Towards Coding Strategies for Forecasting-Based Scheduling in Smart Grids and the Energy Lab 2.0

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ABSTRACT

Development of the power supply system towards a more decentralized system with a growing share of renewable energies constitutes an additional complexity for its reliable, secure, and economic operation. This has a strong impact on a variety of optimization tasks, such as power plant resource scheduling, reactive power management, or the expansion of the system by additional transmission lines, power generators or storage systems. In particular, scheduling and expansion planning depend strongly on a reliable forecast of expected demands and electricity production, the latter being a demanding task for volatile sources, such as wind power plants or photovoltaic power generators (PV). For testing new approaches and strategies, the Karlsruhe Institute of Technology (KIT) develops a test bed comprising different energy grids called Energy Lab 2.0. This test bed will allow studying the effects of new tools, forecasting and scheduling techniques, and other algorithms aimed at managing a smart grid. The lab and applied forecasting techniques will be briefly introduced in the present contribution.

First ideas about metaheuristic scheduling of different energy sources based on production and demand forecasts with the aim of ensuring a reliable and economic energy supply are introduced. Appropriate representations for Evolutionary Algorithms (EAs) are discussed and some experience from earlier scheduling projects for fast scheduling of many jobs to heterogeneous resources are given.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**; Planning and Scheduling;

KEYWORDS

Evolutionary Computation; scheduling; demand forecasting; smart grids

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1 INTRODUCTION

After decades of relative continuity, the electric power system faced two major changes in the last two decades. The first challenge was market deregulation which started in Europe with the EU Directive 96/92/EC in late 1996 [1], and the second one is the present rising integration of renewable energy sources. The former introduced market competition by separating power providers from network operators, whose mission is to distribute the power from different vendors. The latter implies three major transitions of the entire system: Firstly, the change from a centralized system of energy generation and distribution to a more decentralized one. Secondly, the replacement of large energy producers by many comparably small renewable energy producers and thirdly, the substitution of reliable and easily controllable power generation by volatile sources, which are influenced by e.g. the weather and day-and-night-cycles. The corresponding process in Germany, also known under the German term *Energiewende*, was initiated by the German Government and aims at an energy system with more than 80% of renewable primary energy in the electrical power sector by 2050 [2]. This goal can only be achieved if the entire energy system is considered and the electricity system is seen in connection with e.g. the generation

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of heat or cold, the transport system, and industrial processes, particularly the energy-intensive ones. Another important demand is the development and implementation of energy storage systems (after possible conversion) with different capacities and reaction times. For example, thermal energy generated electrically in homes, offices, or supermarkets can be stored by shifting the heating or cooling of thermal storage systems to periods of electricity overproduction [3].

The future energy system needs to be much more flexible, which can only be achieved by means of smart information technology (IT) solutions, thus creating so-called *smart grids*. According to the definition given by Erlinghagen and Markard [4], smart grid architectures consist of three layers:

- Hardware layer (electricity transmission technology, electricity distribution technology, sensors, metering devices),
- Communication layer (gathering metering data, two-way communication, telecommunication technology), and
- Software/application layer (data aggregation/analysis, meter data management system).

Components and applications of a smart grid are among others [5]

- smart network management,

smart customers based on smart homes,

- prosumers, who act as consumers as well as producers of electrical energy,
- control systems to monitor and control smart grids,
- distributed information and communication technology (ICT) which coordinates distributed energy sources and provides supply and demand flexibility,
- integration of electric vehicle charging and buffering facilities, and
- various energy storage systems.

A list of smart grid projects with ICT focus can be found in [6], while an extensive overview of European projects since 2002 is given in [5]. As most of these research projects concentrate on solutions with only a few smart grid components, at KIT a comprehensive experimental test facility called Energy Lab 2.0 is on the way to realization. Besides electrical power, the lab also covers other energy carriers, such as biomass, gas, and heat and their transformations. It is described briefly in Section 2 and the interested reader is referred to [7, 6] for more details.

