the assignment of places of delivery to market areas can change and trading participants are informed about these changes so that they can change their orders before pricing.

Market area is called bidding area at Nord Pool (free Nordic electricity market). The main reason for breaking all delivery places into separate market areas (or bidding areas) is weak physical connectivity (bottlenecks) and impossibility to easily transfer energy between some regions. Note also that place of delivery (TSO zone) corresponds to the market balance area in terms of the Harmonized Electricty Market Role Model [ETS10]. Hour contracts for the same delivery day, delivery hour and market area always have the same joint exchange price. Thus there are different auctions and different prices for each combination of the following three parameters:

- delivery date,
- delivery hour,
- market area.

All hour contracts are summarized in a joint order book and executed in the same auction if their places of delivery (TSO) belong to the same market area. For example, the same exchange price is established for one delivery hour and a delivery day for all places of delivery in Germany and Austria because they form one common market area (MA01). Since Switzerland belongs to a separate market area (MA02), electricity has different price for all its places of delivery. Denmark has two market (bidding) areas: Western Denmark and Eastern Denmark.

Pricing is carried out according to the following procedure (Figure 2):

- All hourly sell orders are aggregated into the so-called supply curve with the price increasing for larger amounts of electricity.
- All hourly buy orders are aggregated into the so called demand curve with the price decreasing for larger amounts of electricity.
- The intersection of these curves represents the balance between buy and sell bids which is the market clearing price (MCP).

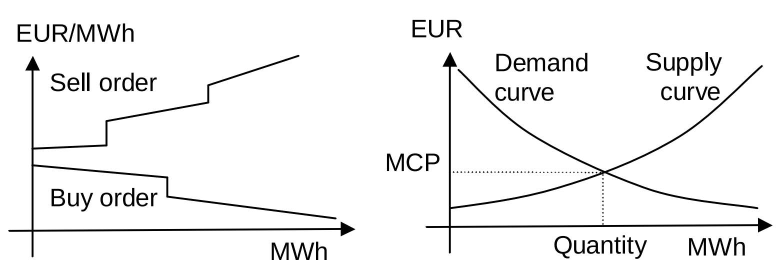

Figure 2: Market clearing price (MCP)

In the case of block bids, the above procedure is repeated iteratively. During each iteration the market clearing price is computed and then used to remove block bids which cannot be executed. The removed blocks (which cannot be executed with the current MCP) do not participate in the next iteration. To check if a block has to be removed, the average price of the hours corresponding to the block (weighted hourly) is computed and then this price is compared with the limit of the block bid. After this procedure converges, the last price is established as the exchange price for this hour, day and market area. This price is used to determine the actual execution of all hour and block bids as well as the entire turnover.

It is possible that the supply and demand curves do not intersect for one market area during some delivery hours. In this case the following actions are performed on EEX:

- Trading participants are notified that the second auction will be carried out in order to enable them to modify their hour or block bids containing the hour(s) concerned.
- EEX is entitled to ask individual market participants to solve the surplus situation.
- EEX management board of the exchange is entitled to cancel all the block bids which contain the delivery hour(s) concerned and which have an adverse impact on the order book situation.
- In case it is now possible to establish exchange prices for all the delivery hours, these form the final market results and the deleted block bids remain unexecuted.
- The management board of the exchange can specify a proportionate allocation.

3.2.4 Trade phases

Buy and sales orders for hour contracts can be entered into the system up to 14 days before the delivery of the electricity.

The daily trading process for hour actions is divided into several trading phases: pretrading, main trading, post trading and batch processing. The main purposes of these phases are described below:

- Pretrading [07:30-08:00]. Entering, deleting, changing and retrieving of orders (closed order book).
- Main trading – Auction [08:00-12:45]:
    - Call [08:00-12:00]. Entering, deleting, changing and retrieving of orders (open order book).
    - Freeze – Pricing [12:00-12:15]. Prices are determined.
    - Commital [12:15-12:45]. Inquiry of results. Auction results are available to the trading participants: executed orders, exchange prices for hour contracts, base load and peak load prices calculated, trade turnover for each hour and the entire day.
- Post trading [12:45-20:00]. Trade administration. Binding electronic trade confirmations are transferred.
- Batch processing [evening]. Preparation of report, Master data management, Data archiving.

