

Compact Optimization Learning for AC Optimal Power Flow

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Abstract—This paper reconsiders end-to-end learning approaches to the Optimal Power Flow (OPF). Existing methods, which learn the input/output mapping of the OPF, suffer from scalability issues due to the high dimensionality of the output space. This paper first shows that the space of optimal solutions can be significantly compressed using principal component analysis (PCA). It then proposes COMPACT LEARNING, a new method that learns in a subspace of the principal components and translates the vectors into the original output space. This compression reduces the number of trainable parameters substantially, improving scalability and effectiveness. COMPACT LEARNING is evaluated on a variety of test cases from the PGLib and a realistic French transmission system having renewable energy changes with up to 30,000 buses. The paper also shows that the output of COMPACT LEARNING can be used to warm-start an exact AC solver to restore feasibility, while bringing significant speed-ups.

Index Terms—Optimal Power Flow, Principal Component analysis, Generalized Hebbian Algorithm, Nonlinear Programming, End-to-end Learning, Deep Learning

I. INTRODUCTION

Optimal Power Flow (OPF) is at the core of grid operations: in many markets, it should be solved every five minutes (ideally) to clear real-time markets at minimal cost, while ensuring that the load and generation are balanced and that the physical and engineering constraints are satisfied. Unfortunately, the AC-OPF problem is nonlinear and nonconvex: actual operations typically use linear relaxations (e.g., the so-called DC-model) to meet the real-time requirements of existing markets.

As the share of renewable energies significantly increases in the generation mix, it becomes increasingly important to solve AC-OPF problems, not their linearized versions. This is exemplified by the IREP-EPG competitions [1] designed to stimulate progress on AC-OPF. In recent years, machine-learning (ML) based approaches to the OPF have received increasing attention. This is especially true for end-to-end approaches that aim at approximating the mapping between various input configurations and corresponding optimal solutions [2]–[9]. The ML approach is motivated by the recognition that OPF problems are solved repeatedly every day, producing a wealth of historical data. In addition, the historical data can be augmented with additional AC-OPF instances, moving the computational burden offline instead of solving during real-time operations.

One of the challenges of AC-OPF is the high dimensionality of its solution, which implies that the ML models, typically deep neural networks (DNNs), have an excessive number of trainable parameters for realistic power grids. As a result, many ML approaches are only evaluated on test cases of limited sizes. For instance, the pioneering works in [2] and [3] tested their approaches on systems with 118 and 300 buses at most, respectively. To the best of the authors' knowledge, the largest AC-OPF test case for evaluating end-to-end learning of

AC-OPF is the French system with around 6,700 buses [10]. Observe also that, since end-to-end learning is a regression task, learning highly dimensional OPF output may lead to inaccurate predictions and significant constraint violations.

To remedy this limitation and learn OPF at scale, this paper proposes a different approach. Instead of directly mapping the inputs to the AC-OPF solutions, this paper proposes to learn a mapping to a low-rank representation defined by a Principal Component analysis (PCA) before translating the vectors into the original output space. The contributions of the paper can be summarized as follows:

- data analysis on the optimal solutions given various input configurations shows that the optimal solutions to the AC-OPF problems can be substantially compressed through PCA with negligible informational loss.
- Motivated by this empirical observation, the paper proposes COMPACT LEARNING, a new ML approach that learns into a subspace of principal components before translating the compressed output into the original output space. In fact, COMPACT LEARNING jointly learns both the selected principal components and the compact mapping function.
- COMPACT LEARNING learns the AC-OPF mapping for very large power systems with up to 30,000 buses. To the best of the authors' knowledge, this is the largest AC-OPF problem to which an end-to-end learning scheme has been applied. The results show that COMPACT LEARNING is comparable in accuracy to the best previous approach, but scales significantly better.
- The paper also demonstrates that the COMPACT LEARNING predictions can warm-start power flow and AC-OPF solvers. When seeding a power flow solver, COMPACT LEARNING exhibits compelling performance compared with plain approaches. The warm-start results, which use both primal and dual predictions, show that COMPACT LEARNING can produce significant speed-ups for AC-OPF solvers, which can be accelerated by a factor of 3.6 to 15.3 \times on the bulk industry size power systems.

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The rest of this paper is organized as follows: Section II presents prior related works. Section III revisits the C-OPF formulation and describes the supervised learning task. Section IV analyzes the structure of optimal solutions. Section V presents COMPTLEARNING in detail. Section VI demonstrates its performance for various C-OPF test cases. Finally, Section VII covers the concluding remarks.

II. RELATED WORK

The *end-to-end learning* approach aims at training a model that directly estimates the optimal solution to an optimization problem given various input configurations. This approach has attracted significant attention in power system applications recently because it holds the promise of decreasing the computation time needed to solve recurring optimization problems with reasonably small variations of the input parameters. For example, a *classification-then-regression* framework [11] was proposed to directly estimate the optimal solutions to the security-constrained economic dispatch problem. Because of the existence of the bound constraints, they recognized that the majority of the generators are at their maximum/minimum limits in optimal solutions. This study observed a similar pattern in C-OPF solutions, but a more efficient way to design the input/output mapping is proposed. Similarly, ML-based mappings have been utilized to approximate the optimal commitments in various unit commitment problems [12]–[14]. Especially for C-OPF problems, various supervised learning (e.g., [2], [3]) and self-supervised learning approaches (e.g., [8], [9]) have been researched. They have used dedicated training schemes such as Lagrangian Duality [3], [15] or physics-informed neural network [7]. Graph neural networks have been also considered in this context [4]–[6] for leveraging the power system topology. However, such direct approaches cannot scale to industry size problems mainly because of the dimension of the output space which is of very large scale. To remedy this, *spatial decomposition* approaches [10], [16] have been proposed to decompose the network in regions and learn the mappings per region.

