Thesis Changes Log

Name of Candidate: Timur Saifutdinov

PhD Program: Engineering Systems

Title of Thesis: Optimal Siting, Sizing and Technology Selection of Energy Storage Systems for Power System Applications

Supervisor: Prof. Janusz Bialek

Chair of PhD defense Jury: Prof. Alexei Buchachenko ***Email**: a.buchachenko@skoltech.ru*

Date of Thesis Defense: 10 March 2020

The thesis document includes the following changes in answer to the external review process.

Response to comments of Prof. Stevenson:
Comment 1
In reading over thesis there are noticed here and there small typos and grammatical miscues. Theses should be corrected in the final version of the thesis.
Response to Comment 1
Author apologizes for the typographic and grammar mistakes. The paper has been proofread one more time to eliminate the mistakes.

Response to comments of Dr. Wade:
Comment 1
Section 3.2 – Use of the augmented Lagrangian relaxation procedure is not explained. The steps to reach (3.19) are not clearly identified. Similar for alternating direction method of multipliers leading to (3.21)
Response to Comment 1
The relaxation of complicating constraints implies considering them within the objective function. First, for relaxing the power balance constraints (3.15), the original objective function (3.1) is enhanced with the auxiliary fixed dual variables $\lambda_{b,s,t}$ multiplied by the constraint itself plus an additional (augmented) 2-norm function of the constraint aimed to penalize its violation with the positive constant value $\frac{\gamma}{2}$. The latter augmented term is included to make the problem reformulation generic for various objective functions, including linear, which cannot always be resolved by means of the conventional Lagrange relaxation approach [124]. Second, for relaxing the power flow limit constraints (3.17), the resulting objective function is enhanced with the logarithm functions, which approach infinity when the constraint is binding. The above clarifications are provided in Section 3.2.
The use of the ALR for the power balance complicating constraints (3.15) is explained by the fact that the Lagrangian multiplier of the constraint (fixed dual variables $\lambda_{b,s,t}$) represents the Locational Marginal Price (LMP) of a node by controlling which it is possible to redistribute the power flows that correspond to economic dispatch. While the logarithm barrier function is used to respect the power flow limit complicating constraints (3.17), while the leverage of power flows is at the former one. To perform a systematic search for the fixed dual variables $\lambda_{b,s,t}$, which correspond to the optimal solution, ADMM performs an iterative procedure with a systematic way to update the value of the fixed dual variables $\lambda_{b,s,t}$ in each iteration. Particularly, ADMM directly fixes each variable of the whole optimization problem to the values obtained in the previous iteration and solves it only with respect to the variables that correspond to a particular subproblem (indexed by *b* and *j*). Thus, the resulting objective function (3.21) consists of the terms that can be influenced by the variables that are related to bus *b* and technology *j*, while the rest of the terms are

considered to be redundant. In (3.21), index *(k)* in superscript indicates the variables with respect to which a particular subproblem is to be solved, while the index *(k-1)* indicates the fixed variables obtained in the previous iteration that does not correspond to bus *b* and technology *j* (not variables of a subproblem).
When the subproblem is solved for all $b \in B$ and $j \in J$, the fixed dual variables λ are updated according to (3.36), where the value of increment (decrement) is determined by the violation of the relaxed power balance constraint (3.15) and constant parameter γ. The procedure of solving subproblems for all $b \in B$ and $j \in J$ and updating the fixed dual variables λ is repeated until the convergence criterion (3.37) is satisfied, which indicate a non-significant change of the fixed dual variables after an iteration. The above clarifications are provided in Section 3.3.

Comment 2
Unclear in section 4.2.2 how the daily operation costs of circa. £3.5M translate to an annual revenue of circa. £30M. Cannot see where the profit side of this equation is provided.
Response to Comment 2
To make it more illustrative, a stacked chart of the network operation cost for all cases is illustrated in Figure 4.3. The difference between the Network Operational Cost of a particular case and the Network Operational Cost of No Storage case from Figure 4.3 gives a daily benefit of energy storage use. The expenditures are defined by per diem investment cost. And the revenue is found as a sum of benefits and expenditures. To get the annual values, one shall multiply them by 365.

