Kernel-Based Lifting for Nonconvex Optimal Power Flow in Converter-Dominated DC Microgrids

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***Abstract*—Traditional convex relaxation methods, such as second-order cone programming (SOCP) and semidefinite programming (SDP), have shown success in addressing bilinear nonconvexities in Optimal Power Flow (OPF) problems. However, in converter-dominated microgrids, realistic converter efficiency curves introduce non-bilinear nonlinearities that cannot be handled directly by standard relaxations. To address this gap, this paper proposes a kernel-based lifting framework that transforms general nonlinear, nonconvex converter characteristics into a higher-dimensional space where they admit a convex representation. Radial basis function (RBF) kernels are used to approximate the composite cost in terms of converter output power, and the resulting kernel expansion is integrated with an SDP relaxation of the power flow equations in a DC microgrid. The combined kernel–SDP formulation yields a single convex OPF problem whose solution can be projected back to the original variables. The approach is validated on a representative medium-voltage DC (MVDC) microgrid, demonstrating high approximation accuracy, good feasibility with respect to network constraints, and improved operating cost relative to a nonlinear OPF benchmark. The proposed lifting framework provides a systematic path toward convexification of converter-induced nonlinearities in OPF problems.**

***Index Terms*—DC microgrids, nonconvex optimization, kernel methods, convex relaxation, semidefinite programming, optimal power flow, MVDC systems.**

I. Introduction

The increasing deployment of converter-interfaced distributed energy resources (DERs) and DC loads and the high efficiency of DC architectures has resulted in increased interest in DC grids [1]. Optimal management of various resources connected to DC microgrids requires solving an Optimal Power Flow (OPF) problem. Typically, OPF minimizes total generation cost or losses subject to nodal power balance, line flow, and device limits. This problem is nonconvex due to quadratic and bilinear voltage terms in the power flow equations. To address this, semidefinite programming (SDP) and second-order cone programming (SOCP) relaxations have been successfully applied to AC and DC networks [2]–[5], and can recover globally optimal solutions under appropriate conditions. However, these techniques are applied when nonconvex terms appear in bilinear and quadratic forms [6]. In converter-dominated DC microgrids, there is another source of nonconvexity that is not bilinear. The converters have nonlinear efficiency curves and various techniques are proposed in literature to model them mathematically [7]. These curves result in non-bilinear nonconvexity and therefore fall outside of the direct application of standard SDP and SOCP relaxation techniques. Nonlinear nonconvex economic dispatch problems are usually tackled by stochastic optimization techniques such as evolutionary algorithms [8], but these approaches do not provide any guarantee of discovering the global optimum solution. Other alternative approaches for handling nonlinear efficiency curves are linearization and mixed-integer programming techniques [9], [10]. While effective, these methods do not yield a single convex optimization problem and require either iterative re-optimization or the use of integer decision variables that introduce combinatorial complexity scaling with system size.

This paper proposes a kernel-based lifting framework for DC microgrid OPF. The central idea is to approximate the nonlinear mappings between converter output power and cost using kernel functions. By embedding the scalar converter power into a higher-dimensional feature space spanned by kernels, the composite cost is represented as a linear combination of kernel bases. The kernel lifting is combined with an SDP relaxation of the voltage-dependent terms, resulting in a jointly convex OPF formulation in the kernel and lifted voltage space. The physical quantities (converter outputs and bus voltages) are then reconstructed in the original space. The main contributions of this paper are: (1) **Kernel-based lifting approach** that convexifies non-bilinear converter efficiency-induced nonlinearities in DC microgrid OPF, extending the reach of standard convex optimization relaxations. (2) **Joint kernel–SDP formulation** that combines kernel lifting with an SDP relaxation of network bilinearities, yielding a single convex semidefinite program for converter-dominated DC microgrids.