Besides the end-to-end learning approach, ML has also helped optimization solve problems faster. In [17], the authors used an ML technique to identify an active set of constraints in DC-OPF. Also in [18], ML is used to identify a variable subset for accelerating an optimality-based bound tightening algorithm [19] for the C-OPF.

By definition, since learning the C-OPF optimal solution is a regression task, the inference from the ML model will not be always correct. A variety of techniques have been used to remedy this limitation, including the use of warm-starts and power flows as post-processing. Newton-based method is used to correct the active power generations and voltage magnitudes at generator buses so that they satisfied the C power flow problem [10], [20]. In [21], the authors corrected voltages at buses by minimizing the weighted least square of the inconsistency in the C power flow using the Newton-Raphson method. In [2], the active power injections and voltage phasors are outputted directly from the ML model and determine the other variables by solving a power flow.

Also, in [22] and [23], the use of the learning scheme was suggested to provide warm-start points for COPF solvers, but only presented the results on small test networks (up to the 300 bus system). In [24], the use of DNN-based learning method for generating warm-start points was suggested. Their method was tested on a power system with 2,000 buses, but no speed-up was reported with the learning-based warm-start point.

In previous data-driven C-OPF approaches, feature reduction has been considered for reducing the parameters to tune using techniques such as PCA [25] or sensitivity analysis [26]. This work in contrast shows that the optimal solutions can be compressed to the low-rank representations defined by PCA without having any significant informational loss. Traditional power network reduction techniques, such as Kron and Ward reduction [27] techniques, have been widely used in the power system industry for more than 70 years. These techniques focused on crafting simpler equivalent circuits to be used by system operators, primarily for analysis. More complex reduction models [28]–[31] have also been developed recently. While it is possible to use classical reduction techniques to reduce the power systems before learning, the resulting prediction model would only be able to predict quantities on the reduced networks with potential accuracy issues. The main focus of the paper is not on general network/grid reduction techniques. Instead, it focuses on devising a scalable learning approach by reducing the number of trainable parameters.

In summary, most previous works for learning C-OPF optimization proxies have not considered industry-size power systems. *This paper shows that COMPTLEARNING applies to large-scale power networks (up to 30,000 buses in the experiments) and produces significant benefits in speeding-up C-OPF solvers through warm-starts.*

III. PRELIMINARIES

This section formulates the C-OPF problem and specifies the supervised learning studied in this paper.

A. C-OPF Formulation

Model 1 presents the C-OPF formulation [32]. The power network can be represented as a graph $(\mathcal{N}, \mathcal{E})$ where \mathcal{N} denotes the set of bus indices containing generators and load units, and \mathcal{E} is the set of transmission line indices between two buses. $(lij) \in \mathcal{E}$ where l is a branch index connected from node i to node j . The set \mathcal{E}^R captures the reversed orientation of \mathcal{E} , i.e., $(lji) \in \mathcal{E}^R, \forall (lij) \in \mathcal{E}$.

generator output $S^g = p^g + jq^g$ is a complex number, where the real part p^g is an active power generation (injection) and the imaginary part q^g is a reactive power generation. In

C voltage $V = v \angle \theta$ is represented by a voltage magnitude v and a voltage angle θ . The objective function (1) minimizes the sum of quadratic cost functions $c_i(\cdot)$ with respect to the active power generations $p_i^g, i \in \mathcal{G}$. At the reference bus r , the voltage angle is set to zero as defined in constraint (2). Constraints (3a), (3b), and (4) capture the bounds on variables p^g , q^g , and v , respectively. Constraints (5a), (5b) represent the complex power flow for each transmission line, which is

Model 1 The C-Optimal Power Flow (C-OPF) Problem

$$\text{Minimize}_{p^g, q^g, v, i \in \mathcal{G}} \sum c_i(p_i^g) \quad (1)$$

subject to:

$$r = 0 \quad (2)$$

$$\underline{p}_i^g \leq p_i^g \leq \bar{p}_i^g \quad \forall i \in \mathcal{G} \quad (3a)$$

$$\underline{q}_i^g \leq q_i^g \leq \bar{q}_i^g \quad \forall i \in \mathcal{G} \quad (3b)$$

$$\underline{v}_i \leq v_i \leq \bar{v}_i \quad \forall i \in \mathcal{N} \quad (4)$$

$$S_{lij} = Y_l \left(j \frac{b_l^c}{2} \right) \frac{v_i^2}{|T_l|^2} - Y_l \frac{V_i V_j}{T_l} \quad \forall (lij) \in \mathcal{E} \quad (5a)$$

$$S_{lji} = Y_l \left(j \frac{b_l^c}{2} \right) v_i^2 - Y_l \frac{V_i V_j}{T_l} \quad \forall (lji) \in \mathcal{E}^R \quad (5b)$$

$$\sum_{k \in \mathcal{G}_i} S_k^g - S_i^d - Y_i^s |V_i|^2 = \sum_{(lij) \in \mathcal{E} \cup \mathcal{E}^R} S_{lij} \quad \forall i \in \mathcal{N} \quad (6)$$

$$|S_{lij}| \leq \bar{s}_{ij} \quad \forall (lij) \in \mathcal{E} \cup \mathcal{E}^R \quad (7)$$

$$\underline{v}_l \leq v_l \leq \bar{v}_l \quad \forall (lij) \in \mathcal{E} \quad (8)$$

governed by *Ohm's law*. Here, Y_l , b_l^c , and T_l are the series admittance, line charging susceptance, and transformer parameter at each branch l , respectively. Constraints (6) ensures that, at each bus, the active and reactive power balance are satisfied. Here, Y^s is the bus shunt admittance and \mathcal{G}_i represents the set of generator indices attached to the bus i . Constraints (7) capture the thermal limits and ensure that the apparent power does not exceed its limit \bar{s}_{ij} for every transmission line.

For the sake of simplicity, in what follows, the input configuration parameters and the optimal solution to the C-OPF are denoted by x and y^* , respectively.