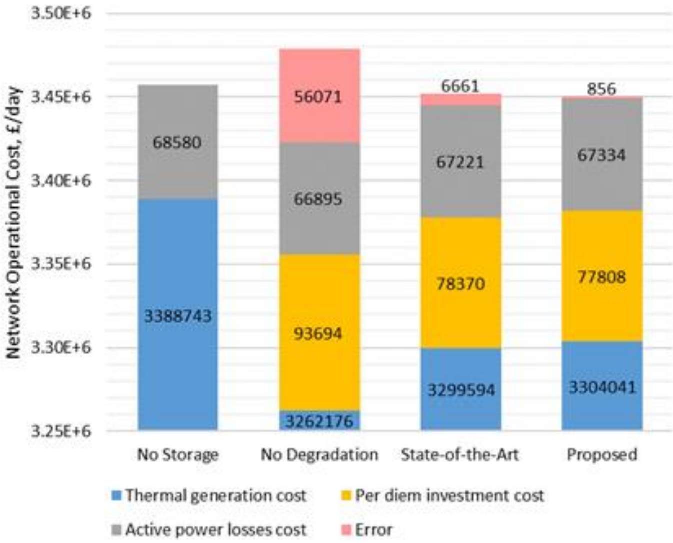


Figure 4.3: Objective Function Stacked Chart

The above clarifications, as well as the new Figure 4.3 are provided in Section 4.2.2.

Comment 3
It is stated that there are 18 applications that storage can be applied to – how many of these can be evaluated using the method that has been developed in this thesis, given, e.g. the linearization of the power-flow equation, which limits power flow solutions to the transmission network, or the segmentation of the demand profile to allow the algorithm to operate?
Response to Comment 3
Given the need to account for degradation (i.e., cycling requirements in Table D.1), DC OPF formulation and time discretization of one hour and assuming that it can be translated to 15-30 minutes, the application of the proposed methodology is suitable for at least nine applications from the list of energy storage applications provided in Table 2.1. Particularly, the methodology can be applied to Energy Time-Shift, Supply Capacity, Load Following, Transmission Support, Congestion Management, Transmission Network Upgrade Deferral and Equipment Life Extension, Retail Energy Time-Shift, and Demand Charge Management applications.
The above discussion is provided in new section *4.4.2. Method Applicability*

Comment 4
Can the candidate give some assurance that the single example of the algorithm delivering a result proves that this method works consistently under a range of conditions?
Response to Comment 4
Even though that a single case study is studied in details through Section 4.2, the proposed methodology has been applied many times for the different variations of the considered case study in Section 4.3 (when studying breakeven cost of new and second-life batteries), as well as for various IEEE benchmark systems, i.e., 9-bus, 14-bus, 24-bus, and 39-bus, in 4.4.4 (when studying scalability of the method). In all cases, the obtained solutions were consistent. The results for other networks are provided in the table below. For the reader's convenience, the table below is also provided in Appendix E.

Table E.1: Results of Optimal Siting, Sizing, and Technology Selection

#	Network	Comp. Time, sec	Solution				
			Objective Function, £/day	Bus	Tech.	Cap., MWh	Operational. Life-time, y
1	9-bus	19,750	391,269	5	NMC	320	8
2	14-bus	47,412	573,434	3	NMC	150	8
				7	NMC	60	8
				10	NMC	20	8
				12	NMC	10	8
				13	NMC	30	8
				14	NMC	40	8
3	24-bus	94,778	1,742,109	3	NMC	140	8
				6	NMC	130	8
				9	NMC	130	8
				10	NMC	150	8
				14	NMC	130	8
4	39-bus	159,782	3,449,182	17	NMC	350	8
				27	NMC	360	8

Comment 5
Referencing requires improvement in areas of introduction/ earlier part of literature review
Response to Comment 5
Author apologizes for the ill referenced resources. The paper has been proofread one more time to eliminate the mistakes.

Comment 6
Typographic/grammar corrections noted in review copy of thesis
Response to Comment 6
Author apologizes for the typographic and grammar mistakes. The paper has been proofread one more time to eliminate the mistakes.

Comment 7
Add tabular summary of service requirements distilled from text
Response to Comment 7
Tabular summary of energy storage applications' requirements is now provided in Table D.1 of Appendix D.

Comment 8
Each constraint from (3.22) to (3.35) requires a line of text above stating what it's for.
Response to Comment 8
The constraints (3.22)-(3.35) for the decomposed subproblem represent the same as for the original problem formulation described in section 3.1.2. However, for the reader's convenience, I allow myself to be redundant in the text and include a description for each constraint from (3.22) to (3.35) in section 3.3.2.