Regardless of the structure and nature of the energy system, the production of the different energy sources must be planned so that the produced and consumed energy are balanced. To achieve this, the production, conversion, and storage of energy or the use of stored energy must be planned carefully with respect to the uncertainties introduced by volatile energy producers. Even when restricting to the electrical power system, this is a more complex scheduling task than the previous planning of comparatively well controllable (large) power plants. In addition, there are also the possibilities of demand side management, which represents the attempt to influence the user behavior in such a way that it corresponds more closely to the conditions of electricity production. This can be achieved by means of an appropriate price design [8] or by control measures such as, for example, the increased cooling of cold stores at low load times. The use of storage systems is another way to support balancing. In case of surplus electrical energy, different storage technologies can be used, it may be sold to other smart grids or the excess energy can be converted into a different form of energy for later use, as done in power-to-gas technologies. In the case of a lack of produced energy, suitable storage systems can be selected for compensation or other smart grids may supply the missing energy. All these possibilities constitute a complex scheduling task.

One core technology for the planning of a balanced operation of smart grids are time series forecasts of energy demand and production. They are based on previously gathered data, on meteorological data, or other data like upcoming events which are likely to cause changed consumption, such as public holidays, special sports events, or the beginning of the holiday season. This issue is dealt with in Section 3. The forecasts of energy consumption and expected production provide the basis for scheduling the different components of a smart grid. The resulting scheduling task is dealt with in Section 4. Finally, in Section 5, a summary and an outlook are given.

2 Energy Lab 2.0

The Energy Lab 2.0 [6] is a joint technology research platform of KIT, the Forschungszentrum Jülich (FZJ), and the Deutsches Zentrum für Luft- und Raumfahrt (DLR, German Aerospace Center) in Stuttgart. Fig. 1 gives an overview. The Lab will be a large experimental test and simulation field for multi-scale and multi-mode energy system facilities and for testing their operation in various smart grid configurations. The major part of the research facilities is located on Campus North of KIT in a quasi-islanded environment: An electrical power grid, a natural gas grid, a lot of consumers (office buildings and experimental plants), a solar power storage park with 1 MW peak capacity and around 1 MWh storage capacity, and a bioliq® chain [9], which transforms biomass (straw and forestry waste) into fuels by flash pyrolysis and gasification. An additional gas turbine linked to the bioliq® chain shown in the center of Fig. 1 is under development and construction. This turbine is to balance the supply and demand of electrical power and several additional storage options that comprise electrical, electrochemical, chemical, and thermal storage (the latter has a direct link to the campus heating grid). The second new component also located at Campus North of KIT is the ICT part of Energy Lab 2.0, the *Smart Energies System Simulation and Control Center* (SEnSSiCC), which is depicted at the bottom of Fig. 1. Its purpose is to coordinate, from an ICT point of view, the balance between supply and demand through generation and storage management and grid operations. SEnSSiCC also integrates facilities of two external partners on the level of data exchange and simulation: It is virtually connected with an electrolysis facility in the megawatt range, which is located at the FZJ and with a thermal storage facility operated by DLR.

SEnSSiCC is the core component of the IT infrastructure of Energy Lab 2.0 and consists of three main parts:

The **Smart Energy System Control Laboratory** (1) is a separate microgrid test field based on a Power Hardware in the

