Energy-Aware Deep Learning for Green Cyber-Physical Systems

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Abstract: Today's green computing has to deal with prevalent Cyber-Physical Systems (CPSs), engineered systems that tightly integrate computation and physical components. Green CPS aims to use electronic/computer devices and resources to perform operations as efficiently and eco-friendly as possible. With the rise of smart technology combining with Artificial Intelligence Deep Learning (DL) in Internet of Things and CPSs, continuing use of these compute intensive CPS software like DL can negatively impact energy resources and environments. Much research has advanced green hardware and physical component development. Our research aims to develop green CPSs by making them energy aware. To do this, we propose an analytical modelling approach to quantifying energy consumption of software artifacts in the CPS. The paper describes the approach through energy consumption modelling of DL in distributed CPS due to the popular deployment of DL in many modern CPSs. However, the approach is general and can be applied to any CPS. The paper illustrates the application of our approach for energy management in scaling and designing smart farming CPS that monitors crop health.

1 INTRODUCTION

Increasing use of electronic/computer devices and its impacts on environments are inevitable. Green computing addresses how to use computers and their resources in an eco-friendly way. This includes designing, manufacturing, using, and disposing these devices to reduce electronic waste and power consumption with the goal to utilize the energy to perform operations as efficiently as possible (Dhaini et al., 2021; Ortiz et al., 2020).

In today's world, cyber-physical systems (CPSs), or engineered systems that tightly integrate computation and physical components (Yu et al., 2020), are everywhere. CPSs drive innovations and enable numerous applications from autonomous vehicles to smart cities and agricultures (Estevez & Wu, 2017; Liang et al., 2018; Yu et al., 2020). With the recent rise of smart technology combining with Artificial Intelligence Deep Learning (DL) in Internet of Things and CPSs, continuing use of these sophisticated computationally intensive CPS software like DL can no longer be ignored as they can unknowingly have negative impacts on energy resources and environments (Estevez & Wu, 2017; Inderwildi et al., 2020). There is a need to develop green computing for CPS.

Research has been studied extensively to develop green CPSs including improving infrastructures (e.g., cloud and data centers) (Ortiz et al., 2020) and finding energy-efficient solutions (e.g., lightweight protocols (Haseeb et al., 2020), energy harvesting (Zeng et al., 2020), or optimizing scheduling (Fu et al., 2019; Liang et al., 2018)) to reduce energy waste and consumption. Some deals with estimating energy consumption (Horcas et al., 2019; Liang et al., 2018) and some (Bouguera et al., 2018) focuses on energy usage of certain communication protocols and sensor devices. While much work has advanced green hardware and physical component development, it appears that green computing software has lagged. To build and sustain green computing systems, the ability to monitor and quantify energy usage of software is as crucial as that of hardware artifacts. The estimated energy consumption can be useful for managing energy resources, planning and designing greener systems, or identifying possible power/energy savings.

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Existing approaches employ power measurement tools (Faviola Rodrigues et al., 2018; Horcas et al., 2019; Li et al., 2016; Mitchell et al., 2018), simulation (Yang et al., 2018) and analytical modeling (Yang et al., 2018). Although these tool-based technique is simple, it is system-specific and relies on probing that may not always be accessible. Using simulation requires understanding of computational behavior of the system and can also take a long time to run.

Our research aims to develop green CPSs by making them *energy aware*. To do this, we propose an analytical modelling approach to quantifying energy consumption of software artifacts in the CPS. Unlike previous analytical approach by Yang et. al, our approach shows explicit modelling using two basic core elements, namely number of MAC operations and frequencies of data access. The paper describes the energy quantification approach through energy consumption modelling of DL in distributed CPS due to the popular deployment of DL in many modern CPSs. The approach is general and can be applied to any CPS. The paper illustrates the application of our approach for energy management in scaling and designing smart farming CPS that monitors crop health.

In summary, the paper has the following contributions: (1) a foundation for energy modeling of software components using primitive basic elements relying on data computation and movement, (2) energy quantification of DL, specifically convolution and artificial neural nets, and (3) application of the DL energy models in designing and scaling smart farming CPS for crop health monitoring.

The rest of the paper is organized as follows. Section 2 discusses related work and Section 3 presents the proposed approach. Section 4 gives details of the approach on specific computing units, particularly, the execution of the trained deep learning model. Our illustration of energy modeling approach on smart farming, including experimental design and setup, is given in Section 5, followed by experimental results in Section 6. The paper concludes in Section 7.

2 RELATED WORK

Most research on energy-related issues in CPSs includes energy management (Ortiz et al., 2020; Zhu et al., 2021), improving infrastructures such as cloud and data centers (Ortiz et al., 2020), energy harvesting (Zeng et al., 2020), and energy efficient solutions. The latter includes scheduling optimization (Fu et al., 2019; Liang et al., 2018; Zhu et al., 2021), energy optimization strategies (Horcas et al., 2019; Hossain et al., 2020) and energy efficient protocols (Haseeb et al., 2020). While useful, all of these approaches, however, either does not estimate energy consumption (Zeng et al., 2020; Zhu et al., 2021) or does that of physical components (Fu et al., 2019; Hossain et al., 2020; Liang et al., 2018). Unlike these studies, we consider energy consumption of software or computing units.