Response to comments of Dr. Pozo:
Comment 1
About globality and uniqueness. The student referred in section 1.2., first paragraph, that "convex programming and mixed-integer programming […] allows finding the globally optimal solution, which

uniqueness is mathematically proven." On page 28, it appears similar statement: "a mixed-integer problem reformulation is proposed, where continuous variables that cause nonconvexity are replaced with integer ones with respect to which the rest of the problem remains convex." It also appears in several parts of the text similar declaration. Firstly, uniqueness only is proven if the problem is convex, and the objective is strictly convex. Second, a mixed-integer problem is not convex. However, there are algorithms, like B&B, that guarantee optimal global solution with enough time.

Response to Comment 1

I completely agree with the above statements of the Reviewer. And indeed, this is exactly what I rely on in my dissertation. Numerical methods (i.e., zero-order methods, first-order methods) applied to strictly convex problems guarantee that the obtained optimum is global and unique. While the brute force for Mixed-Integer Convex Programming (MICP) problems requires solving a convex problem for every combination of fixed integer variables. In this case, the globality of the solution is also indisputable and it corresponds to the particular combination of integer variables for which the solution of convex problem possesses the least objective function (if we talk about the minimization problem). This is just a general logic on how to approach MICP problems. In practice, to reduce the number of iterations, various partial enumeration techniques are applied to solve mixed-integer problems, i.e., Branch-and-Bound, cutting planes, various heuristic algorithms. This way, the partial enumeration algorithms consistently search for the more optimal solution (a combination of integer variables) and do not perform calculations for the apriori non-optimal ones. This is exactly what is done in the numerical study of my dissertation. The proposed methodology has been formulated in JuMP (Julia for Mathematical Optimization). The Ipopt solver has been used to solve the convex optimization problems, and GLPKMIP solver, which performs Branch-and-Bound, has been applied for the mixed-integer problem. The corresponding clarifications have been given in section 1.2, section 1.3, and section 3.2.

Comment 2

Equations (3.11) and (3.12) require knowing the initial and end time epoch of each cycle. IIn chapter 4, is described that it is approached by looking at the demand profile. However, this profile it could be very different with massive penetration of renewable generation, but most importantly at the local level, i.e., that at the very particular node that battery will be connected, the demand profile could be quite different of the demand aggregated system profile (see an example of ERCOT system). Please, elaborate more on the discussion section about the limitations of this approach.

Response to Comment 2

The Reviewer is right, the formulation of cycle depth of discharge (3.11) and temperature (3.12) constraints require knowledge of the initial and final time moments of a cycle. Such a formulation has been influenced by the RainFlow Cycle (RFC) counting mechanism initially used for estimating the fatigue life of materials [129] but then accommodated for estimating degradation of energy storage [96]. Particularly, it is used to identify charge-discharge cycles and their depth of discharge based on the battery state of charge profile. The main drawback of the RFC mechanism resides in its sequential structure (basically, it is a flowchart with logical structure) [130], which cannot be directly incorporated into a formal optimization problem, as the latter allows using only equalities and inequalities. And given the fact that the optimal siting, sizing, and technology selection problem is solved with respect to the optimal scheduling of assets (energy storage state of charge profile is a variable of optimization problem), it is essential to predict cycle timeframes somehow. Studying the results of various case studies showed that the plausible suggestions for the start and the end time moments for each cycle could be made based on the demand profile. The similar is applied to renewable generation data, as in the stochastic problem formulation, we consider it predefined with a certain probability of occurrence. However, if the considered timeframes do not coincide with the optimal solution, it is proposed to update them according to the results of the optimization problem and solve it again. Alternatively, an auxiliary binary variable might be incorporated to introduced the logic of RFC within the optimization problem. This would require having one binary variable per each pair of charge/discharge power output variables ($\boldsymbol{P}_{b,j,s,t}^{\mathbf{Ch}}$ and $\boldsymbol{P}_{b,j,s,t}^{\mathbf{Dis}}$), leading to a substantial increase in the problem size. This way, the number of auxiliary variables is a product of time intervals T, scenarios S, energy storage technologies J and number of buses B, which is considerably larger than observed for the original MICP problem. The above discussion is provided in a new section *4.4.3 Cycle Counting Method*

Comment 3

In the abstract, it is said that "The present thesis addresses the problem of optimal siting, sizing, and technology selection of energy storage systems for power system applications by applying the formal optimization methods." It is confused in terms of optimization methods. This thesis does not develop optimization methods, but instead, it uses off-the-shelf solvers. The mathematical strength of this thesis is in the modeling and the problem reformulation in some of the existing canonical format of optimization problems. In addition, a decomposition method is applied.