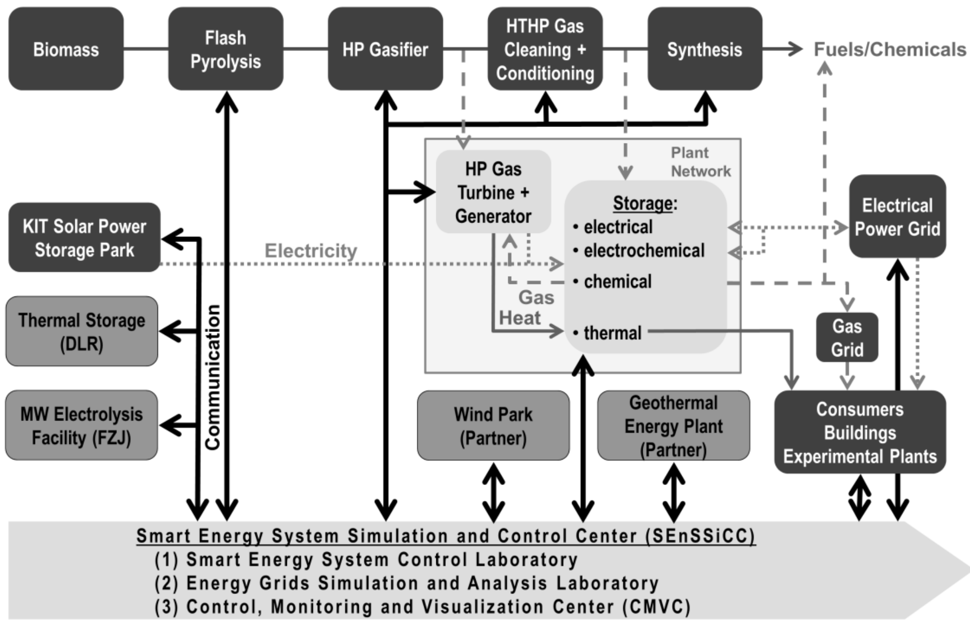

Figure 1: Energy Lab 2.0 components and connections [6]. Communication links are shown as solid black lines, while the energy and material flow is indicated by gray lines, which are solid, dotted, or dashed according to the transported medium. The figure shows existing facilities (dark gray), new components (light gray: SEnSSiCC, energy conversion and storage plant network), and external facilities (gray). Abbreviations: HP: High Pressure; HT: High Temperature.

Loop (PHIL) field in the 200 kW range. It allows for the verification of theoretical concepts under realistic conditions. It will support the creation and validation of models and in particular their parameterization. The Smart Energy System Control Lab will also serve educational purposes.

The **Energy Grids Simulation and Analysis Laboratory** (2) is used to develop software power network models for various types and/or combinations of energy grids based on electricity, heat, gas, and fuel. It allows for simulations and optimizations on a wide scaling range, starting from the microgrid scale, to the regional and national scale, to the European level. To achieve this, a suite of open-source, commercially available, or self-developed software tools will be used, with an emphasis being placed on open source tools.

The **Control, Monitoring and Visualization Center** (3) (CMVC) will integrate all parts of Energy Lab 2.0 into a research environment for the monitoring, visualization, simulation, and modeling of smart grid constellations. The components of the Energy Lab communicate with the CMVC through a supervisory control and data acquisition (SCADA) infrastructure according to IEC 61850 [10]. Based on this commercial infrastructure, a modular and highly scalable software platform for smart grid-related research will be designed and implemented based on Big Data technologies. This will provide large-scale parallel data analysis and co-simulations of different physical domains and allow scientists to combine live data from Energy Lab plants or equipment of the grid laboratory with data from various software-only or power hardware-in-the-loop simulators. Like other functions, different forecasting and scheduling algorithms will be provided as interchangeable SEnSSiCC services. For more details the interested reader is referred to [7].

As shown in Fig. 1, the following generators and storage systems are components of the smart grid located on the campus of KIT. Fully controllable electricity generators are the gas turbine powered by gas from the bioliq® chain, electrical and electrochemical storage systems, and the storage system of the solar power park. The storage systems can be used for scheduling within their actual capacity ranges, while the gas turbine is continuously available. Another source or consumer of electrical energy, which can be taken into account for scheduling, is the connected conventional grid of the campus. Volatile generators, such as the solar power park, can be planned only within the limits of their expected energy production. For this, reliable forecasts are required, as will be discussed in the next section.