B. Supervised Learning

The end-to-end learning approach in this paper consists in using supervised learning to find a mapping from an input x to an optimal solution y^* to C-OPF. This work assumes that the set of commitment decisions and generator bids are predetermined. This setting is common in prior end-to-end learning studies for C-OPF (e.g., [2], [10], [15]). Existing supervised learning schemes exploit the instance data $\{x_i, y_i^*\}$. However, it often suffers from the high dimensionality of the output when dealing with power networks of industrial sizes. Table I reports the specifications of the nine power networks from PGLib [32] and a realistic version of the French system (denoted by *France_2018*) used in the experiments. The French system¹ uses the realistic grid topology of the French transmission system captured in 2018 with annual time series data for the renewable generation capacity and load demand.

For the PGLib test cases, each instance has different active and reactive load demands p^d and q^d , i.e., $x := \{p^d, q^d\}$. For *France_2018*, the generation capacity of the renewable generators is also varying in addition to the load demands. As such, for the PGLib cases, the dimensions of x is $\dim(x) = 2|\mathcal{L}|$, and for *France_2018*, the input of the mapping is increased to $x := \{p^d, q^d, \{\bar{p}_i^g\}_{i \in \mathcal{G}^r}\}$, where \bar{p} represents the upper bounds of the active generation, and \mathcal{G}^r is the set of renewable generator indices. Note that among 1890 generators

Test case	$ \mathcal{N} $	$ \mathcal{G} $	$ \mathcal{L} $	$\dim(x)$	$\dim(y)$
300_ieee	300	69	201	411	402
793_goc	793	97	507	913	1014
1354_pegase	1354	260	673	1991	1346
3022_goc	3022	327	1574	4135	3148
4917_goc	4917	567	2619	6726	5238
6515_rte	6515	684	3673	9037	7346
9241_pegase	9241	1445	4895	16049	9790
13659_pegase	13659	4092	5544	20467	11088
30000_goc	30000	3526	10648	35393	21296
France_2018	6708	1890	6262	8965	14133

TABLE I: Specifications of the C-OPF Test Cases.

in this system, there are 1609 renewable non-dispatchable generators including hydro, solar, and wind generators.

From Table I, observe that the dimension of the output y is much higher than that of x : this implies that the DNN for the OPF will necessitate an excessive number of trainable parameters. It is the goal of this paper to propose a scalable approach that mitigates this curse of dimensionality.

Note that one can recover the whole optimal solution estimates from the active generations and voltage magnitudes by solving a power flow problem as in [2]. This could be combined with the methods proposed herein to provide further reduction in the output space at the cost of a more costly training or inference procedure. However considering the full output space, i.e., $y := \{p^g, q^g, v, \theta\}$, makes it possible to use Lagrangian Duality [3], [15] or Primal-Dual Learning [9] frameworks to improve the learning procedure further.

IV. LOW RANK REPRESENTATION OF THE C-OPF SOLUTION

This section presents data analysis to motivate COMPACT LEARNING. Again, Table I describes the test cases. They range from 300 to 30,000 buses and from 69 to 3526 generators. The table also specifies the input and output dimensions of the learning problem: the output dimension is large in sharp contrast to many classification problems in computer vision for instance. The experiments in this section are based on 20,000 instances for each test case: their optimal solutions were obtained via IPOPT [34]. To generate the instances for each test case in PGLib, the active loads were sampled from a truncated multivariate Gaussian distribution as

$$p^d \sim \mathcal{TN}(p_0^d, \Sigma, (1 - \mu)p_0^d, \mu p_0^d), \quad (9)$$

where p_0^d is the baseline active loads and Σ is the covariance matrix. The element of the covariance matrix Σ_{ij} is defined using correlation coefficient ρ as $\Sigma_{ij} = \rho \sigma_i \sigma_j$ where σ_i and σ_j are standard deviation of p_i^d and p_j^d , respectively. Also, $\rho = 1$ when $i = j$ and $\rho = 0.5$ otherwise. μ is set to 0.5, meaning that the active load demands were set to be perturbed by $\pm 50\%$. The reactive loads q^d were sampled from a uniform distribution ranging from 0.8 to 1.0 of the baseline values. This perturbation method follows the protocols used in [2], [8], [9]. For *France_2018*, the experiments use the historical 2020 load demand and renewable generations data at the 30-minute granularity, which is publicly available at [35].

¹Refer to [33] for more details on this test case.

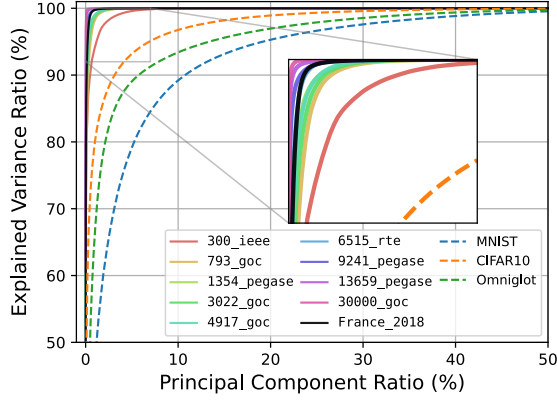


Fig. 1: Explained Variance Ratios of PC for the Various Principal Component Ratios for C-OPF Instances (solid lines) and Natural Image Data (dashed lines).

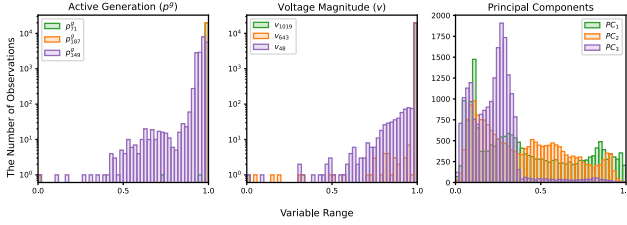


Fig. 2: Histograms of Active Generations (left), Voltage Magnitudes (middle), and Principal Components (right) of the 20,000 Optimal Solutions in 1354_pegase. Three largest components on average are illustrated. The x-axis is normalized to $[0, 1]$ using the minimum and maximum values.