Response to Comment 3

The Reviewer is right, the contributions of the research reside in modeling a degradation behaviour of Li-ion battery storage, incorporating it into investment problem, problem reformulation, and decomposition to ensure tractability and global optimum of a solution. Particularly, the methodology implies using off-the-shelf solvers to approach the initially nonlinear and nonconvex problem. To avoid misperception, the above clarifications have been included in the Abstract.

Comment 4

Please, elaborate on the convergence of the ADMM developed in the thesis. Can be guarantee globality? Is feasibility always guarantee when reformulating the problem with barrier methods?

Response to Comment 4

The convergence of ADMM is still an open question. Even though in [132], *Boyd et al.* identified conditions for ADMM to converge, it only relates to ADMM for two-block (two subproblems) structures. Actually, it has been shown by *Chen et al.* [133] that even a three-block linear problem may diverge under some conditions. However, in practice, ADMM converges to modest accuracy even for large-scale problems [132], [134].

As for the proposed problem formulation, it satisfies the conditions identified in [132] but contains a multi-block structure, which does not allow proving its convergence for a general case. However, in the extensive numerical tests performed for studying breakeven cost in Section 4.3 and scalability of the method in the previous section, the problem formulation has been solved many times for the different variations of the considered case study, as well as for various IEEE benchmark systems, i.e., 9-bus, 14-bus, 24-bus, and 39-bus. In all cases, ADMM showed good performance and convergence properties. Figure Error**! No text of specified style in document.**.1 shows a primal residual of the auxiliary fixed dual variables of ADMM (i.e., the value of penalty) during the optimization process.

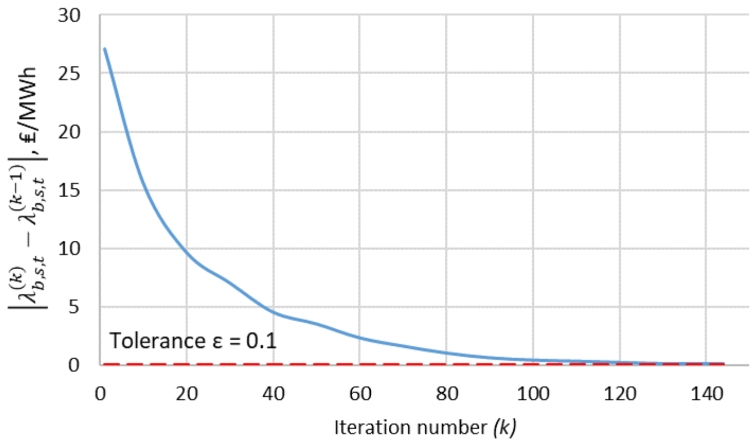


Figure **Error! No text of specified style in document.**.1: Primal Residual during the Optimization

The corresponding clarifications, as well as the new Figure 4.13 were given in new Section 4.4.5.

Comment 5

When referring to the size of the problem, it is common to use the number of binary variables for mixed-integer programming instead of all possible combinations. Please correct it along the thesis body, see one case on page 135.

Response to Comment 5

The proposed problem reformulation implies substituting continuous variables that cause nonconvexity with integer ones (not binary). And each of these integer variables might have a different cardinality, which is not equal to 2. Thus, it might be confusing to make evaluations only in terms of binary variables. Especially taking into account that there may not be any in the problem formulation. Therefore, to avoid confusion and make it convenient for a reader, the MICP problem size is now assessed in both (a number of combinations and an equivalent number of binary variables). The corresponding changes have been made along the thesis body.

Comment 6

Page 136. The student stated: "Energy storage yields benefit from an energy arbitrage (buy low – sell high) and reduction of active power losses within a network." However, it is not true always, especially the last part. Please reformulate.