The rest of the paper is organized as follows. Section II presents the mathematical formulation of the DC microgrid OPF problem. Section III discusses the sources of nonconvexity. Section IV introduces the proposed framework. Section V presents simulation results, and conclusions and future directions are discussed in Section VI.

II. Problem Formulation

Objective Function: A typical objective for an OPF problem is to minimize the total generation cost [2]:

$$\min_{\boldsymbol{P_{DER}}} \sum_{i=1}^{N} C_i(P_{DER_i}), \tag{1}$$

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where N is the number of buses, P_{DER_i} is the power generated by DER i at, and $C_i(\cdot)$ is the cost function associated with DER i.

Converter Efficiency Modeling: Converter efficiency is typically specified as a function of the converter's output power. This curve can be represented using a set of linear segments between measured points [7]. A *piecewise affine* (PWA) function of the converter output power can be defined as:

$$\eta_i(P_i^{conv}) = \begin{cases} a_{i,1}P_i^{conv} + b_{i,1}, & P_i^{conv} \in [P_{i,0}, P_{i,1}] \\ a_{i,2}P_i^{conv} + b_{i,2}, & P_i^{conv} \in [P_{i,1}, P_{i,2}] \\ \vdots & \\ a_{i,K_i}P_i^{conv} + b_{i,K_i}, & P_i^{conv} \in [P_{i,K_i-1}, P_{i,K_i}], \end{cases} \tag{2}$$

where $\eta_i(\cdot)$ is the converter efficiency function, $(P_{i,k}, \eta_{i,k})$ denote the measured breakpoints from the converter efficiency curve, and $(a_{i,k}, b_{i,k})$ are the affine coefficients of segment k.

The input power of the DER connected through converter i is related to the converter output by:

$$P_{DER_i} = \frac{P_i^{conv}}{\eta_i(P_i^{conv})}. \tag{3}$$

Consequently, the generation cost can be expressed in terms of the converter output power as:

$$C_i^{conv}(P_i^{conv}) = C_i\left(\frac{P_i^{conv}}{\eta_i(P_i^{conv})}\right), \tag{4}$$

which is piecewise nonlinear.

Constraints: The OPF problem is subject to the standard DC network and device constraints [3]. The nodal power balance at each bus i is:

$$P_i^{conv} - P_{D_i} = \sum_{j=1}^{N} Y_{ij}(v_i^2 - v_i v_j), \tag{5}$$

where P_{D_i} is the load demand at bus i, Y_{ij} is the line admittance between buses i and j, and v_i, v_j are the corresponding bus voltages. Each converter and load unit is bounded by local operating limits:

$$P_{i,\min}^{conv} \le P_i^{conv} \le P_{i,\max}^{conv}, \tag{6}$$

$$P_{D_i,\min} \le P_{D_i} \le P_{D_i,\max}, \tag{7}$$

and the bus voltage must remain within an allowable range:

$$v_{i,\min} \le v_i \le v_{i,\max}. \tag{8}$$

Final OPF Formulation: Combining the objective function and constraints, the complete OPF problem incorporating converter efficiencies is formulated as:

$$J = \min_{\boldsymbol{P^{conv}}, \boldsymbol{v}} \quad \sum_{i=1}^{N} C_i\left(\frac{P_i^{conv}}{\eta_i(P_i^{conv})}\right) \quad \text{s.t.} \quad (5),\ (6),\ (7),\ (8). \tag{9}$$

III. Convexity Analysis of the Problem

The optimization problem in (9) contains two distinct sources of nonconvexity: (1) **Network nonconvexity**: The power flow constraint (5) includes bilinear terms of the form $v_i v_j$ and quadratic voltage terms v_i^2 which make the feasible set nonconvex. (2) **Converter-related nonconvexity:** Even if each generation cost function $C_i(P_{DER_i})$ is convex in the DER power output, substituting the nonlinear efficiency relation $P_{DER_i} = P_i^{conv}/\eta_i(P_i^{conv})$ yields a composite cost $C_i(P_i^{conv}/\eta_i(P_i^{conv}))$ that can be nonconvex, as shown in Fig. 1. The figure is obtained by composing a convex quadratic DER-side cost ($C(P) = 0.1P^2 + 0.5P$ for normalized power P) with a piecewise-affine efficiency curve exhibiting low efficiency at light load and peak efficiency of 96% (breakpoints similar to row 1 of Table II), and then evaluating (4) over $P_i^{conv} \in [0, 1.4]$ p.u.