Besides these physically available components, other grid elements provided by partners are integrated virtually for planning and simulation among others. These include the thermal storage system of the DLR, the electrolysis facility of FZJ, or planned components of future partners, such as a wind park or a geothermal energy plant.

3 Time Series Forecasting

Moving towards the development of Smart Grids calls for further integration of volatile renewable energy systems (i.e. wind and solar). Unfortunately, those systems are inherently uncertain and, thus, complicate the balancing of demand and supply [11]. The negative effects of such uncertainty can be mitigated by utilizing forecasting models to gain information about the future load and volatile renewable power generation that can then be used as the basis for creating a schedule.

Due to the fact, that load, as well as volatile renewable power are normally described as time series, the present section offers information regarding energy time series forecasting.

Energy-related time series forecasting models can be divided into three main categories:

- **White-box models**: Models that define the relation between the utilized inputs and the future of the time series of interest by using known relations, expert knowledge, etc. (e.g., physical models for volatile renewable power forecasting).
- **Black-box models**: Models that apply data mining techniques to infer the relation between used inputs and future time series values from available data.
- **Gray-box models**: Models obtained by combining models of the previous two types.

Regardless of their type, forecasting models estimate the future developments of a time series at a given forecast horizon by using the available information; for example, current and previous values of the desired time series and/or values from exogenous time series, like e.g. weather forecasts, calendar functions, etc.

A promising type of forecasting models for smart grids are data-driven forecasting models (i.e. black-box models), such as artificial neural networks, support vector regressions, polynomial regressions, etc. Such models have the advantage that system-specific properties (e.g., wind power curves, photovoltaic modules' tilt, power line losses, customer behavior) do not need to be explicitly modeled. Instead, information about them is implicitly contained in the used data. Moreover, the forecast horizon is defined as a free parameter and, hence, can be changed depending on the application of the model (e.g., 24 hours for a one-day-ahead schedule). In industrial use cases, schedules, for e.g. a power plant, are usually decided upon several days in advance. However, the nature of the explanatory variables should also be taken into account when choosing the forecast horizon. The rapidly changing nature of weather variables, for example, makes "long-term" forecasts of energy loads prone to more uncertainties. Likewise, the temporal resolution of the given forecasts can be chosen freely in some cases, or changed by interpolating or aggregating the forecasting results or the time series utilized as input.

The creation of data-driven forecasting models for energy-related time series requires certain considerations: For example, the use of forecast weather data – if available -, due to the strong correlation between the weather and volatile renewable power generation and load (e.g. solar irradiation in the case of solar power and wind speed in the case of wind power, and ambient temperature in the case of load). Furthermore, properties, such as the repeating nature of both solar power and load, can also be taken into account when creating forecasting models, even if weather data are not available [12]. However, generation of accurate forecasting models is a non-trivial task; for example, aspects like price influences in demand response scenarios [8] or the integration of local storage systems with underlying decentralized optimization strategies might complicate the forecast of future load values.

The majority of energy-related forecasting models found in literature can be classified as so-called point forecasting models [13]. Point forecasting models deliver time series values that are to be expected according to the models' criteria. However, they do not provide any information regarding their forecast uncertainty, information that might be important for some scheduling tasks. For such cases, probabilistic forecasting models describing the forecast uncertainty are of relevance. A type of probabilistic forecasts are interval forecasts consisting of upper and lower bounds in which the future values will lie with a certain probability. For the sake of illustration, Fig. 2 shows examples of both types of forecast for a normalized PV power time series (the power values are normalized to values between zero and one) taken from the Australian Solar Home Electricity dataset [14]. All forecast values are obtained with models whose forecast horizon equals 24 hours; in addition, the probabilistic forecast (shown on the right side of Fig. 2) is created by combining pairs of quantile regressions centered on a quantile regression that approximates the future power values median. Such quantile regressions are created by utilizing a technique presented in [15].