Response to Comment 6

The statement above has been made from the network operator point of view based on the results obtained from the case study. Since an individual case cannot be generalized on the rest of the cases, the state above has been reconsidered as follows: "For the particular case study, energy storage yields benefit from an energy arbitrage (buy low – sell high) and reduction of active power losses within a network." The corresponding changes have been made in Section 5.1.

Comment 7

Please, elaborate on how can be estimated the price of active power losses (eq. 4.1).

Response to Comment 7

I would like to thank the Reviewer for pointing out this issue. In fact, the term "cost of active power losses per MWh" was used improperly. What I actually meant is indeed the price for energy to approximate the cost (price*value) of active power losses on power lines. The corresponding changes have been made for every instance of the "cost of active power losses."

The main reason for considering active power losses in the optimal siting, sizing, and technology selection problem is because power losses contribute to the nonuniform Locational Marginal Price (LMP) distribution within network nodes, hence, affects the optimal siting decision making. The proposed problem formulation extends traditional DC OPF by approximating power losses within an objective function, which are not considered in the power balance equality constraint as the quadratic dependence of power losses does not meet the affinity requirement of a convex problem formulation. For the same reason, to be able to approximate the cost of active power losses while keeping the objective function convex, the energy price for active power losses is considered constant but different for each bus and time moment. To make sure that a reader is aware of that extension, the corresponding explanations have been included in Section 4.1.1.

As for the Reviewer's question, in the demonstrated numerical study, the price of active power losses corresponds to the LMPs obtained beforehand by running DC OPF without storage, which was done during the initialization of variables for ADMM in Section 3.3.3. However, since active power losses correspond to a power line between two nodes, the average energy price of two nodes is found. To make sure that the reader is aware of that, the corresponding explanations have been included in Section 4.1.1.

Comment 8

Page 95. The student mentioned: "Particularly, as was shown in the previous section, the degradation from idling might be represented as a convex hull." There has not been mentioned or introduced what a convex hull is. This concept is neither used later in this dissertation.

Response to Comment 8

I would like to thank the Reviewer for pointing out this issue. In fact, in this phrase, I was referring to the paper by *Fortenbacher et al.* [81] which was considered in the literature review in section 2.5.

In [81], *Fortenbacher et al.* represent a degradation of energy storage as a piecewise-affine map (or, as the author refers, convex hull) as a function from the state of charge and power output. To avoid confusion, the corresponding modifications have been made in Section 2.5 and Section 2.6.

Comment 9

In section 4.4.2., it is mentioned that the optimality gap was set to 0.1%. It represents 3452 pounds per diem on your problem. On page 120, it is said that the current approach "adds up additional 856 £/day to average network operation cost" … with regard to the existing state-of-the-art methodology. The error from the optimality gap is more significant that the accuracy increase. Besides, according to the results obtained (page 120), degradation adds up an additional 6,661 £/day. Gap error could be more than half of the degradation cost. Please, review the results and extend the discussion on it.

Response to Comment 9

I would like to thank the Reviewer for pointing out this issue. In fact, the term "optimality gap" was used here improperly. What I actually meant is "convergence tolerance ε," which is used in (3.37) to define a stopping

criterion and has nothing to do with the actual optimality gap. The corresponding changes have been made in Section 4.4.4.
Also, it is worth noting that the considered error in section 4.2.2 represents the difference between the objective function obtained from the optimal solution and an accurate post-process degradation-aware simulation described in [96]. The latter does not correspond to the solution of the original problem but it is used for evaluating error in degradation estimations obtained from the optimization problem. To avoid dittology, the corresponding clarifications have been given in Section 4.2.2 and Table 4.3.

