

Paper Proposal : *Surrogate Estimators for Collaborative Decision.*

Revision.

Letter to the Reviewers.

We just performed a major revision of this paper, while following the recommendations of the reviewers and trying to answer the questions that they raised.

More specifically:

- *One of the dearth of the paper is in the second section (2 The PBVSync Problem) which does not clarify unambiguously with citations whether which models exist in the previous literature and what the contribution of the paper is. Whether the contribution is applied computer science through customizing the general theories and algorithms or systems according to Frascati categorization.*

If we refer to Frascati categorization, we explain in the introduction (page 2, lines 8-20) that our contribution mainly refers to Informatics and Information Sciences, with specific developments related to Combinatorial Optimization and Operations Research. It contains both fundamental research features about multi-level complex models and collaborative decision, and applied research features, since, in order to make things easier to understand, we rely on a case study derived from a partnership with a power production company.

As for the fundamental issues, we provide several references in page 1 (Introduction) and in page 11 (at the beginning of section 4 about Collaborative Decision). We make appear (page 1, lines 11-14) that even when they address those issues through the design of heuristic algorithms, authors usually do it while adopting the centralized point of view of a unique decider, provided with all required knowledge. As for the case study related to the joint management of photovoltaic energy production/consumption, we provide in page 2 (third paragraph) references about macroscopic models related to tactical energy production and to energy consumption. We comment (page 2, third paragraph, lines 22-30) that few authors have addressed the interaction issue and that those who did it adopted the centralized point of view.

So we explain, in both the introduction (first paragraph of page 3) and in Section 2 (pages 5 and 6, paragraph *Our Goal and Contribution*) that our main contribution here is the design of the heuristic algorithms of Section 4.4 that tends to emulate the decentralized point of view of a specific player, possibly provided with partial information. In the case of our case study, this specific player is the *job scheduler*. We focus on 2 specific points, related to the constraints and to the objective function. In Sections 3 and 4.2, we introduce a *projection* mechanism (Section 3.2, Page 10, Remark 5) that turn the constraints related to the part of the system that the *job scheduler* cannot see into (*surrogate*) constraints that he may handle. In Section 4.3, we introduce (*surrogate* objective function) pricing and learning mechanisms that help the *job scheduler* in getting an approximation of the part of the costs that it does not fully control.

- *“Remark 1: PVSynC and the RCPSP Problem” informs the reader that the outlined approach is an extension, “customization” of “Resource Constrained Scheduling Problem”, however, it is not clear whether the reference literature overview contains the extension or the extension is the novelty of the paper under review (the cited paper cannot be accessed and read).*

PVSync may be viewed as an extension of the standard RCPSP problem (that is usually related to renewable resources, with no relation between the resources) in the sense that it considers here both renewable and no renewable resources, linked together by an encapsulation relation (the renewable batteries are containers for the no renewable energy). This extension or variant is a novelty ([see Page 5, Remark 2, Line 2](#)). Yet this extension is not the main purpose of the paper, in the sense that we do not cast it into a general framework involving jobs and resources and that we do not insist on the design of exact algorithms for its handling (usually, contributions about the RCPSP put the focus on the design of fast running exact algorithms). We provide an additional reference ([24]) about the RCPSP.

- *“Theorem 1 and Theorem 2” are not interesting theorems from the point of view of mathematics. The referenced book that contains the grounding theorems is an old monograph, and there are more modern monographs and textbooks that discuss the NP-Completeness and the NP-Hard problems.*

We follow the recommendation of the reviewers by withdrawing those 2 results (then Theorem 3 becomes Theorem 1 and Theorem 4 becomes Theorem 2) and by adding a more recent reference about algorithmic complexity ([42]). We only leave a short explanation about the fact that the scheduling level of PVSync is NP-complete ([Page 9, Section 3.1, paragraph The Scheduling Level](#)) and ([in Section 3.2, page 10, lines 36-50](#)), that the *Idle Battery* constraint, which is at the core of our *surrogate* constraint mechanism, is also NP-Complete.

- *The progress in SAT solvers make it possible to handle NP-Complete problems in reasonable computing resources and computing time at the cost of transforming the problem into conjunctive normal form. The optimization and integer linear programming can be formulated as a SAT problem at the expense of increasing the size of the models and the number of variables. It is worth considering that approach because the computing cost of the NP-Complete problem can be kept in hand even with the increment in the size of the problem.*

As for the use of SAT models and software, we provide, ([Page 6, Section 2.2, lines 1-17](#)), a short discussion about the fact that we might have used the SAT framework instead of the MILP framework. The truth is that we used the MILP framework (which is also very efficient) because we are familiar with the CPLEX Library. But the fact is that our focus here is not about the design of exact algorithms for the PVSync problem since, in more realistic contexts, the complexity of the production level (the PV-Plant) and the incompleteness of available information is going to forbid the design of such algorithms. On the contrary, our purpose is to design heuristic algorithms adapted to such complex contexts. So we explain at the beginning of sections 2.2 ([Page 6, Section 2.2, lines 1-17](#)), and 5 ([paragraph purpose of the experiments](#)), that the main purpose of our MILP setting is to get an unambiguous formulation of the PVSync problem and to help us in evaluating heuristic algorithms designed while adopting the restricted point of view a specific player.