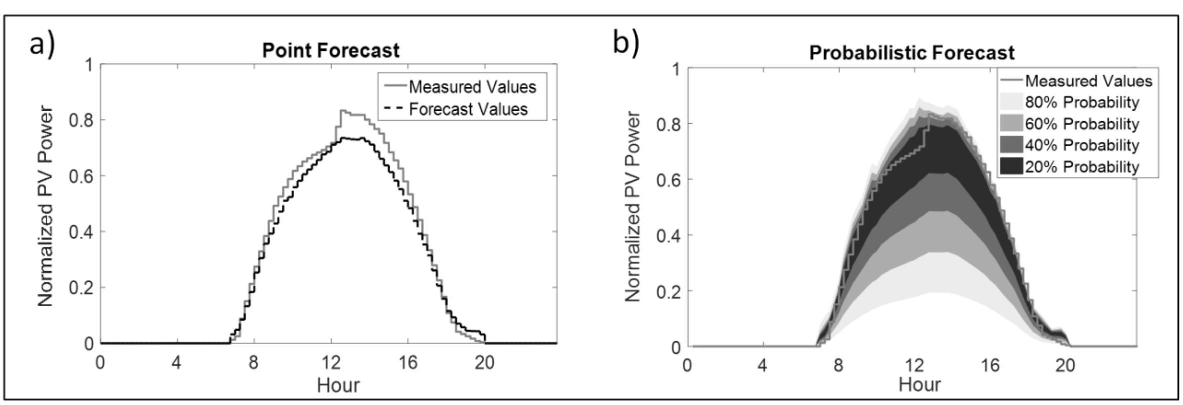

Figure 2: Examples of normalized PV power point and probabilistic forecasts: a: Point forecast; b: Probabilistic forecast: The intervals with lighter shades of gray encompass the darker intervals.

Figure 3: Comparison of fixed parameter estimation, used for the whole testing set (top), and rolling re-estimation of parameters with a repeated update of the training set (bottom).

Furthermore, it can be decided whether the estimated forecasting model parameters are updated or remain fixed throughout the testing period. With white-box models, this will happen only, if new evidence becomes available about e.g. physical relationships or parameter change due to aging. Data-driven models, however, can improve accuracy when applying a so-called rolling re-estimation of parameters [16]. In this case, the model's coefficients are updated after a specific time horizon (e.g. weekly) using a moving window of training data. As illustrated in Fig. 3 [17], the training set is moved for each new estimation. Although this approach is computationally less efficient, the accuracy can improve, as newer information is taken into account and the model actually detects changes in the relationships among coefficients.

4 Scheduling

Of the virtually unlimited number of scheduling problem types [18], Brucker and Knust name the so-called *resource-constrained project scheduling problem* (RCPSP) as one of the basic complex scheduling problems [19], which is NP-complete. They define it as follows: "The objective is to schedule some activities over time, such that scarce resource capacities are respected and a certain objective function is optimized".

4.1 Scheduling in Smart Grids

In smart grids we are faced with the problem of appropriate timely assignments of the production of different energy sources to the extent of their controllability in order to meet a given consumptive demand in the future. Both expected demand and energy production are the result of more or less reliable forecasts as described in Sect. 3. The scheduling task corresponds to some extent to the *unit commitment* problem of traditional power plant deployment planning, which was largely based on thermal generation. Thermal generators will continue to exist not only for a transitional period, but also in general. The aim of the Energiewende is to reduce CO_2 emissions and to significantly increase the use of renewable energies. However, these can also be gas power plants which are operated with bio-gas, gas from power-to-gas storage or, if necessary, with natural gas. A more detailed description and a formal definition of this non-linear, multi-modal, and highly constrained task can be found in [20].