Nonconvexity implies that standard optimization solvers will not guarantee global optimality. There may exist operating points with lower cost that are not discovered in practice. Therefore, effective convexification strategies that increase the likelihood of finding globally optimal solutions can translate directly into economic savings.

IV. Proposed Convex Reformulation

The proposed method convexifies the original nonconvex OPF problem by combining a kernel-based lifting for converter nonlinearities with an SDP relaxation for network bilinearities.

Offline Sampling and Kernel Training: For each converter i, n_i representative samples of the converter output power are generated within the feasible range:

$$P_{i,k}^{conv} \in [P_{i,\min}^{conv}, P_{i,\max}^{conv}], \quad k = 1, \ldots, n_i.$$

At each sample point, the composite cost is evaluated as:

$$C_i^{conv}(P_{i,k}^{conv}) = C_i\left(\frac{P_{i,k}^{conv}}{\eta_i(P_{i,k}^{conv})}\right),$$

This captures the nonlinear relationship between converter output and its corresponding DER-side power. To approximate this nonlinear mapping, a set of radial basis functions (RBFs) are defined:

$$\phi_{i,k}(P_i^{conv}) = \exp\left(-\frac{(P_i^{conv} - c_{i,k})^2}{2\sigma_i^2}\right),$$

with centers $c_{i,k} = P_{i,k}^{conv}$ and width parameter σ_i. The corresponding feature vector is:

$$\boldsymbol{\phi}_i(P_i^{conv}) = [\phi_{i,1}(P_i^{conv}),\ \phi_{i,2}(P_i^{conv}),\ \ldots,\ \phi_{i,n_i}(P_i^{conv})]^{\mathsf{T}}.$$

Using the sampled data, the kernel matrix K_i is constructed as:

$$K_i = \begin{bmatrix} \phi_{i,1}(P_{i,1}^{conv}) & \phi_{i,2}(P_{i,1}^{conv}) & \cdots & \phi_{i,n_i}(P_{i,1}^{conv}) \\ \phi_{i,1}(P_{i,2}^{conv}) & \phi_{i,2}(P_{i,2}^{conv}) & \cdots & \phi_{i,n_i}(P_{i,2}^{conv}) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{i,1}(P_{i,n_i}^{conv}) & \phi_{i,2}(P_{i,n_i}^{conv}) & \cdots & \phi_{i,n_i}(P_{i,n_i}^{conv}) \end{bmatrix},$$

so that the entry $[K_i]_{pq} = \phi_{i,q}(P_{i,p}^{conv})$.

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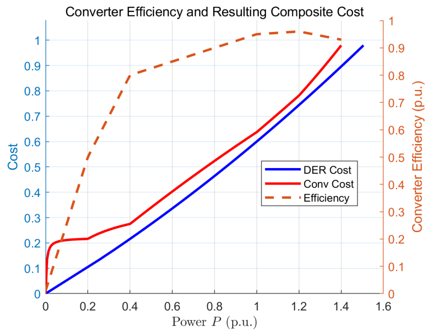