- *The problem of generating energy from photovoltaic sources and storing it in batteries involves various technology, engineering and economic models. However, there is no clear references to the starting points of these models, and how they are reconciled with the scheduling algorithms. To ensure the usability of the model, it is important to couple the variables and parameters to established technology and economic models, which can make the model more convincing.*

We mention in the Introduction ([page 2, last paragraph, lines 1-12](#)) and in ([Section 2, page 4, Remarks 1 and 1-Bis](#)), models that address the physics and the economics of the batteries and the PV-platforms at a microscopic level and that refers to existing technologies. Notice that those technologies evolve very fast. We also introduce references ([page 2, third paragraph, lines 8-15](#)) about the use of swapping policies in the management of the batteries

At the macroscopic level, that means at the level of the management of distributed production and consumption within a given time space of one day or more, all models must undergo significant simplifications. We explain in [page 2, fourth paragraph, lines 1-12](#), and in [Section 2, page 4, Remarks 1 and 1-Bis](#), that those simplifications most often consist in assuming that the recharge and discharge processes are linear and that the behavior of the PV-Plant is deterministic. This is almost true as long as the load of the battery remains inside some safety interval and that we do not care of the inverters and the trackers. We come back to the link between those macroscopic and microscopic level in [page 5, Remark 4](#), and in [page 8, Section 2.3](#) where we discuss the variants of the model.

- *The numerical experiment tables are difficult to decipher due to the use of acronyms for variables and column heads.*

As for the tables 5, 6, 7 in Section 5, we simplify the acronyms for the outputs with respect to the former version of the paper. UB and LB are respectively the upper bound and lower bound of the PVSynC model computed by the MILP library. PR1, PR8 are the values of the heuristic algorithm that relies on an approximation of the production cost by a pricing mechanism. ML is the value of the heuristic algorithm that relies on an approximation of the production cost by a neural network.

- *It is concerning that the widely accepted and important metrics in machine learning and advanced statistics are not utilized to support and confirm the effectiveness of the Data Science model.*

As for the Machine Learning approach, we provide in [pages 16, 17, Section 5.1](#), an additional description of the tests performed in order to train the neural network and to calibrate the hyper-parameters of the training process. We explain ([page 17, Section 5.1, lines 16-22](#)) and ([page 14, section 4.3.3, lines 1-21](#)), that the fact that we use a neural network with a relatively small number (467) of synaptic coefficients simplifies the training process, making the error gap evolve in a monotonic way along the epochs and stabilize itself in a natural way. The stochastic gradient algorithm behaves as if it were dealing with a standard optimization problem, with a small number of variables and an objective function defined by an average violation of a larger set of constraints. A consequence is that we do not need to observe the evolution of the error gap along the epochs in order to identify the epoch that induces the best error gap. We also explain ([page 13, Section 4.3, Remark 7](#)) and ([page 17, Section 5.1, Paragraph Comments](#)) that the accuracy of the neural network is not at stake here, rather its ability to drive our heuristic algorithms toward satisfactory solutions.

- *At present, the parameters of the run-time only demonstrate that the model can be executed, without verifying and validating the models to ensure their accuracy.*

The numerical section 5 mainly aims at evaluating the ability of our *2 job scheduler* oriented heuristic algorithms to provide good approximations of the theoretical optimal value of the PV-SynC problem ([Paragraph Purpose at the beginning of Section 5](#)). Tables 5, 6, 7 provide

values of the PVSyn problem such they are computed by the reference MILP model and by the heuristic algorithms. We get an evaluation of the accuracy ([Pages 17, 18, Section 5.2, Lines 7 to 30](#)) of those approximated algorithms by comparing the UB, LB reference values computed by the MILP model (Table 5) and the PR1, PR8, ML values obtained by the approximated algorithms (tables 6 and 7). It is difficult to talk in terms of error gaps (in %) because the optimal theoretical values of PVSyn may be null, negative or positive ([page 18, Section 5.2, paragraph Comments](#)). But comparing the real values provides an estimation of the accuracy of the heuristic algorithms.

- *The low number of instances for training a machine learning model, only 4000, is insufficient to guarantee a stable and reliable model. Convolutional Neural Networks (CNNs) are commonly used for tasks related to image classification and recognition.*

We ran once more the training process while augmenting the number of training/validation instances (9000 instances: 90% for the training and 10% for the validation). That means that we use 20 times more instances than the number of synaptic coefficients. We get results close to what they were with 4000 instances. We update table 7 accordingly and describe the way we have been training the CNN in order to identify the best values for the hyper-parameters, while using the Tensor Flow/Keras software ([Page 17, Section 5.1, table 4](#)). In fact, the stability of the model derives from the large ratio between the number of training instances and the number of synaptic coefficients ([page 14, section 4.3.3, lines 1-21](#)) and ([page 17, Section 5.1, lines 16-22](#)). This ratio almost equal to 20 makes the error gap evolve in a monotonic way throughout the training process.

- *However, it is not clear from the paper which category of machine learning problem the CNN application belongs to. It appears that only one or two numerical parameters are calculated by the CNN. Thus, the objective of using CNN in this context is not clearly defined.*

It is true that CNN are mainly used for 2D-pattern recognition, since images are very large size inputs and since the convolutional masks are well fitted to the recognition of local patterns. In the present case, we explain ([page 14, section 4.3.3, lines 22-42](#)) that our goal here is to learn the optimal value of a combinatorial optimization problem (the optimal cost related to the production sub-problem induced by fixing the decision of the job scheduler), in order to drive a heuristic scheduling algorithm. We also explain that an important feature of the CNN is that, at the contrary of most neural networks, it can deal with flexible inputs of different sizes. It is our case here, since the size of our target combinatorial optimization problem may vary and that is why we choose to work with a CNN. Notice that the error gap induced by the the CNN is not at stake here ([page 13, section 4.3 , lines 1-5, page 14, section 4.3.3, lines 40-42, page 17, Section 5.1, Paragraph Comments](#)), rather its ability to drive the heuristic collaborative algorithmic scheme toward good solutions.