Network Orchestration in Mobile Networks via a Synergy of Model-driven and AI-based Techniques

Yantong Wang
Department of Engineering
King’s College London
London, WC2R 2LS, U.K.
yantong.wang@kcl.ac.uk

Vasilis Friderikos
Department of Engineering
King’s College London
London, WC2R 2LS, U.K.
vasilis.friderikos@kcl.ac.uk

Abstract—As data traffic volume continues to increase, caching of popular content at strategic network locations closer to the end user can enhance not only user experience but ease the utilization of highly congested links in the network. A key challenge in the area of proactive caching is finding the optimal locations to host the popular content items under various optimization criteria. These problems are combinatorial in nature and therefore finding optimal and/or near optimal decisions is computationally expensive. In this paper a framework is proposed to reduce the computational complexity of the underlying integer mathematical program by first predicting decision variables related to optimal locations using a deep convolutional neural network (CNN). The CNN is trained in an offline manner with optimal solutions and is then used to feed a much smaller optimization problems which is then used to solve the optimal caching allocation problem using Mixed Integer Linear Programming (MILP) formulations that take into account resource availability in different edge clouds and communication cost. However, we end up with NP-hard optimization problems which cannot be deemed suitable to support real-time decision making.

Deep learning (DL) frameworks are gaining significant attention in network research and already DL techniques have been used for resource management, routing and other network related operations. DL techniques has also made their way into the caching problems. However, most of them focus on the content popularity prediction and there are few works dealing with the problem of finding optimal caching locations. Closely related works can be find in [10] and [11], where the former trains a deep neural network (DNN) for solving linear programming problem and the latter apply DNN to answer linear sum assignment problem. As aforementioned, the caching allocation problem belongs to NP-hard family and it is harder than solving linear programming or linear sum assignment problem. In this paper, the principal idea is representing the proposed optimization problem as a grayscale image which is then used to train a deep CNN with optimal solutions. Even though caching problems belong to the general class of NP-hard problems, this relate to the worst case complexity. In other words, the difficulty of solving these type of problems are considered under their hardest case and in reality many small to medium search space instances can be solved very efficiently. It is this feature and characteristic of the problem that we aim to explore with the proposed CNN. In that respect the CNN provides an estimation of suitable edge cloud locations for hosting popular content that can be used for real-time decision making. As will be discussed in the sequel, the proposed technique manages to provide better decision making than nominal real time techniques that are based on greedy heuristics. Hence the proposed framework can be considered as an amalgamation between model based and data-driven techniques.

I. INTRODUCTION

SINCE 2016 when AlphaGo managed to win the 18-times world champion Lee Sedol at the Go match[1], AI techniques started to attract significant attention from both academia and industry within the ICT sector for a plethora of different diverse complex network management applications both at the control and data plane. Even though we are still in a rather embryonic stage in adopting these types of technologies, the potential benefits of deep learning techniques are significant to tame the underlying complexity of the emerging highly heterogeneous 5G and beyond mobile networks. In current work, our attention is on the issue of proactive caching of popular content using an amalgamation of model based techniques and deep learning in the form of convolutional neural networks (CNNs). Caching of popular content is a key technique to enhance user experience and overall network performance; it has attracted an overwhelming research attention recently [11].

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II. SYSTEM MODEL

A mobile network is represented with a graph (undirected) \( \mathcal{G} = \{ \mathcal{V}, \mathcal{L} \} \), in which \( \mathcal{V} \) represents the nodes in the network and \( \mathcal{L} \) denotes the communication links. A subset \( \mathcal{E} \subseteq \mathcal{V} \)}
of the network nodes are the edge clouds (ECs), or content routers (as commonly named). By \( \mathcal{A} \subseteq \mathcal{V} \), the set of access routers (ARs) is that mobile users connect to as they change point of attachment due to their mobility. Hereafter we assume that mobility information is readily available using historical data that an operator can explore. Also note that the following might hold \( \mathcal{E} \cap \mathcal{A} \neq \emptyset \), which means a subset of access routers can be deemed suitable to cache popular content.