Fig. 1. Composite cost can be nonconvex despite the DER cost being convex

Two least-squares mappings are then trained to capture both the cost and power relationships in this feature space: *(a) Cost mapping:*

$$C_i^{conv}(P_i^{conv}) \approx \mathbf{w}_i^T \boldsymbol{\phi}_i(P_i^{conv}), \qquad \mathbf{w}_i^* = (K_i K_i^T)^{-1} K_i \mathbf{y}_i,$$

where $\mathbf{y}_i$ contains the sampled cost values, and *(b) Power mapping:*

$$P_i^{conv} \approx \mathbf{w}_{P,i}^T \boldsymbol{\phi}_i(P_i^{conv}), \qquad \mathbf{w}_{P,i}^* = (K_i K_i^T)^{-1} K_i \mathbf{p}_i,$$

with $\mathbf{p}_i = [P_{i,1}^{conv}, \ldots, P_{i,n_i}^{conv}]^\mathsf{T}$. These trained mappings lift converter nonlinearities into a higher-dimensional convex feature space during optimization and later enable projection back to the physical domain.

Remark 1. RBF kernels are widely used for approximating smooth nonlinear mappings, due to their universal approximation properties, and can achieve high accuracy with a moderate number of basis functions. Other kernel choices are also possible, and exploring them is left for future work.

Kernel Representation in Optimization: During optimization, instead of directly using P_i^{conv}, the kernel feature vector is expressed as a convex combination of training features through a vector $\boldsymbol{\beta}_i = [\beta_{i,1}, \ldots, \beta_{i,n_i}]^\mathsf{T}$:

$$\boldsymbol{\phi}_i^{\text{opt}} = K_i \boldsymbol{\beta}_i, \qquad \sum_k \beta_{i,k} = 1,\ \beta_{i,k} \geq 0.$$

This constrains $\boldsymbol{\phi}_i^{\text{opt}}$ to the convex hull of physically feasible operating points, ensuring that all reconstructed powers are realizable. The converter quantities then enter the OPF linearly:

$$P_i^{conv} = \mathbf{w}_{P,i}^{*T}(K_i \boldsymbol{\beta}_i), \qquad C_i^{conv} = \mathbf{w}_i^{*T}(K_i \boldsymbol{\beta}_i),$$

SDP Lifting of Network Constraints: The nodal power balance constraint in the kernel space remains nonconvex due to bilinear voltage terms:

$$\mathbf{w}_{P,i}^{*T}(K_i \boldsymbol{\beta}_i) - P_{D_i} = \sum_j Y_{ij}(v_i^2 - v_i v_j).$$

To convexify this relation, a lifted voltage matrix $V = \mathbf{v}\mathbf{v}^\mathsf{T}$ is introduced, where $V_{ij} = v_i v_j$ and $V_{ii} = v_i^2$. Substituting yields:

$$\mathbf{w}_{P,i}^{*T}(K_i \boldsymbol{\beta}_i) - P_{D_i} = \sum_j Y_{ij}(V_{ii} - V_{ij}), \quad \forall i \in N,$$

with voltage limits $v_{i,\min}^2 \leq V_{ii} \leq v_{i,\max}^2$ and the positive semidefinite constraint $V \succeq 0$. The matrix V should satisfy the rank-one condition $\operatorname{rank}(V) = 1$, ensuring $V = \mathbf{v}\mathbf{v}^\mathsf{T}$. However, enforcing this constraint is nonconvex; hence, it is *relaxed* as part of the SDP formulation, yielding a convex feasible set that approximates the original network physics [3].

Final Convex OPF Formulation: The complete lifted problem is:

$$\begin{aligned} \hat{J} = \min_{\{\boldsymbol{\beta}_i\}, V} \ & \sum_{i=1}^{N} \mathbf{w}_i^{*T} K_i \boldsymbol{\beta}_i \qquad (10) \\ \text{s.t.} \ & \mathbf{w}_{P,i}^{*T}(K_i \boldsymbol{\beta}_i) - P_{D_i} = \sum_j Y_{ij}(V_{ii} - V_{ij}),\ \forall i, \\ & P_{i,\min}^{conv} \leq \mathbf{w}_{P,i}^{*T}(K_i \boldsymbol{\beta}_i) \leq P_{i,\max}^{conv}, \\ & v_{i,\min}^2 \leq V_{ii} \leq v_{i,\max}^2,\ \sum_k \beta_{i,k} = 1,\ \beta_{i,k} \geq 0, \\ & V \succeq 0. \end{aligned}$$

All variables now appear within convex expressions for the cost and constraints, making (10) a convex semidefinite program.