These historical time series data are disaggregated spatially and interpolated to have 5-minute granularity following the protocol introduced in [33]. PC was performed on the 20,000 optimal solutions for each test case, which led to a number of interesting findings.

a) (Almost) Lossless Compression: A key observation of the analysis is that PC achieves an almost lossless compression with a few principal components. This is highlighted in Figure 1 where the x-axis represents the principal component ratio (i.e., the ratio of the number of the principal components in use to the dimension of the optimal solution) and the y-axis represents the explained variance ratio (i.e., the ratio of the cumulative sum of eigenvalues of the principal components in descending order to the sum of the all eigenvalues). The explained variance ratio is a proxy for how much the information is preserved within the chosen low-rank representation. For instance, the figure shows that 1% of principal components preserves the 99.92% of information of the C-OPF optimal solutions for 13659_pegase. The detailed values are shown in Table II, which highlights that the compression is almost lossless with a 10% principal component ratio. This contrasts with data instances in computer vision, as exemplified by the MNIST [36], CIFAR10 [37], and Omniglot [38] datasets. This result is encouraging: it suggests that optimal solutions could be recovered with negligible losses when learning takes place

Test case	Principal Component Ratio			
	1%	5%	10%	20%
300_ieee	93.92	99.56	99.97	99.99
793_goc	98.05	99.98	100.00	100.00
1354_pegase	99.04	99.98	100.00	100.00
3022_goc	98.64	99.99	100.00	100.00
4917_goc	99.03	99.99	100.00	100.00
6515_rte	99.74	99.99	100.00	100.00
9241_pegase	99.76	100.00	100.00	100.00
13659_pegase	99.92	100.00	100.00	100.00
30000_goc	99.99	100.00	100.00	100.00
France_2018	99.75	99.99	100.00	100.00
MNIST	44.45	79.12	89.17	95.27
CIFAR10	62.09	82.34	88.37	93.29
Omniglot	16.55	44.26	59.06	73.31

TABLE II: Explained Variance Ratios (%) on Various Principal Component Ratios from 1% to 20%.

in a low-rank space of a few principal components, potentially reducing the size of the mapping function substantially.

b) Larger Test Cases Need Fewer Principal Components: Figure 1 and Table II also highlight a desirable trend: larger test cases need a lower ratio of principal components to obtain the same level of explained variance ratio. For instance, the explained variance ratios of 13659_pegase and 30000_goc with a principal component ratio of 1% are 99.92% and 99.99% respectively. In contrast, 300_ieee, the smallest test case, has 93.92% of explained variance ratio. This observation shows that reducing the dimensionality through PC is more effective for the bigger test cases and will be used in deciding the learning architecture for different test cases.

c) Smoother Distributions on the Principal Components: Figure 2 provides some intuition for why learning in the space of the principal components is appealing. The figure shows the distributions of three active powers (left) and voltage magnitudes (middle) in the optimal solutions for the 1354_pegase test case. The values are plotted in log-scaled, highlighting the skewed nature of the active powers and voltage magnitudes: indeed, most values lie on their extreme limits. This has been observed before, leading to the use of the *classification-then-regression* approach [11]. However, fortunately, Figure 2 (right) shows that the distribution on the principal components is well-posed: it is more convenient to learn the regression to the low-rank space with a few principal components rather than to the original optimal solution space directly. As a result, the regression learning in the space of principal components should be easier than in the original space.

V. COMPACT OPTIMIZATION LEARNING

The findings in Section IV suggest a COMPACT LEARNING model whose outputs are in the subspace defined by the principal components. This enables to decrease the number of trainable parameters in the DNN-based mapping function, reducing the memory footprint significantly.

A. Compact Learning

The idea underlying COMPACT LEARNING is to *jointly learn the principal components and the mapping between the*

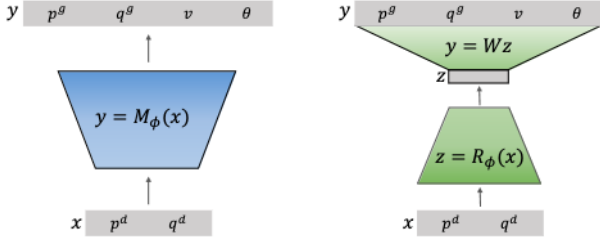


Fig. 3: Schematic View of the Plain approach (left) and COMP CT LE RNING (right).

original inputs and the outputs in the subspace of the principal components. Figure 3 contrasts the overall architecture of the COMP CT LE RNING with the conventional plain learning approach. The plain approach learns a mapping $y = M_\phi(x)$ from an input configuration x to an optimal solution y , where ϕ are the associated trainable parameters. Since y is high-dimensional, it is desirable to have a large number of parameters to obtain accurate solution estimates. COMP CT LE RNING in contrast learns a mapping $z = R_\phi(x)$ from an input configuration x into an output z in the subspace of principal components before recovering an optimal solution prediction as $y = Wz$. The output dimension of R_ϕ , $\dim(z)$, in COMP CT LE RNING should be substantially smaller than the dimension of y , making it possible to reduce the number of trainable parameters. In the upcoming sections, the way of learning R and W simultaneously is detailed.

B. Learning the Principal Components

Let p and d be the dimensions of z and y , respectively, i.e., $p = \dim(z)$ and $d = \dim(y)$. The goal of COMP CT LE RNING is to have p substantially smaller than d , i.e., $p \ll d$. Matrix $W \in \mathbb{R}^{d \times p}$ is unitary, i.e., $W^\top W = I$, and its columns are composed of the orthonormal principal components of the output space associated with p largest eigenvalues. It is obviously possible to obtain W through PC, but this computation takes a substantial amount memory when there are many instances.