In the sequel a salient assumption is that there is one flow request per user and \( k \in \mathcal{K} \) is defined as the set of flows routed through the network. Each request \( k \) characterized by the following 3-tuple properties: \( s_k \), which represents the requested memory space for caching content of flow \( k \); \( b_k \), the requested data rate of flow \( k \) and \( p_{ka} \) which denotes the likelihood for flow \( k \) to move to AR \( a \), where \( a \in \mathcal{A} \). With the same token, for each candidate EC \( e \in \mathcal{E} \) we denote with \( w_e \) the available memory for storage in EC \( e \) and for each link \( l \in \mathcal{L} \) we denote the remaining capacity as \( c_l \). Additionally, \( N_{ae} \) is the hop counter between connected point \( a \) and caching host \( e \) via the shortest path. Expressly, \( N_{ae} = 0 \) iff \( a = e \); by \( N_T \) the number of hops is represented from access point to data center, whose average value is between 10 and 15 in the current network [13]. \( \alpha \) and \( \beta \) are the weight of hosting and transmission cost respectively. The following 0/1 decision variables are introduced that will lead to the proposed integer programming formulation in the sequel,

\[
\begin{align*}
x_{ke} &= \begin{cases} 
1, & \text{if content for flow } k \text{ is hosted at EC } e \\
0, & \text{otherwise}
\end{cases} \\
y_{kl} &= \begin{cases} 
1, & \text{if flow } k \text{ use link } l \\
0, & \text{otherwise}
\end{cases} \\
z_{kae} &= \begin{cases} 
1, & \text{if flow } k \text{ connect with } a \text{ and retrieve the cached content from EC } e \\
0, & \text{otherwise}
\end{cases}
\end{align*}
\]

The total cost (\( TC \)) in this paper consist of two pieces:

\[
TC = \alpha \cdot C^C + \beta \cdot C^T
\]  

Specifically, \( C^C \) is the hosting cost as follows [14]:

\[
C^C = \sum_{k \in \mathcal{K}} \sum_{e \in \mathcal{E}} \frac{x_{ke}}{1 - U_e}
\]  

and \( U_e \) is the space utilization level at EC \( e \). So those ECs with less memory usage take the priority over the others in host selection. The value of \( U_e \) relies on how many contents have been allocated to this EC:

\[
U_e = \frac{\sum_{k \in \mathcal{K}} s_k \cdot x_{ke}}{w_e} = \sum_{k \in \mathcal{K}} q_{ke} \cdot x_{ke}, \forall e \in \mathcal{E}
\]  

where \( q_{ke} = s_k / w_e, \forall k \in \mathcal{K}, e \in \mathcal{E} \), which indicates the effect of caching selection on space utilization level. Then \( C^C \) can be expressed as

\[
C^C = \sum_{k \in \mathcal{K}} \sum_{e \in \mathcal{E}} \frac{x_{ke}}{1 - \sum_{k \in \mathcal{K}} q_{ke} x_{ke}}
\]

In that case \( C^C \) is the ratio of two linear terms, where the decision variable \( x_{ke} \) in the denominator makes it non-linear. So we can apply some integer linear programming solvers if \( C^C \) is transformed to a linear function. It is noting that the value of the denominator is positive due to the fact that the memory used for caching should be less than the entire available space, which is a constraint in the sequel. According to [2], the main trick is introducing auxiliary decision variables \( \chi_{ke} = t_e \cdot x_{ke} \) and we define

\[
t_e = \frac{1}{1 - \sum_{k \in \mathcal{K}} q_{ke} \cdot x_{ke}}, \forall e \in \mathcal{E}
\]  

This definition is equivalent to the following constraints:

\[
\begin{align*}
t_e &= \sum_{k \in \mathcal{K}} q_{ke} \cdot x_{ke} t_e = 1, \forall e \in \mathcal{E} \\
t_e &> 0, \forall e \in \mathcal{E}
\end{align*}
\]