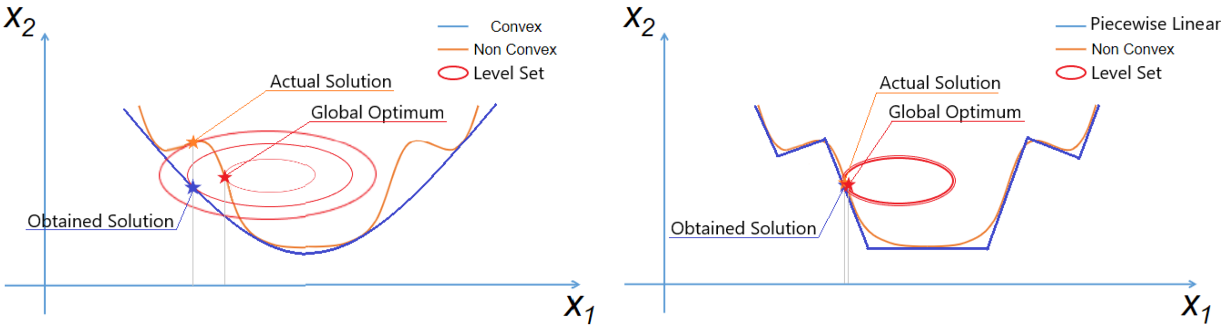
Comment 10
Please consider presenting figures from 4.8. to 4.10 with additional axes that represent a percentage of a reference value.
Response to Comment 10
An additional axis has been included in Figures 4.8 - 4.10. Since the performance of storage technologies is opposed to the most cost-effective solution (NMC), its maximum performance is taken as 100%.

Comment 11
Please, reconsider reformulating the assertion on page 123. "As it can be seen from Figure 4.5, each of the considered cycles is limited within the proposed time frames, meaning that DoD limit constraints (3.31) and cycle temperature constraints (3.32) are properly formulated." It has not been proved that they are "properly formulated," they worked well for your particular case study.
Response to Comment 11
The Reviewer is right, based on the phrase above, the reader may get an impression that this is a proof of the method to choose cycle timeframes proposed in section 4.1.3. However, it is not. To make sure that the reader is aware of that, the phrase above has been reformulated as follows: "As it can be seen from Figure 4.5, each of the considered cycles is limited within the proposed timeframes, meaning that DoD limit constraints (3.31) and cycle temperature constraints (3.32) have been formulated appropriately for the particular case study. If they were not, the timeframes have to be updated according to the results of the optimization problem."

Response to comments of Prof. Buchachenko:
Comment 1
The flexibility of the power system is an important requirement and storage systems can greatly enhance it. It would be instructive to comment to what extent this aspect is (or can be) considered within the proposed model.
Response to Comment 1
According to EPRI White Paper on Electric Power System Flexibility [R1] power system flexibility is defined as the ability of the system to adapt to dynamic and changing conditions, for example, balancing supply and demand by the hour or minute, or deploying new generation and transmission resources over a period of years. Overall, the term includes a wide range of meanings. When it comes to energy storage, it can be used to manage peak load, follow power system ramps, provide a reserve, relieve transmission and distribution congestions, and mitigate service outages [R1]. In principle, it can be concluded that the storage increases system flexibility when it provides one of the 18 applications considered in the literature review. Thus, to elaborate on the comment above, I refer to the newly added section 4.4.2 Method Applicability. Particularly, depending on the need to account for degradation (i.e., cycling requirements in Table D.1), DC OPF formulation and time discretization of one hour and assuming that it can easily be translated to 15-30 minutes, the application of the proposed methodology is suitable for at least nine applications from the list of energy storage applications provided in Table 2.1. Particularly, the methodology can be applied to Energy Time-Shift, Supply Capacity, Load Following, Transmission Support, Congestion Management, Transmission Network Upgrade Deferral, and Equipment Life Extension, Retail Energy Time-Shift, and Demand Charge Management applications, all of which enhance power system flexibility.

Comment 2
Experience with convex optimization models in the field is likely enormous. Are there bright examples or common understanding that simplifications in functions and constrains maintain the global minimum of the full non-convex model?
Response to Comment 2
There are many approaches used to represent an initially non-convex function as a convex one. To avoid going deep into each of these methods, I would like to touch the extreme options. First, it is possible to approximate a non-convex characteristic with standard convex functions (e.g., quadratic) as a lower bound estimate. On a

two-dimensional space, this would look similar to something that is depicted in Fig. R.1 A. This is probably the most effective way (in terms of computation); however, one can notice that there might be a significant divergence with the obtained and actual solutions, as well as with the global optimum. In contrast to the previous approach, it is possible to approximate a non-convex function with piecewise linear functions, as it is depicted in Fig. R.1 B. Depending on the number of linear functions used (i.e., resolution), it is possible to represent a non-convex function very accurately, which comes at the cost of increased computation time. The latter arises from the fact that a piecewise linear approximation requires reformulating initially continuous problem into a mixed-integer type of problem, which is much harder to solve.