Solution and Projection: Solving (10) provides the optimal kernel coefficients $\boldsymbol{\beta}_i^*$ and voltage matrix V^*. The physical quantities are reconstructed as:

$$P_i^{conv*} = \mathbf{w}_{P,i}^{*T}(K_i \boldsymbol{\beta}_i^*), \qquad \mathbf{v}^* \approx \sqrt{\lambda_1(V^*)}\,\mathbf{u}_1, \qquad (11)$$

where $\lambda_1(V^*)$ and $\mathbf{u}_1$ are the dominant eigenvalue and eigenvector of V^*. If $\operatorname{rank}(V^*) = 1$, the relaxation is exact and $\mathbf{v}^*$ is obtained directly. Otherwise, the projection is an approximation [3].

The overall concept of the proposed lifting framework is shown in Fig. 2. The original OPF problem in the low-dimensional physical space is nonconvex. The *kernel lifting* removes converter-related nonlinearities by mapping them into a convex feature space, while the *SDP relaxation* convexifies the voltage-dependent network relations. Together, they yield a single convex OPF formulation in a higher dimension space that can be solved efficiently with standard semidefinite optimization tools.

Remark 2. Consider the original OPF with true objective $J(\cdot)$ and the kernel-based lifted OPF with approximate objective $\hat{J}(\cdot)$. Assume that the reconstructed solution $\hat{x}^*$ is feasible for the original OPF, that the true global optimizer x^* is representable by the lifted formulation, and that $|J(x) - \hat{J}(x)| \leq \varepsilon$ for all feasible x. Then,

$$\begin{aligned} J(\hat{x}^*) - J(x^*) = & \big(J(\hat{x}^*) - \hat{J}(\hat{x}^*)\big) + \big(\hat{J}(\hat{x}^*) - \hat{J}(x^*)\big) \\ & + \big(\hat{J}(x^*) - J(x^*)\big). \end{aligned}$$

The first and third terms are bounded by ε due to $|J(x) - \hat{J}(x)| \leq \varepsilon$. Since $\hat{x}^*$ is the global minimizer of $\hat{J}(\cdot)$, the second term is non-positive. Therefore, $J(\hat{x}^*) - J(x^*) \leq 2\varepsilon$, establishing a bound on the sub-optimality of the reconstructed solution in terms of the approximation error.

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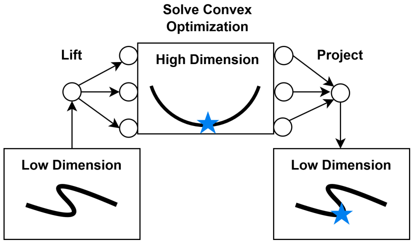

Fig. 2. Concept of the proposed kernel–SDP lifting framework.

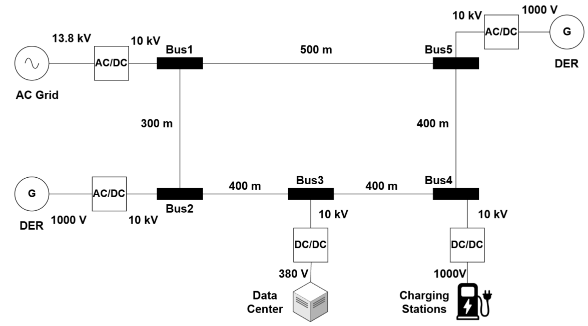

Fig. 3. Schematic of the test MVDC microgrid.