Considering \( t_e \) is a fractional variable while \( x_{ke} \) is binary, the value of \( \chi_{ke} \) is bounded by constraints:

\[
\begin{align*}
\chi_{ke} &\leq t_e, \forall k \in \mathcal{K}, e \in \mathcal{E} \\
\chi_{ke} &\leq M \cdot (x_{ke} - 1), \forall k \in \mathcal{K}, e \in \mathcal{E}
\end{align*}
\]

and \( M \) is a sufficiently large number. Then we rewrite \( C^C \) in the terms of \( \chi_{ke} \)

\[
C^C = \sum_{k \in \mathcal{K}} \sum_{e \in \mathcal{E}} \chi_{ke}
\]

\( C^T \) denotes the communication cost which is considered as hop count distance from mobile user to the caching host or data center,

\[
C^T = C^H + C^M = \sum_{k \in \mathcal{K}} \sum_{a \in \mathcal{A}} \sum_{e \in \mathcal{E}} p_{ka} N_{ae} z_{kae} + \sum_{k \in \mathcal{K}} \left( 1 - \sum_{a \in \mathcal{A}} \sum_{e \in \mathcal{E}} p_{ka} z_{kae} \right) N_T
\]

where \( C^H \) and \( C^M \) describes the cost of cache hitting and missing respectively. The connected AR \( a \) of user \( k \) is not determined but narrated by the moving probability \( p_{ka} \) so \( C^T \) is the expected value of transmission hops in [9]. If the requested content is caching in the connected access point, the transmission cost will not be paid since \( N_{ae} = 0 \); another case is that the mobile user attach in AR and retrieve to EC, then \( C^H \) is going to be considered for the transport; otherwise the system will suffer from large transmission cost \( C^M \) due to cache missing.

Therefore, the proactive caching problem with the aim of providing interested contents allocations to minimize total cost is formulated as follows,

\[
\begin{align*}
\min_{t_e, x_{ke}, \chi_{ke}} & \quad \alpha \sum_{k \in \mathcal{K}} \sum_{e \in \mathcal{E}} \chi_{ke} + \beta \left( \sum_{k \in \mathcal{K}} \sum_{a \in \mathcal{A}} \sum_{e \in \mathcal{E}} p_{ka} N_{ae} z_{kae} + \left( 1 - \sum_{a \in \mathcal{A}} \sum_{e \in \mathcal{E}} p_{ka} z_{kae} \right) N_T \right) \\
\text{s.t.} & \quad \sum_{e \in \mathcal{E}} x_{ke} \leq 1, \forall k \in \mathcal{K}
\end{align*}
\]
\[ \sum_{k \in K} s_k \cdot x_{ke} \leq w_e, \forall e \in E \]  
\[ \sum_{e \in E} z_{kae} \leq 1, \forall k \in K, a \in A \]  
\[ w_{ke} \leq x_{ke}, \forall k \in K, a \in A, e \in E \]  
\[ \sum_{k \in K} b_k \cdot y_{kl} \leq c_l, \forall l \in L \]  
\[ y_{kl} \leq \sum_{a \in A, e \in E} B_{lae} \cdot z_{kae}, \forall k \in K, l \in L \]  
\[ M \cdot y_{kl} \geq \sum_{a \in A, e \in E} B_{lae} \cdot z_{kae}, \forall k \in K, l \in L \]  
\[ t_e - \sum_{k \in K} q_{ke} \chi_{ke} = 1, \forall e \in E \]  
\[ \chi_{ke} \leq t_e, \forall k \in K, e \in E \]  
\[ \chi_{ke} \leq M \cdot x_{ke}, \forall k \in K, e \in E \]  
\[ \chi_{ke} \geq M \cdot (x_{ke} - 1) + t_e, \forall k \in K, e \in E \]  
\[ x_{ke}, y_{kl}, z_{kae} \in \{0,1\}, \forall k \in K, l \in L, a \in A, e \in E \]  
\[ t_e \cdot \chi_{ke} > 0, \forall k \in K, e \in E \]  