Uncertainties regarding intensity and speed of short-term fluctuations vary widely among the various electricity producers at the time of deployment planning: They are the highest in PV systems, somewhat weaker in the case of wind power, and e.g. the lowest in hydroelectric power, biomass, or storage systems. In order to be able to meet a predefined safety margin for the supply, the corresponding low forecast values must be used, see also Fig. 2b. Important restrictions are unit capability limits, ramp-up times, minimum up- and down-times especially for thermal units, crew availability, required reserve power, real-power balance, and limits of transmission lines [20, 21]. The objective is to determine an appropriate schedule, so that the load demands are fulfilled at a certain safety level, the total costs are minimized, and the restrictions are adhered to. This requires multi-objective optimization, as most of the restrictions are subject to evaluation - and there are conflicting objectives, like average costs, costs in worst case scenarios, maximization of safety margins, or as few switching operations as possible.

In many cases, the power of generators can also be retrieved partly only, so that power specifications can go beyond just switching on or off. Thus, we have up to three parameters for a single scheduling operation of a unit: Start time, duration, and a unit-specific power parameter. This results in a mixed combinatorial and continuous and/or integer optimization problem. The desired balance of production and consumption can be formulated with the inclusion of electricity storages as shown in (1), where K is the number of time intervals to be considered. The different power values in every time interval k are the generated power $P_{G,k}$, the power $P_{FS,k}$ taken from or $P_{TS,k}$ transferred to the storage system, the actual stored power $P_{S,k}$, and the consumed power $P_{C,k}$. As storage systems have a capacity limit $P_{S,max}$ the constraints (2) must be adhered to.

$$\sum_{k=1}^{K} \left| P_{G,k} + P_{FS,k} - P_{C,k} - P_{TS,k} \right| = 0 \tag{1}$$

$$0 \leq P_{S,k} + P_{TS,k} - P_{FS,k} \leq P_{S,max} \quad k = 1, \ldots, K \tag{2}$$

A more detailed definition of the quality function and the constraints will be given later, when the exact components to be scheduled are defined. Until then, the interested reader is referred to [20, 21]. Another requirement may be the inclusion of maintenance intervals, so that an integrated production and maintenance planning task results. Smart grids will be interconnected so that other grids may act as producer of missing energy or as a consumer of surplus energy, as already mentioned in Section 2. Thus, scheduling will be done on different levels, local and more fine-grained planning for single grids and in a more general way at a higher level. We focus here on the task of scheduling in a single interconnected grid.

Besides scheduling approaches based on metaheuristics like EAs, there are also other attempts to tackle the task or parts of it by e.g. model predictive control-based scheduling [22, 23] or multi-agent systems [24, 25]. Whatever approach is preferred, it must be kept in mind that the given scheduling task is NP-complete, so that only approximate solutions can be expected for realistic problem sizes.

4.2 An Already Tackled Scheduling Task of Comparable Complexity

In the previous section the grid scheduling problem was characterized as a mixed combinatorial and continuous and/or integer optimization problem based on scheduling operations with two parameters or more depending on the device to be scheduled. As the authors already tackled a more or less similar task in a computational grid [26, 27], it will be briefly presented to see what can be learned from it. Computing jobs organized in workflows have to be scheduled to a grid of heterogeneous resources, such as computing nodes, storage devices, application software and their licenses, communication links, and the like. All these resources usually differ in size, performance, costs, and their availability may be restricted to certain hours of the day or days of the week, etc. To meet the requirements of both users and resource owners, a multi-objective optimization comprising *execution time* and *costs* is needed. A detailed description of the task and a formal definition of the fitness function can be found in [26]. A single scheduling operation has to select resources out of a set of feasible ones and it depends on each job, how many resources are needed. Thus, we again have a varying number of parameters per scheduling operation. A two-step approach is used: Firstly, some common heuristics are used to create some basic solutions which are used to seed the initial population of the subsequent EA run. Among them is the "earliest due date" heuristic, which is known to be optimal for minimizing the maximum tardiness of single machine problems and the more general and well known Giffler-Thompson algorithm [28]. Other heuristics were tested and discarded, as they yielded poorer results [29]. In contrast to many other scheduling problems, a grid job schedule is usually executed to a more or less small extent only due to new jobs, job cancelations, or changes in the availability of resources. This requires an updated plan, resulting in a permanent and fast replanning process, so that each EA run is limited to a few minutes. The replanning situation is comparable to smart grids due to updated forecasts or new values of demand or energy production.