Instead, COMP CT LE RNING uses the Generalized Hebbian algorithm (GH), also called Sanger's rule [39], to learn W in a stochastic manner. GH is specified in Algorithm 1. Using the mini-batch of optimal solutions $\{y^{*(i)}\}$, it first updates the element-wise running mean μ and variance σ^2 of optimal solution using the momentum parameter. The momentum parameter is set to zero for the first iteration, and from the second iteration it is set to a value ranged (0.0, 1.0). The optimal solution $y^{*(i)}$ is normalized using the running mean and variance as shown in line 5 in Algorithm 1. GH uses Gram-Schmidt process to find out the W of the p leading principal components, where $\mathcal{LT}[\cdot]$ represents the lower triangular matrix. Once W is determined, W is updated by adding γW , where γ is the learning rate that decreases as the epoch number e increases, i.e.,

$$\gamma = \max\{\gamma_{\min}, \gamma_{\text{init}}/(0.01e)\},$$

In the update rule, γ_{init} and γ_{\min} are hyperparameters representing the initial and minimum learning rate, respectively.

Algorithm 1 Generalized Hebbian algorithm,
GH ($\{y^{(i)}\}_{i \in [B]}, W, \mu, \sigma$)

Parameters:

- : a momentum parameter
 - γ : a learning rate for updating W
 - ϵ : a small positive for numerical stability
- 1: $m \leftarrow \frac{1}{B} \sum_{i=1}^B y^{(i)}$
 - 2: $s^2 \leftarrow \frac{1}{B} \sum_{i=1}^B (y^{(i)} - m)^2$
 - 3: $\mu \leftarrow \mu + (1 - \gamma)m$ ▷ update running mean
 - 4: $\sigma^2 \leftarrow \sigma^2 + (1 - \gamma)s^2$ ▷ update running variance
 - 5: $\hat{y}^{(i)} \leftarrow (y^{(i)} - \mu)/\sqrt{\sigma^2 + \epsilon}, \forall i \in [B]$ ▷ normalize y
 - 6: $W \leftarrow \frac{1}{B} \sum_{i=1}^B \hat{y}^{(i)} \hat{y}^{(i)\top} W - W \mathcal{LT}[W^\top \hat{y}^{(i)} \hat{y}^{(i)\top} W]$
 - 7: $W \leftarrow W + \gamma W$ ▷ update W
 - 8: **return** W, μ, σ .
-

Algorithm 2 COMP CT LE RNING

- 1: **for** $k=1 \dots$ **do**
 - 2: Sample $\{(x^{(i)}, y^{*(i)})\}_{i \in [B]}$ from \mathcal{D}
 - 3: $W, \mu, \sigma \leftarrow \text{GH}(\{y^{*(i)}\}_{i \in [B]}, W, \mu, \sigma)$
 - 4: $z^{(i)} = R_\phi(x^{(i)}), \forall i \in [B]$
 - 5: $y^{(i)} = \sqrt{\sigma^2 + \epsilon} W z^{(i)} + \mu, \forall i \in [B]$
 - 6: Update ϕ with $\mathcal{L} = \frac{1}{B} \sum_{i=1}^B \|y^{(i)} - y^{*(i)}\|_1$
 - 7: **end for**
-

One can simply use deterministic PC to define W instead of using GH. However this requires significant computing time before starting the training, especially when dealing with a large number of data instances of high dimensionality. In contrast, GH amortizes the computational effort over the training procedure leading to a better handling of the largest test cases.

C. Training the Compact Learning Model

The training process of COMP CT LE RNING is summarized in Algorithm 2 which jointly learns the principal components W and the mapping R . Each iteration samples a mini-batch of size B and applies the GH algorithm (line 3 in Algorithm 2). The mapping R then produces $z^{(i)}$ for each input $x^{(i)}$ and the output $y^{(i)}$ is obtained through the mapping $W z^{(i)}$ and a denormalization step (line 5 in Algorithm 2). Finally, the parameters ϕ associated with R are updated using backpropagation from the loss function \mathcal{L} , which captures the mean absolute error between the prediction $y^{(i)}$ and the optimal solution $y^{*(i)}$ (ground truth).

D. Restoring Feasibility

The predictions from COMP CT LE RNING may violate the physical and engineering constraints of the C-OPF. Some applications are required to address these infeasibilities and this study considers two post-processing methods for this purpose: (1) solving the power flow problem; and (2) warm-starting the exact C-OPF solver.

1) *Power Flow*: The power flow problem, seeded with a prediction from the COMP CT LE RNING model, restores the

feasibility of the physical constraints. Formally, the power flow problem can be formulated as:

$$\begin{aligned} &\textbf{find} && p^g, q^g, v, \theta, \\ &\textbf{subject to} && \text{Eq. (5a), (5b),} \\ &&& \text{Eq. (6).} \end{aligned} \quad (10)$$

In the power flow problem, like in [10], the active power injections and voltage magnitudes at the PV buses are fixed to the predictions. The power flow problem can then be solved by the Newton method to satisfy the physical constraints, i.e., *Ohm's law* (Eq. (5a) and (5b)) and *Kirchhoff's Current Law* (Eq. (6)). Finding a solution to the PF problem typically takes significantly less time than solving the C-OPF. However, the solution may violate some of the engineering constraints of the C-OPF.

2) *Warm-Starting the C-OPF solver*: It is possible to remove all infeasibilities by warm-starting an C-OPF solver with the COMP CT LE RNING predictions. This study uses the primal-dual interior point algorithm IPOPT as a solver, which is a standard tool for solving C-OPF problems [32], [40]. Moreover, warm-starts for the primal-dual interior point algorithm seem to benefit significantly from dual initial points. Hence, the COMP CT LE RNING model was generalized to predict dual optimal values for all constraints in addition to the primal optimal solutions. IPOPT is then warm-started with both primal and dual predictions to obtain an optimal solution.