Remark 3. The formulation in (10) is a standard SDP with worst-case polynomial computational class [11] (with interior point methods). Since SDP-OPF computational cost is largely determined by the lifted semidefinite matrix [12], and the kernel lifting does not alter this matrix (V), the proposed method preserves the same computational complexity as standard SDP-based OPF.

Remark 4. Compared with piecewise linearization and mixed-integer programming, the proposed method avoids combinatorial complexity growth associated with integer variables and yields a single convex optimization problem. In contrast to metaheuristic-based methods, the method is deterministic and convex, and can be solved using standard off-the-shelf convex optimization solvers. Compared with Sequential Convex Programming (SCP) approaches, it avoids iterative approximations and provides a single-shot convex representation.

V. Numerical Studies

To validate the proposed kernel-based lifting technique, we have used a representative MVDC microgrid. As shown in Fig. 3, this grid consists of $N = 5$ DC buses operating at a nominal voltage of 10 kV and interconnected through resistive distribution lines. Power is supplied by two gas turbine generators connected at buses 2 and 5 and a main AC grid connection at bus 1. All sources interface with the DC network through AC/DC converters. Two major DC loads are modeled: a data center at bus 3 and multiple fast-charging stations at bus 4, each interfaced via DC/DC converters. Each converter follows an efficiency curve represented by a piecewise-affine function. Gas turbine generators have quadratic fuel cost functions:

$$C_i(P_{DER_i}) = a_i P_{DER_i}^2 + b_i P_{DER_i} + c_i, \tag{12}$$

where (a_i, b_i, c_i) denote unit-specific fuel coefficients. The cost of drawing power from the AC grid connection is a linear energy cost:

$$C_{AC}(P_{AC}) = p_{ac} P_{AC}, \tag{13}$$

where p_{ac} represents the energy price at the AC interface and P_{AC} is the imported power. Bus voltage limits are defined as $v_{i,\min} = 9.5$ kV and $v_{i,\max} = 10.5$ kV. Tables I and II summarize the key simulation parameters.

The total system demand is set to 2.74 MW (1.68 MW at bus 3 and 1.06 MW at bus 4). Each converter operated within its rated efficiency curve and 12 RBF kernels per converter

TABLE I
MVDC Microgrid Network Parameters

Parameter	Value
Nominal bus voltage	10 kV
Voltage limits	[9.5, 10.5] kV
Line resistance per km	0.1 Ω/km

were employed in the lifted formulation. The proposed kernel–SDP problem was implemented in MATLAB R2024b using CVX with SDPT3 as the solver. The nonlinear OPF benchmark was implemented using the default interior-point algorithm of MATLAB's Optimization Toolbox.

Fig. 4 illustrates the kernel-based approximation of the converter cost function at Bus 1. The converter PWA efficiency curve, the corresponding generator-side power $P_{DER,i}$, and cost $C_i(P_{DER,i})$ are sampled across the operating range. Using these samples, the cost function is approximated via the RBF expansion introduced in Section IV. It is seen that with 12 kernels, the approximation is highly accurate, with $R^2 = 0.9999$. This procedure is independently applied to all the other converters.

After the kernel lifting step, the overall OPF problem is further relaxed using the semidefinite lifting described in Section IV, leading to the convex formulation (10). The optimization is solved in the joint kernel–SDP space, where the decision variables are the kernel coefficients $\boldsymbol{\beta}_i$ and the lifted voltage matrix $V = \mathbf{v}\mathbf{v}^\mathsf{T}$. Each converter's output power is then reconstructed from its optimal kernel coefficients using (11). Fig. 5 illustrates the optimal kernel coefficients $\boldsymbol{\beta}_5^*$ for the converter at Bus 5 and the corresponding reconstructed converter output power P_5^{conv*}. The kernel–SDP solution was compared against a standard nonlinear OPF solved using an interior-point algorithm [13]. Both methods converged successfully. Table III summarizes the results for the test operating condition. In this case, the kernel–SDP approach yields a lower operating cost while maintaining voltages within limits and keeping power-balance violations at a very small fraction of the total load. The improvement in cost is attributed to the convex reformulation in the kernel space, which avoids convergence to poor local minima that may affect the nonconvex solver.