As it is usually not possible to assess the effect of EA-based scheduling by a comparison with known solutions, two criteria were used instead [26]: Firstly, the best heuristic results had to be improved by the EA, which is measured by the fitness values. For the second criterion, the time and cost budgets of about 20% of the work-flows were reduced so that the heuristics failed to produce suitable schedules. It was now the task of the EA to solve that resulting in a success rate, which in each case reflects the share of the violation-free schedules of 100 runs per benchmark task. The investigation was based on four benchmark classes with small or large resource alternatives and degree of dependencies of the workflows (abbreviated e.g. by sRsD for small amount of resources and small dependencies in Fig. 4). The first three sets of benchmarks used 50, 100, and 200 jobs with 10 resources each. The fourth set also used 200 jobs, but with 20 resources (indicated by 200d). Fig. 4 shows the success rates for the 16 benchmarks, which were obtained from 100 three-minute runs per benchmark on the left. In all but two cases, all runs were successful. On the right, the increase of fitness values, which are all statistically significant (t-tests), is depicted [26]. In addition, it was examined to what an extent quality improvements over the heuristics can be achieved within the given three minutes. For a common desktop PC, the limit is about 7000 jobs and 700 resources [30]. These results encourage us to propose our EA approach in general and the coding in particular for the scheduling task in smart grids.

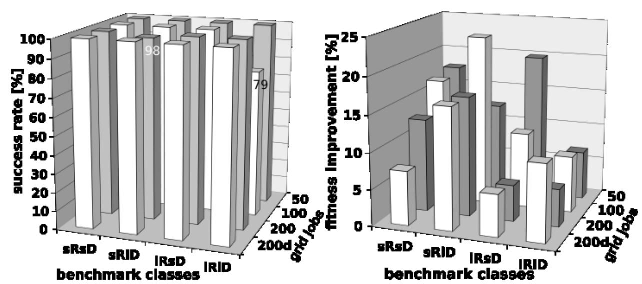

Figure 4: Success rates for all 16 benchmarks (left) and fitness improvements compared to the best heuristic solutions (right).

4.3 EA-based Scheduling

What is an appropriate coding of scheduling operations with a varying amount of parameters as described in the last sections? As early as in 1994, Nissen stated that "the solution representation and the coding should be derived as directly from the given problem as possible. In particular, structural features (regularities) of the solution space should be preserved by the coding to the extent to which they facilitate the search process" [31, translated by the author]. This statement meets the experience of the authors very well and thus, we suggest that a single scheduling operation is represented and determined by one gene. It consists of a start time, a duration, and an optional power fraction as decision variables, which are subject to evolutionary change. Furthermore, there is a fixed number identifying the unit to be scheduled, called *unit id*. Fig. 5 shows two prototypes of such a gene. As scheduling is usually performed with a predetermined temporal resolution, e.g. in 15-minute intervals, integers are sufficient for the representation of start time and duration. The optional power fraction parameter may be given as a whole number or as a continuous value, as on the left of Fig. 5, depending on the corresponding power generation unit.

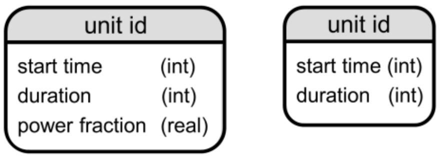

Figure 5: **Structure of the proposed gene types for scheduling a generator unit with (left) and without (right) a unit-dependent power fraction parameter.**

The order of the genes within the chromosome determines the scheduling sequence so that an early assignment may be overwritten by a subsequent gene with the same unit id. This is illustrated in Fig. 6, which shows an example of two such genes. At first, the left gene is processed resulting in the assignment of time intervals 22 to 31 to unit 42 at a power fraction of 0.3. The corresponding row of the activity matrix of generator units is shown on the right of the first gene. This is followed by the processing of the second gene, which overwrites the assignments already made for the time intervals 24 to 28, as shown at the bottom of Fig. 6. The example illustrates how the operation of a generator with a varying production quantity can be constructed easily from this coding concept.