The most important point is that the prices (and the amount of electricity) for the next day are determined at approximately 12:00 on the basis of the bids collected for the previous 14 days. Then these figures (prices, amounts etc.) are distributed among participants and used to create schedules for energy production and consumption.

3.3 Multi-agent negotiation

3.3.1 Automatic negotiation in the DEZENT project

DEZENT is a joint R&D project between the School of Computer Science and the College of Electrical Engineering at the University of Dortmund funded by the German Research Foundation (DFG). The main goal of this project consists in developing a distributed real-time multi-agent architecture for decentralized and adaptive electric power management. For the MIRACLE project it is important that this problem is considered in the context of a growing number of clean and renewable energy sources where adequate management of these networked resources is of high importance. In particular, the project assumes that the producers of energy are also its consumers and the focus is made on managing unpredictable consumer requests and producer problems taking into account distributed control and local autonomy.

One of the results of the project is a distributed real-time negotiation algorithm involving agents on different levels of negotiation [WLH+06]. These agents act on behalf of producers and consumers of electricity which are collected at the lowest levels into groups managed by a Balance Responsible Party (BRP). They make their bids for demand or supply of energy. BRP coordinates the negotiations and makes contracts between producers and consumers with matching conditions. Bids which cannot be satisfied within one group are routed to the next higher level of negotiation where they meet agents from other balance groups. At the top, there is a central balance point which is responsible for balancing the whole net in the case it cannot be done at lower levels.

The approach used in this project is based on the following main assumptions:

- Energy is provided (available) to the whole grid (independent of the level).
- Energy is negotiated only for the next negotiation interval (no long-term contracts or discounts for the amount of energy – this make the system robust against exchange-like attacks).
- During negotiation, consumers increase their prices and produces decrease their prices and the speed depends on their negotiation strategy.
- The system can achieve the negotiation interval about 0.5 seconds.
- 1 negotiation period (no new consumers/producers, it is not possible to change a role within one period) = many negotiation cycles (one cycle for one level and balance group, 10ms) = 10 negotiation rounds (it is possible increase/decrease price at the end of this round so that sellers and buyers move towards each other asymptotically).
- Negotiation on each level k will be performed within one price interval and this interval narrows with higher ranks (shrinking factor).
- Unmatched agents are sent to the BRP of the next higher level.

This multi-agent system is shown to exhibit high robustness against power failures compared to centrally controlled architectures. This model is also shown to be able to avoid another problem of free (deregulated) markets: no coalition of malicious users can take advantage of extreme situations. Such situations might arise from any (artificial) shortage of electricity. It is shown that using this decentralized approach customers pay less in comparison with any conventional (global) management policy or structure. The algorithms developed within this project were demonstrated to cope well with unforeseen needs and production specifics in a very flexible and adaptive way. It was shown that

DEZENT is immune against exchange and market attacks. This architecture was tested on some realistic settings of the German power system structure.

3.3.2 Automatic negotiation in the HomeBots project

The objective of the HomeBots project [AYG96] is to develop the high-level software and knowledge methodology and technology needed for the collaboration of intelligent-acting utility and customer equipment. The intelligent agents, called HomeBots exist in a hierarchical structure where they communicate and negotiate, in a free-market bidding like manner, to achieve energy and cost savings both for the utility and the customer. HomeBots represent every load in the system, which buy energy in a system of forward non-combinatorial auctions.