Constraint (10f) forces at most 1 EC to provide caching service for a mobile user, (10g) considers the storage limitation for each EC and (10h) represents the bandwidth capacity for individual link. The retrieved path is expressed in (10i) and (10j), where the former enforces the route is unique when flow and AR are determined and the latter guarantee the destination store the required information. Furthermore, constraint (10k) indicates that once the path is selected for retrieving, all the links on this route should be taken into consideration and (10l) describe the contrary case, where (10m) is a binary indicator which is set to 1 if the link \( l \) locates in the shortest path between AR \( a \) and EC \( e \) and is set to 0 otherwise. This three dimension matrix can be constructed from network topology. The constraint (10n) as well as (10o) to (10p) constitute the definition of auxiliary variable \( t_e \) and \( \chi_{ke} \) respectively, which are used to linearize the objective function (10q).

### III. PROPOSED AI-BASED APPROACH

#### A. Training Process

The training process mainly comprise four steps as illustrated in Figure 1. In step i, we construct the mathematical model from the network as represented in Section II.

In step ii, we generate the grayscale image by extracting the main characters of optimization model (10). Depending on the analysis of optimal solutions, we find that once the network topology is fixed, these parameters which relies on the network topology, such as \( N_{ae} \) and \( B_{lae} \), have very limited contribution to the final allocations. On the contrast, those variables describing the user behavior, resource requirements and current network resource distribution play an important role in the cache assignment. For instance, those ECs, which have more available storage space and more closed to mobile users, have higher probability to be picked as caching host than the others. In our problem, we extract the user moving probability \( p_{ka} \), interested content storage requirement \( s_k \), required bandwidth \( b_k \), available space in each EC \( w_e \) and available link capacity \( c_l \) as the key parameters of problem (10) to construct the grayscale image. However, these five variables have different dimensions. For the aim of dimension matching, we use \( q_{ke} \) which is introduced in Section III as a combination of \( s_k \) and \( w_e \). Similarly, \( r_{kl} \) is defined as the ratio of \( b_k \) and \( c_l \), indicating the impact of caching selection on link bandwidth utilization level. Consequently, the two-dimensional grayscale image is composed of \( p_{ka} \), \( q_{ke} \) and \( r_{kl} \) whose size is \( |K| \times (|A| + |E| + |L|) \).

We use the grayscale image as the feature to be learnt by CNN in step iii. The proposed CNN structure is illustrated in Figure 2. It is worth noticing that the original problem is determining the position of each request cache content, i.e. \( x_{ke} \). Similarity to (10), for the aim of reducing the design complexity, the original caching assignment problem is decomposed into a number of independent sub-problems via the first order strategy (15), which demonstrates that the CNN training can be processed in parallel. Each CNN corresponds to a related flow request, whose output is a vector representing the probability of each potential EC for a specific flow.

![Figure 2. Designed CNN Architecture](image_url)

In step iv, we estimate the quality of CNN prediction with the optimal solution via cross entropy loss function:

\[
\text{loss} = - \sum_{i=1}^{\lvert T \rvert} \sum_{e \in E} x_{ke}^i \ln \hat{x}_{ke}^i, k = 1, 2, \cdots, |K| \tag{11}
\]

where \( T \) represents the training dataset, \( x_{ke}^i \) is the training label of \( i^{th} \) sample and \( \hat{x}_{ke}^i \) is the prediction accordingly. CNN is trained recursively to reduce the value of loss function (11).

#### B. Testing Process

Figure 3 illustrates the testing process, where step i, ii and iii are same with training process in subsection III.A.