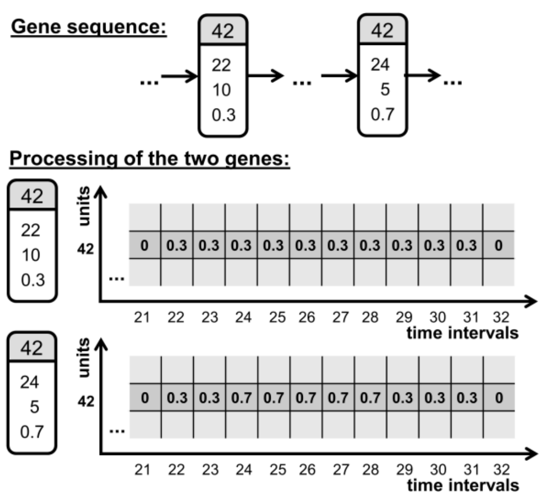

Figure 6: **Example of the processing of two subsequent genes and the resulting rows of the activity matrices.**

All genes assigned to a unit have not only the same ID, but also decision variables with the same properties. Thus, certain restrictions like e.g. minimum up-times required by some generator types can be mapped directly to minimal values of the duration. The same holds for the power fraction, which can be tailored to the properties of its unit. This leads to the concept of *gene types*, each representing a unit or a class of units with the same properties that define the data types and ranges of their decision variables.

These gene types form the so-called *gene model*, which configures the EA and allows implementing a set of general genetic operators. For instance, mutations can now respect the limits of each decision variable as well as their data types. Therefore, explicit restrictions common in real-world problems can be easily and advantageously integrated, because lethal mutations as in the ES are now avoided.

Since the necessary number of scheduling operations is not known in advance, chromosomes of dynamic length are required. Chromosomes are generated based on an expected length interval and each gene type may be included with one or more genes or not at all. This is determined by chance. The dynamic chromosome length is achieved by mutations that duplicate, delete, or insert single genes or gene segments. In accordance with the combinatorial nature of the task, mutations are also necessary, which change the order of genes by shifting individual genes or entire sections. Another advantage of such an encoding compared to string-like chromosomes of whole or real numbers is that all parameters associated with a scheduling operation remain together when gene positions within a chromosome are mutated. This is closer to the principle of strong causality compared to shifting or changing single values of a string. Furthermore, the integration of problem-specific genetic operators is facilitated.

The introduced application-oriented coding concept is implemented by an EA called GLEAM (General Learning Evolutionary Algorithm and Method) [32, 27]. Chromosomes are realized as linear linked lists. And the above-mentioned gene sequences are implemented as chromosome segments, whose limits are subject to evolution. GLEAM was successfully applied to different scheduling tasks [27], among them the one introduced in section 4.2, and to collision-free robot path planning. The latter is mentioned here, because it requires chromosomes of dynamic length, consisting of genes with varying numbers and types of decision variables [27, 32].

5 Conclusions and Outlook

After a short introduction of the comprehensive and complex test field for smart grids at KIT, the Energy Lab 2.0, we report about some forecasting techniques and their possible results, which serve as an input for the task of scheduling power-generating and power-storing units in smart grids. As a consequence of an application-oriented view, a somewhat unusual representation scheme is presented, which is based on one gene per schedule with as many parameters as required by the scheduling operation and the associated power unit.

The next step will be a first implementation of the scheduler based on that concept implemented in GLEAM and its integration into SEnSSiCC. Furthermore, a parallel version using Big Data techniques is planned.

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