A. Convex representation B. Piecewise linear representation

Figure R.1: Examples of convexification

Comment 3

Discussing the convergence of ADMM algorithms, the author refers to previous experience. Are the direct tests for few-bus systems possible? To the same point. It is mentioned that decomposition to subproblems allows one to consider each separately. Does the author expect great benefits from parallel computing?

Response to Comment 3

Given the fact that the search space of a combinatorial problem, such as the MICP problem, increases in a power law dependence with the number of integer variables, which in the case of the proposed problem formulation increases with network size and a number of storage technologies, the problem become intractable even for small-scale networks. Such that, the search space of the initially reformulated MICP problem for the smallest 9-bus network, considered within the study on scalability, contains more than 10^{216} combinations of integer variables, which could not be resolved using a desktop computer. Even though considering even smaller networks and a smaller number of storage technologies would probably result in a more tractable problem formulation. The extrapolation of conclusions on larger problems could be questionable. However, this study has still been conducted as a proof of concept for 3-bus network and one storage technology, which resulted in a MICP problem with $\sim 10^{18}$ combinations of integer variables. The obtained results matched the results obtained by ADMM, with an error strongly influenced by the convergence tolerance ε defined for the stopping criterion of ADMM in (3.37). The less ε we take, the less error we obtain in the result with the cost of increased computation time.

As for the second question, potentially, parallel computing is able to decrease the computational time by a factor equal to the number of subproblems. In the case of the considered in the case study 39-bus network and four storage technologies, it has been decomposed to 156 subproblems and solved in 142 iterations for $\varepsilon = 0.001$. It took 44 hours and 23 minutes to solve it on my laptop computer without parallel computing. Potentially, when parallelizing, if we assume that there are at least 156 processors to solve all subproblems in parallel, this time could be reduced to 7 minutes.

Comment 4

Formulating the problem on p.98, the author comments that reward is usually predetermined by the policies. It somehow contradicts the previous material, which exposes various benefits from energy storage. Indeed, considering the case study in Section 4 (p.116), the author introduces quite sophisticated reward term that depends on system variables.

Response to Comment 4

The reward term that I refer to in the problem formulation on p.98 is a mathematic formulation of a revenue (reward) from energy storage operation that a prospective owner would expect for a particular case study. In its turn, as per the objective function (3.1), the benefit is found as a difference between the revenue and investment cost. This is exactly what I elaborate on in the literature review when providing general ideas on how energy storage use might be beneficial for various stake-holders. For electric energy time-shift application, time-shifting may be done by electric utilities to reduce energy-related cost or by merchant storage owners seeking to profit by energy arbitrage on wholesale electric energy – buying low and selling high. For electric supply capacity application, the benefit arises from reduced or avoided costs related to building and owning new generation equipment. A similar elaboration is given for other applications. Such that, for the considered in the case study transmission congestion management application, where benefit accrues when storage use reduces congestion-related charges, decreasing network operational cost (i.e., generation and transmission costs). However, when it comes to the real-life operation, all assets that operate within the power system have to follow certain rules (policy), which may influence the formulation of a reward function. This is particularly true for ancillary services, where the functions delivered by a particular asset, e.g., energy storage, are remunerated according to some rule defined by the system operator. This is exactly what meant when stating, "In most of the cases, the reward term in (3.1) is determined by the reward policy for a particular application."

Additional References

The following list of references has been added in the updated version of the thesis:

[52] G. Wang, M. Ciobotaru, and V. G. Agelidis, "Power Management for Improved Dispatch of Utility-Scale PV Plants," Power Syst. IEEE Trans., vol. 31, no. 3, pp. 2297–2306, 2016.

[124] A. J. Conejo, E. Castillo, and R. M. R. García-Bertrand, Decomposition techniques in mathematical programming: engineering and science applications. Springer Science & Business Media, 2006.

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[133] C. Chen, B. He, Y. Ye, and X. Yuan, "The direct extension of ADMM for multi-block convex minimization problems is not necessarily convergent," Math. Program., vol. 155, no. 1–2, pp. 57–79, 2016.

[134] Y. Nie, M. Farrokhifar, and D. Pozo, "Electricity and Gas Network Expansion Planning : an ADMM-based Decomposition Approach," in 2019 IEEE Milan PowerTech, 2019, pp. 1–6.

[R1] Electric Power Research Institute, "White Paper: Electric Power System Flexibility: Challenges and Opportunities," 2016.