In step iv, the output of each CNN is a vector where each element representing the confidence of prediction. For example, the output of a CNN is \([0.8, 0, 0.2, 0, 0, 0, 0]\), which
means the CNN is more confident to put the content in EC1 whose value is 0.8 compared with caching in EC3 and the rest ECs are not in consideration. By combining these outputs together, we can get a matrix indicating the preference of caching locations. Based on the previous training progress, we believe it is a small-probability event that the optimal solution locates in these 0 value positions. For the purpose of reducing the number of non-zero elements in the matrix, a threshold $\delta$ is set for the predicted probability which force the value less than the threshold to be zero or to be one otherwise. Using a similar methodology with [9], the matrix $O = \{a_{ke}, \forall k \in K, e \in E\}$ after threshold filter can be used to reduce the number of decision variables in optimization problem (10) by adding the following new constraint

$$x_{ke} \leq a_{ke}, \forall k \in K, e \in E$$ (12)

In step $v$ we can efficiently solve the MILP to obtain a caching assignment when a significant part of $O$ is zero.

**IV. NUMERICAL INVESTIGATIONS**

In this section, we evaluate the quality of performance among the solutions derived from the MILP, the proposed CNN and the Greedy Caching Algorithm (GCA) which attempts to assign each flow to its nearest available EC respectively. For the aim of comparing fairly, a penalty would be added to the total cost when constraints are invalided. Table I provides a summary of the key parameters used for numerical investigations.

The data set is constructed via solving the mathematical model (10) by MILP and the samples are based on different scenarios which are represented by the combination of $p_{ke}$, $s_k$, $b_k$, $w_e$ and $c_l$. For the case of $|K| = 5$, we generate 1000 samples where 900 are used for training and the rest for testing. In the training process, 5 CNNs are trained independently with same input grayscale image but different outputs where each output corresponds to a specific mobile user request assignment. Then every 100 samples are built for the scenario of 10, 15 and 20 users respectively to estimate the performance of different approaches, i.e. MILP, CNN and GCA. In order to use trained CNN solving these scenarios, we split the input grayscale image into several same size sub images whose height matches the number of batched CNNs which is 5 in this paper. After that trained CNNs are used for predicting the allocation of sub images and update the unassigned sub images. For instance, when reading a grayscale image representing 15 users, we separate them into 3 sub images whose size is 5 users. Then we call the trained batched CNNs to solve the first sub image and update the rest two depending on the preceding allocation by selecting the EC with the maximum predicted probability, such as updating the value of $q_{ke}$ via

$$q_{ke} = \frac{s_k}{w_e - \sum_{k' \in K'} s_{k'k'}}, \forall k \in K - K'$$

where $K'$ is the set of mobile users who have already been assigned. We keep doing that process recursively until all the users’ requests are allocated.

In Table II the performances of these approaches are compared. The mean computation time can be viewed as the time complexity for these three algorithms. When it comes to CNN, time is tracked between loading the grayscale image and receiving the solution of optimization problem excluding the period used for training. Then we calculate the average total cost with invalided constraints penalty among these methods. Next, we collate the final precision of these solutions of 100 test samples which is calculated by

$$\text{precision} = \frac{1}{100} \sum_{i=1}^{100} \frac{|X^i \cap \hat{X}^i|}{|X^i|}$$

where $X^i$ is the optimal solution of $i^{th}$ sample and $\hat{X}^i$ is the solution of estimated algorithms. After that the feasible ratio are investigated which is the percentage of the constraint-satisfied assignments. In addition, the maximum total cost difference with the optimal solution MILP are analyzed, which represents the quality gap of solutions in the worst case. Finally, the average number of decision variables of MILP and CNN in the 100 testing samples are expressed.

As shown in Table II the GCA can finish caching allocations within 0.1s in all scenarios, which is the fastest

| Parameter | Value |
|-----------|-------|
| degree per node | 2–5 |
| mobile end users (|K|) | {5, 10, 15, 20} |
| number of links (|E|) | 20 |
| number of access routers (|A|) | 7 |
| number of edge clouds (|K|) | 6 |
| weight of hosting a cache ($\alpha$) | [0, 1] |
| weight of communication cost ($\beta$) | [0, 1] |
| threshold of prediction probability ($\delta$) | 0.001 |
| end user request content size ($s_k$) | [10, 50] MB |
| available cache size in EC ($w_e$) | [100, 500] MB |
| user request transmission bandwidth ($b_k$) | [1, 10] Mbps |
| link available capacity ($c_l$) | [50, 100] Mbps |