VI. COMPUTATION EXPERIMENTS

A. The Experiment Setting

The performance of COMP CT LE RNING is demonstrated using nine test cases from PGLIB v21.07 and the realistic version of the French power system (denoted as *France_2018*) as described in Table I. A total of 52,000 instances were generated. 50,000 instances are used for training and the remaining 2,000 instances are tested for reporting the performance results. For the PGLib cases, these instances were obtained by perturbing the load demands as Eq (9) in Section IV: For *France_2018*, 100,000 instances for training are generated by perturbing the instances in September. Specifically, the upper bounds of active generation of the wind and hydro renewable generators are perturbed by replacing with the samples from $\mathcal{N}(\bar{p}_i^g, 0.2(\bar{p}_i^g - p_i^g))$. Also, the upper bounds of solar generators and load demands are perturbed by multiplying factor sampled from multivariate Gaussian $\mathcal{N}(\cdot, \Sigma)$ where Σ is based on the correlation coefficient of 0.8. Those perturbed upper bound of active generation is ensured to be greater than or equal to the lower bound of it. Also, 2000 realistic test instances are extracted from the instances in October for reporting the performance. As such, for this test case, the distribution of test instances is not necessarily the same as that of the training instances. Note that accurate renewable forecasting would improve the quality of the training instances, but this experiment setting for *France_2018* should provide realistic and difficult circumstances where the model may be deployed for real operations. The instances were solved using Pyomo [41] and IPOPT v3.12 [34] with the HSL ma27 linear solver.

The performance of COMP CT LE RNING is compared with the plain approach that directly outputs the optimal solution. In [10], four fully-connected layers followed by ReLU activations are used for the mapping functions for both COMP CT LE RNING and plain learning approaches. For the plain approach, two distinct models are experimented; the first model, which is named PL IN-L RGE, has d hidden nodes for each fully-connected layer (where d is the output dimension). The second baseline, which is named PL IN-SM LL, has the p hidden nodes for each layer (where p is the number of principal components considered in COMP CT LE RNING). The COMP CT LE RNING model has the same number of weight parameters as PL IN-SM LL, but the last layer of the COMP CT LE RNING model is learned through GH . Indeed, PL IN-SM LL has an encoder-decoder structure as the number of the hidden nodes is smaller than that of the output. The ratio of p to d , which is also called principal component ratio, is set to 5% for six smaller test cases (up to 6515_rte) and to 1% for four bigger cases. Mini-batch of 64 instances is used, and the maximum epoch is set to 1,000. The models are trained using the Adam optimizer [42] with a learning rate of $1e-4$, which is decreased at 900 epochs by 0.1. The overall implementation used PyTorch and the models were trained on a machine with a NVIDIA Tesla V100 GPU and Intel Xeon 2.7GHz. For GH (Algorithm 1), the momentum parameter is set to 0.9999 from the second iteration. The initial and minimum learning rate (γ_{init} and γ_{min}) are set to $1e-4$, and $1e-8$, respectively. The parameter ϵ to prevent ill-conditioning is set to $1e-8$.

B. Learning Performance

Table III reports the accuracy of the models for predicting optimal solutions. Five distinct models with randomly initialized trainable parameters per method were trained: the results report the average results and the standard deviations (in parenthesis). The table shows the averaged value of optimality gaps and maximum constraint violations on the 2,000 test instances. The optimality gap is calculated as $100 \times \left| \frac{f(y) - f(y^*)}{f(y^*)} \right|$ where $f(y)$ is the objective function (1). It also reports the maximum constraint violations (in per unit), which is computed as

$$\max_i \{ \max_j \{ \max \{ g_j(y), 0 \}, \max \{ |h_j(y)| \} \} \}, \quad (11)$$

where $g_i(y)$ and $h_i(y)$ are, respectively, the inequality and equality constraints enumerated in Model 1. The first two sets of columns represent the performance of the plain approaches. Note that, because of the high dimensionality of the output and the limited GPU memory, PL IN-L RGE is only applicable to the four smaller test cases (up to 3022_goc): this is the limitation that motivated this study. When comparing the two plain models, PL IN-L RGE performs better than PL IN-SM LL as PL IN-SM LL trades off the accuracy for scalability. COMP CT LE RNING almost always performs better than the two plain approaches. In particular, it produces predictions with significantly fewer violations (sometimes by an order of magnitude), while also delivering smaller optimality gaps on the larger test cases.

Test case	PL IN-SM LL		PL IN-L RGE		COMP CT LE RNING (proposed)	
	Opt. Gap(%)	Viol.	Opt. Gap(%)	Viol.	Opt. Gap(%)	Viol.
300_ieee	0.9886(0.0287)	3.7282(0.0758)	0.1804 (0.0087)	0.9256(0.0117)	0.1859(0.0079)	0.5509 (0.0025)
793_goc	0.0579(0.0067)	3.1791(0.0985)	0.0182 (0.0013)	0.5825(0.0046)	0.0305(0.0046)	0.2768 (0.0033)
1354_pegase	0.1494(0.0142)	6.6858(0.1248)	0.0711 (0.0094)	3.0360(0.1221)	0.0942(0.0089)	0.5044 (0.0081)
3022_goc	0.0745(0.0105)	3.2394(0.0846)	0.0588(0.0094)	1.5837(0.1432)	0.0485 (0.0076)	0.3906 (0.0185)
4917_goc	0.0852(0.0118)	2.6590(0.1006)	-	-	0.0527 (0.0087)	0.5456 (0.0276)
6515_rte	0.7232(0.0364)	5.8648(0.2185)	-	-	0.3065 (0.0177)	0.7519 (0.0290)
9241_pegase	0.1521(0.0138)	6.7379(0.1980)	-	-	0.1344 (0.0097)	1.1791 (0.0725)
13659_pegase	0.0910(0.0057)	4.8141(0.0685)	-	-	0.0745 (0.0046)	1.2915 (0.0497)
30000_goc	0.2296(0.0224)	4.7172(0.0678)	-	-	0.1091 (0.0112)	0.0770 (0.0188)
France_2018	1.4872(0.1352)	47.4012(3.4524)	-	-	1.2869 (0.0845)	2.1041 (0.2218)

TABLE III: Performance Results of COMP CT LE RNING (Proposed) and Conventional Plain Learning approaches (Baselines). Std. dev. in parenthesis is evaluated across five independent runs. *Viol.*: the mean value of the maximum constraint violations (in per unit) on the test instances. The best optimality gap (*Opt. Gap*) and maximum violation values are in bold.