The HomeBots project represents a customer-based and service-oriented approach to load balancing positioned at the end of the utility's value chain. It is based on two-way communication between utility and customer where traditional electricity distribution net is supplemented with an information network. This information network is then used for two-way communication between customers and the utility. It introduces a society of constrained but knowledgeable computational agents that operate in an open, dynamic, market-like environment with incomplete information. Load management by HOMEBOTS is performed as a cycle of Assess-Negotiate-Monitor subtasks. The simplest scheme for negotiations is a three-stage Announce-Bid-Award process.

3.3.3 Bilateral negotiation

The model for bilateral negotiation in a multi-agent energy market proposed in [LNC09] considers a number of strategies based on rules-of-thumb distilled from behavioural negotiation theory. It handles bilateral multi-issue negotiation and formalizes a set of negotiation strategies studied in the social sciences and frequently used by human negotiators. If A = {ag1, ag1,...} is a set of agents then the set of issues to be deliberated, agenda, is represented by a number of quantitative variables over continuous intervals: Agenda = {is1, is2,...}. During pre-negotiation the issues are prioritized by each agent by ordering them where each issue is assigned some number which determines its position among other issues. In other words, all issues are represented as a list with the first most important issues, second most important issue and so on. The issues can also be weighted by a number which represents its relative importance. Each issue is also assigned a limit or resistance point which is a point the agent decides to stop negotiation because any result below this point is not acceptable. The target point or level of aspiration is the value which the agent considers as acceptable and expects to achieve a settlement at this point. This approach uses an alternating offers protocol [OR90] where two agents bargain over the division of the surplus of 2 or more issues by alternately proposing offers at discrete times. During negotiation, agents bargaining over the allocation of the entire endowment stream simultaneously which is called "joint-offer procedure". A division of the n goods is represented as an offer vector (x1,...,xn). Once an agreement is reached, the agreed-upon allocations of the goods are implemented.

The model proposed in [RKM06] is an agent-based negotiation method for bilateral contracts of energy which is based on considering similarity trees for the seller and buyer agents using their preferences and then finding the most suitable ones. Sellers are supposed to advertise their product offers and buyers issue product requests. A match-making procedure pairs similar offers and requests, and then the agents carry out final negotiations to produce a contract. The idea and distinguishing feature of this approach is that descriptions of products or services are represented as a weighted tree [BHY03] which is essentially describes the objectives of this agent. The weights assigned to branches reflect their relative importance. The system then uses these trees to find pairs of matching agents and to construct a priority table. The negotiation is performed in a loop where the first matching pair is chosen based on the rankings in the priority table. If the negotiation fails then the next highest rank agent is chosen until a matching pair is found and a contract is signed.

4 Conclusion

Scheduling of energy consumption and production is a demanding and highly constrained optimization problem. Its difficulty arises from numerous entities and huge amounts of data involved, conflicting optimization criteria, and dynamically changing environment. Furthermore, interaction of a scheduler with a negotiation mechanism is needed to determine how to optimally match energy consumption and production.

This report reviews the state-of-the-art in scheduling and negotiation approaches in view of their potentials for the MIRACLE conceptual and infrastructural approach. MIRACLE is aimed at supporting electricity distributors in managing higher amounts of energy from renewable sources and efficiently balance supply and demand. The report shows a number of existing methods, systems and applications of both technologies. In scheduling, these range from traditional deterministic to advanced meta-heuristic, with a notable trend towards supporting the processes on deregulated energy markets. In negotiation, both bilateral negotiation and auction mechanisms are applied in electronic systems to support energy exchange.

Based on this review of the existing methods and their capabilities, we see meta-heuristic optimization techniques as an appropriate algorithmic platform to be adjusted for the MIRACLE scheduling framework. Their suitability is due to robustness and ability to find near-optimal solutions in uncertain and changing environments. Concerning negotiation, the existing mechanisms will have to be extended with the capability of handling the time attribute of micro-requests for energy demand and supply, and the ability to interact with the scheduling framework in two directions: taking a preliminary schedule to define negotiation goals and applying negotiation to adapt and improve the schedule.

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