2 Simulations run on MATLAB 2019b in a 64-bit Windows 10 environment on a machine equipped with an Intel Core i7-7700 CPU 3.60 GHz Processor and 16 GB RAM.
Table II

| Methods | Computation Time | Mean TC | Precision | Feasible Ratio | Maximum Diff | number of decision variables |
|---------|------------------|---------|-----------|----------------|--------------|-----------------------------|
| 5 requests |                 |         |           |                |              |                             |
| MILP    | 0.49s            | 10.83   | 100.0%    | 100.0%         | 0.03         | 376.0                       |
| CNN     | 0.08s            | 10.83   | 98.8%     | 100.0%         | -            | 246.6                       |
| GCA     | 0.01s            | 17.98   | 63.5%     | 99.8%          | 67.20        | -                           |
| 10 requests |              |         |           |                |              |                             |
| MILP    | 80.96s           | 23.31   | 100.0%    | 100.0%         | -            | 746.0                       |
| CNN     | 0.85s            | 24.32   | 95.4%     | 100.0%         | 1.90         | 484.7                       |
| GCA     | 0.03s            | 58.28   | 57.1%     | 95.2%          | 329.00       | -                           |
| 15 requests |             |         |           |                |              |                             |
| MILP    | 1.38h            | 39.04   | 100.0%    | 100.0%         | -            | 1116.0                      |
| CNN     | 74.94s           | 41.05   | 76.8%     | 100.0%         | 13.70        | 727.9                       |
| GCA     | 0.04s            | 124.75  | 51.9%     | 89.0%          | 463.90       | -                           |
| 20 requests |             |         |           |                |              |                             |
| MILP    | 2.40h            | 64.91   | 100.0%    | 100.0%         | -            | 1486.0                      |
| CNN     | 1.30h            | 68.20   | 67.8%     | 100.0%         | 32.23        | 960.2                       |
| GCA     | 0.08s            | 269.46  | 44.4%     | 80.8%          | 646.10       | -                           |

among the three methods. However, it also has the largest cost payment and the average cost gap with MILP increases from 39.6% to 75.9%. Additionally, the other criteria, such as feasible ratio and maximum difference with optimal solution, become worse with the increment of mobile users due to the penalty cost of infeasible constraints. From this aspect, GCA can be viewed as the lower-bound of caching assignment. On the other hand, MILP outperforms the rest two approaches with the increase of the number of requests and is the upper-bound which limits the ceiling of performance. The CNN can provide a competitive solution with less time complexity compared with MILP. In the scenario of 5 requests, the proposed CNN performs similarly as MILP where the cost gap is less than 3% even in the worst case. Furthermore, the computation process is accelerated by 6 times because the number of decision variables is decreased by more than 34.4%. Even in the case of 15 flow requests, CNN speed up the computation process by 75 times with less than 5% loss on total cost. However, the calculation time of proposed algorithm becomes more than 1 hour in 20 requests since the number of decision variables 960.2 is still relatively large for an optimization problem even after CNN reduction. Moreover, the feasible ratio of CNN keeps 100% in the testing. This is expected because the constraints in proposed algorithm is stricter than MILP with one more limitation (12).

V. CONCLUSIONS

AI-based data-driven techniques are attracting significant research attention in taming the complexity of 5G and beyond networks. This work presents a framework where a data-driven technique in the form of a deep convolutional neural network is amalgamated with a model based technique in the form of an integer programming optimization problem. The CNN is trained offline with optimal decisions for the network is amalgamated with a model based technique in

Leveraging on recent promising results in the area of artificial intelligence is a promising direction for taming the complexity in the operation of emerging and future 5G and beyond networks. To this end, there are various future avenues of research in the area of utilizing AI techniques to provide high quality decision making in real-time. Issues of reliability of the decision making and robustness of the solutions require significant attention.

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