Next, we perform a sensitivity analysis by varying the

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TABLE II
CONVERTER AND SOURCE PARAMETERS WITH EFFICIENCY DATA

Component	**Location**	**Key Parameters**	**Efficiency Data** [Power (W), η]
AC grid interface	Bus 1	$p_{ac} = 0.12\$/\mathrm{kWh}$	(1k,0.10), (200k,0.93), (500k,0.95), (800k,0.96), (1.2M,0.95)
Gas turbine 1	Bus 2	$(a, b, c) = (1.0\times 10^{-7}, 0.05, 10)$	(1k,0.1), (200k,0.88), (400k,0.92), (600k,0.94), (800k,0.93)
Data center load	Bus 3	$P_D = 1.68$ MW	–
EV chargers load	Bus 4	$P_D = 1.06$ MW	–
Gas turbine 2	Bus 5	$(a, b, c) = (1.2\times 10^{-7}, 0.045, 12)$	(1k,0.80), (200k,0.86), (400k,0.91), (700k,0.93), (900k,0.92)

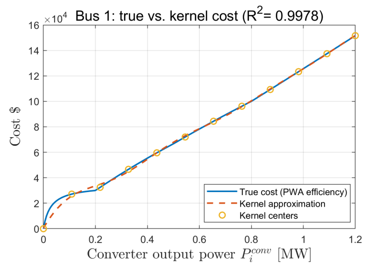

Fig. 4. Kernel-based approximation of the converter cost function for Bus 1.

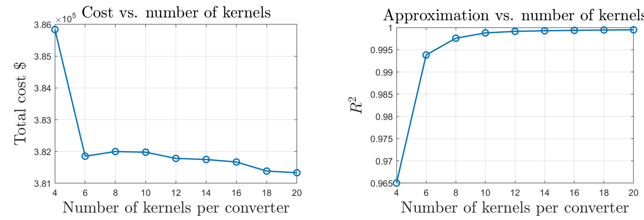

Fig. 6. Impact of kernel count on optimization cost and kernel approximation quality.

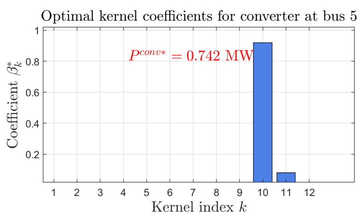

Fig. 5. Optimal kernel coefficients and reconstructed converter output power

TABLE III
COMPARISON OF NONLINEAR AND KERNEL–SDP OPF SOLUTIONS

Metric	**Kernel–SDP OPF**	**Nonlinear OPF**
Total cost [$]	3.8178×10^5	4.0693×10^5
Min–Max voltage [kV]	9.99–10.0	9.99–10.0
Constraint violation [% of load]	7×10^{-7}	0
Conv outputs (Bus 1, 2, 5) [MW]	1.20, 0.80, 0.74	1.04, 0.80, 0.90

number of kernel bases per converter. As shown in Fig. 6, increasing the number of kernels reduces the approximation error in the kernel cost fit (measured via average R^2 across converters) in agreement with Remark 2. Beyond approximately 12 kernels per converter, the improvement becomes marginal, indicating that a moderate number of kernel bases provides an effective trade-off between approximation quality and problem size.

VI. CONCLUSION

A kernel-based lifting framework for convexifying nonbilinear converter-induced efficiency curves was proposed. By approximating cost functions with RBF kernels and combining this representation with an SDP relaxation, the originally nonconvex OPF problem is reformulated as a single convex program. The framework is general and can accommodate a broad class of nonlinearities in OPF problems for DC grids. Future work will focus on scalability studies, application to other types of nonlinearities, and deeper theoretical analysis.

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