Table IV shows the number of trainable parameters of the COMP CT LE RNING model and the plain approaches. The architectures of COMP CT LE RNING and PL IN-SM LL are exactly the same, except for the last layer: hence the number of trainable parameters of COMP CT LE RNING is smaller than those for PL IN-SM LL by the dimension of W . Table IV clearly shows that COMP CT LE RNING has the smallest number of trainable parameters. Overall, Table III and Table IV indicate that COMP CT LE RNING provides an accurate and scalable approach to predict C-OPF solutions.

C. Post-processing: Power Flow

One model among five trained models was randomly chosen for testing post-processing approaches and the results were evaluated on the same 2,000 test instances. Table V reports the constraint violations after applying the power flow model seeded with the predictions from the COMP CT LE RNING and PL IN-SM LL models. The table also reports the time to solve the power flow problem. The results show that COMP CT LE RNING produces power flow solutions with the smallest constraint violations, sometimes by an order of magnitude. The results of COMP CT LE RNING are particularly impressive because the majority of the constraints are satisfied after applying the power flow. Note also that the power flow is fast enough to be used during real-time operations, opening

Test case	PL IN-SM LL	PL IN-L RGE	COMP CT
300	0.045	2.479	0.019
793	0.274	14.487	0.122
1354	0.818	46.041	0.321
3022	3.631	200.572	1.499
4917	9.795	-	4.074
6515	17.202	-	7.353
9241	6.796	-	2.268
13659	16.954	-	4.442
30000	60.610	-	16.067
France	51.612	-	30.510

TABLE IV: The Number of Trainable Parameters (in Millions) in the Models Trained by COMP CT LE RNING and Plain approaches.

interesting avenues for the use of learning and optimization in practice.

D. Post-processing: Warm-start

Table VI and Figure 4 report the results for warm-starts. The proposed warm-starting approach, WS:COMP CT(P+D), is compared with the following warm-starting strategies:

- Flat Start: p^g, q^g, v are started with their minimum values, and initial θ is set to zero. This is a default setting without warm-start.
- WS:DC-OPF(P): Motivated from [20], the primal solution of the DC-OPF is used as a warm-starting point for solving C-OPF.
- WS: C-OPF(P): The primal solution of the C-OPF is used as a warm-starting point for solving C-OPF again.
- WS:PL IN-SM LL(L RGE)(P): The primal predictions from the plain approaches are used as warm-starting points.
- WS:PL IN-SM LL(L RGE)(P+D): The primal and dual predictions from the plain approaches are used as warm-starting points.
- WS:COMP CT(P): The primal predictions from COMP CT LE RNING are used as warm-starting points.
- WS:COMP CT(P+D): The proposed warm-starting approach. The primal and dual predictions from COMP CT LE RNING are used as warm-starting points.

Obviously, WS:DC-OPF(P) and WS: C-OPF(P) need to solve the first problem to obtain the warm-starting points. For those, the time taken to solve the first problem is excluded in the reported elapsed time performance. Note that WS: C-OPF(P) gives a virtual upper bound of the speed-up for primal-only warm-start for the primal-dual interior point algorithm. Also note that except for DC-OPF, the experiment does not include other convex relaxations of C-OPF (e.g., the quadratic convex relaxation [43] and the semidefinite programming relaxations [44]), since solving those relaxed problems takes significant time.

To predict dual solutions, an additional mapping function consisting of four fully-connected layers is trained for COMP CT LE RNING and the plain approaches. The sizes of these networks are the same as those for the primal solutions. When

Test case	PL IN-SM LL					COMP CT LE RNING				
	Eq.(3a-4)		Eq. (7)		Time sec.	Eq.(3a-4)		Eq. (7)		Time sec.
	Viol.(p.u.)	Sat(%)	Viol.(MV)	Sat(%)		Viol.(p.u.)	Sat(%)	Viol.(MV)	Sat(%)	
4917_goc	0.1148	99.77	13.5821	99.47	1.07	0.0739	99.88	2.3134	99.50	1.15
6515_rte	0.2220	99.80	6.0533	99.92	1.54	0.0841	99.92	1.5261	99.95	1.58
9241_pegase	0.1338	99.47	10.3893	99.98	3.63	0.0893	99.82	2.4869	99.97	3.58
13659_pegase	0.2192	99.85	14.5279	99.99	7.11	0.0852	99.97	3.1203	100.00	7.01
30000_goc	0.0249	99.97	4.5279	100.00	10.27	0.0192	100.00	1.1958	100.00	10.11
France_2018	0.4073	99.98	11.5033	99.02	1.86	0.3788	99.98	3.2053	99.08	1.93

T BLE V: veraged Maximum Violations and Ratio of Satisfied constraints (%) after pplying the Power Flow to C-OPF Problems with >4,000 Buses.

	Primal Dual	4917	6515	9241	13659	30000	France
Flat Start		8.90s	69.90s	44.67s	42.79s	163.48s	26.78s
WS: C-OPF(P)	X	6.64s(1.34x)	10.10s(7.06x)	20.27s(2.22x)	28.45s(1.53x)	116.33s(1.43x)	9.66s(2.62x)
WS:DC-OPF(P)		10.68s(0.83x)	75.55s(0.90x)	53.59s(0.83x)	51.35s(0.83x)	196.17s(0.83x)	30.11s(0.85x)
WS:PL IN-SM LL(P)		6.69s(1.33x)	10.06s(7.09x)	20.24s(2.22x)	28.24s(1.54x)	116.23s(1.43x)	10.04s(2.54x)
WS:COMP CT(P)		6.63s(1.34x)	10.05s(7.10x)	20.38s(2.21x)	28.41s(1.53x)	116.65s(1.43x)	9.83s(2.61x)
WS:PL IN-SM LL(P+D)		3.16s(2.89x)	5.12s(14.79x)	17.31s(3.17x)	14.31s(3.05x)	16.54s(10.98x)	7.98s(3.65x)
WS:COMP CT(P+D)		2.49s(3.62x)	4.86s(15.26x)	15.59s(3.58x)	10.32s(4.23x)	15.66s(11.43x)	5.90s(4.84x)

T BLE VI: veraged Elapsed Times (s) to Solve the C-OPF Problems with >4,000 Buses and veraged Speed-up Factor to Flat Start. The Best Values are in Bold.

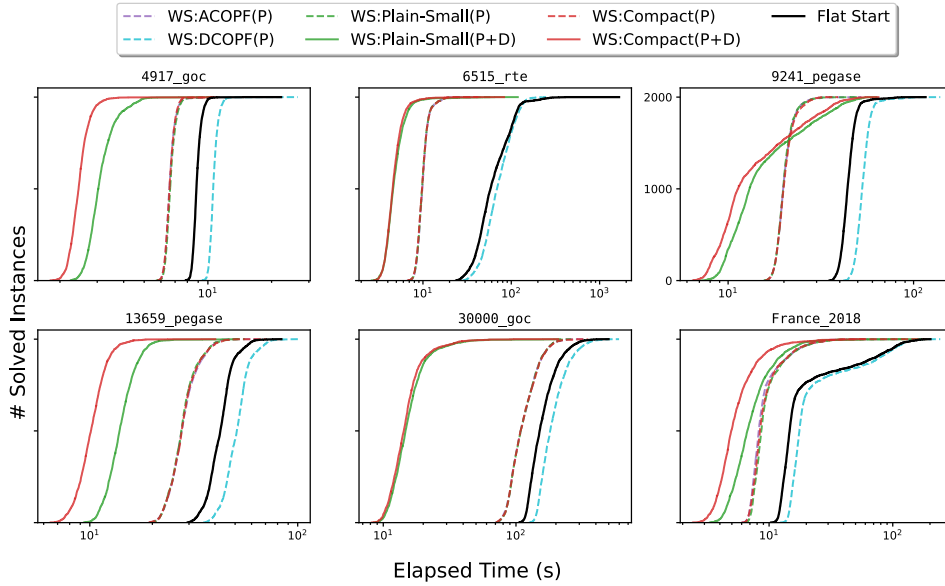


Fig. 4: The Number of C-OPF Instances Solved Within Various Elapsed Time Limits by Warm-Start (WS) and Flat Start.

using both the primal and dual warm-starting, the initial barrier parameter of IPOPT is set to $1e-6$ because the initial warm-starting point is closer to the optimal than the flat start. The convergence tolerance is set to $1e-4$ for all cases.

Table VI reports the elapsed times and the corresponding speed-up ratio for the warm-start approaches. The first key observation is that it is critical to use both primal and dual warm-starts: only using the primal predictions is not effective in reducing the computation times of IPOPT. This is not too surprising given the implementation of interior-point methods. Primal-dual warm-starts however produce significant

benefits. WS:COMP CT(P+D) produces the best results for all test cases. In particular, it yields a speed-up of $15.26\times$ for 6515_rte. Iso, even for the realistic French system (France_2018), WS:COMP CT(P+D) gives a speed-up of $4.84\times$. This is significant given the realism of this test case and highlights the potential of the combination of COMP CT LE RNING and optimization to deploy C-OPF in real operations. Observe also that WS:COMP CT(P+D) strongly dominates the other approaches, including its (WS:PL IN-SM LL(P+D) counterpart. This was anticipated by its prediction errors reported earlier. Figure 4 depicts these results

visually: it plots the number of C-OPF instances solved over time by the various warm-starting methods. The plot clearly demonstrates the benefits of COMP CT LE RNING for predicting both primal and dual solutions.

VII. CONCLUSIONS

This paper has proposed COMP CT LE RNING, a novel approach to predict optimal solutions to industry size OPF problems. COMP CT LE RNING was motivated by the lack of scalability of existing ML methods for this task. This difficulty stems from the dimension of the output space, which is large-scale in industry size C-OPF problems. To address this issue, COMP CT LE RNING applies the PC on the output space and learns in the subspace of a few leading principal components. It then combines this learning step with the GH to learn the principal components, which is then used to transform the predictions back into the output space. Experimental results on industry size OPF problems show that COMP CT LE RNING is more accurate than existing approaches both in terms of optimality gaps and constraint violations, sometimes by an order of magnitude.

The paper also shows that the predictions can be used to accelerate the C-OPF. In particular, the results show that the power flow problems seeded by the COMP CT LE RNING predictions have significantly fewer violations of the engineering constraints (while satisfying the physical constraints) for systems with up to 30,000 buses. Moreover, and even more interestingly, COMP CT LE RNING can be used to warm-start an OPF solver with optimal predictions for both the primal and dual variables. The results show that COMP CT LE RNING can produce significant speed-ups.

Together these results indicate that COMP CT LE RNING is the first method to produce high-quality predictions for the industry size OPFs that translate to significant practical benefits. There are also many opportunities for future research. COMP CT LE RNING is general-purpose and can be applied to other problems with large output space, which is typically the case in optimization. Nonlinear compression through autoencoder structure can be also considered for general-purpose optimization learning. On OPF problems, the performance of COMP CT LE RNING can be improved by adopting concepts from Lagrangian Duality, physics-informed networks, and different types of backbone architectures. The dual solution learning is particularly challenging in the experiments given its high dimensionality, and it would be interesting to study how it could be improved and simplified. Also, COMP CT LE RNING can be extended to learning solutions to more challenging problems such as Optimal Transmission Switching and Security-Constrained OPF in power system applications.

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