Research in estimating energy consumption of software components uses various techniques. Most rely on power measurement tools e.g., hardware sensors (Mitchell et al., 2018; Zhu et al., 2021), WattsUp? Pro (Horcas et al., 2019), Intel's Running Average Power Limit (RAPL) interface and/or nvidia-smi (Li et al., 2016), and the Streamline Performance Analyser (Faviola Rodrigues et al., 2018). These tools are used to measure actual energy consumption, then report energy usage or build energy model. However, these tool-based approach can be hardware specific and can only measure energy at the device level. They are unable to measure specific software computation.

Another technique uses simulation to estimate energy consumption of software units (Yang et al., 2018). It estimates energy consumption of deep learning based on two factors: number of Multiply-and-Accumulate (MAC) operations and data movement in the hierarchy. The number of MACs and data accesses are obtained through simulation. In general, although the approach gives accurate results, it requires long runtime for large software component. Moreover, it requires a knowledge of and is specific to certain hardware system.

To overcome the above limitations, few studies employ analytical approach (Mo & Xu, 2020; Yang et al., 2018; Z. Yang et al., 2021). Work in (Mo & Xu, 2020; Z. Yang et al., 2021) presents a mathematical model to estimate software computing units based on numbers of CPU cycles, CPU frequency, and floating-point operations. They do not consider energy consumed by data movement within memory hierarchy which is rather significant to the overall consumption. Work in (Yang et al., 2018) presents a tool for estimating software component using analytical modeling approach. However, there is no details on the analytical models employed. Our work is most similar to (Yang et al., 2018) in applying basic elements of MACs and data movement. Specifically, both (Yang et al., 2018) and our approach present energy modeling of energy consumption during deep learning execution (i.e., testing of deep learning model). However, this work differs from ours in that it does not show how the core elements (i.e., the number of MACs and data movement) are obtained, whereas we do. Our model explicitly defines how to calculate number of MAC operations as well as frequencies of data access to quantify energy consumption of deep learning.

3 ENERGY MODELING FOR COMPUTING UNITS IN CPS

Figure 1 shows a conceptual architecture of CPS, where cyber and physical systems are tightly integrated. The physical system sends data to the cyber system (via sensors). The cyber system takes sensed data as inputs and computes and produces output to the physical system (via actuator). The interactions can be intensive and may be required at different system granularities, thus CPS needs a tight component integration for efficiency.

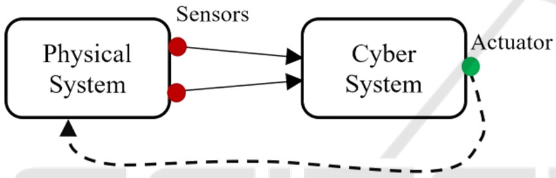

Figure 1: Conceptual architecture of CPS1

Physical systems (or components/units) include human engineered systems (e.g., manufacturing, building) and natural systems (e.g., solar, climate, habitat, environments) and Cyber (or Software) systems (or components/units) include computing artifacts as well as relevant infrastructures (e.g., data storage and transmission network). We refer to sensors and actuators as interface devices and use the term "computing units" and "cyber/software components" synonymously.

Although some objects are of physical system (e.g., sensors, network cables), in estimating energy consumption of computing units in a CPS, we include energy consumption consumed by relevant physical components in computation and data transmission (or communication). Thus, energy consumption includes energy consumed by a sensor for sensing and transmitting the data to a server.

In this section, we describe our approach to estimating energy consumption of computing units in CPS. We start with the methodology to estimate consumption per unit in Section 3.1 then present the estimation of the system in Section 3.2.

3.1 Unit Energy Estimation

Energy consumption of a computing unit consists of: (1) energy consumed from computation (E_{comp}), (2) energy consumed from the associated data movement (E_{data}) and (3) energy consumed from transmission to other units (E_{trans}), i.e.,

$$E = E_{comp} + E_{data} + E_{trans} \quad (1)$$

Figure 2 summarizes an overall concept of how to compute E in (1).

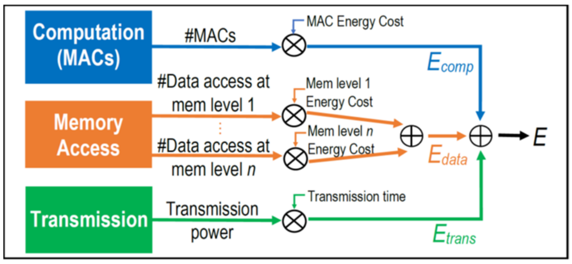

Figure 2: Energy consumption methodology of a computing unit1

Details on the modeling the energy from computation, data access, and transmission are presented below in Subsections 3.1.1, 3.1.2, and 3.1.3, respectively.

3.1.1 Computation Energy

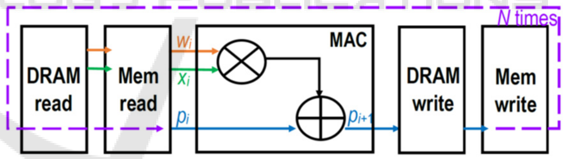

Figure 3: A MAC operation1

The fundamental element of the computation is a multiply-and-accumulate (MAC) operation (Yang et al., 2018). Suppose we want to compute $\sum_{i=0}^{n} w_i x_i$. Figure 3 depicts a MAC operation, where for each iteration i, two inputs w_i and x_i are multiplied and the result is added to the (accumulated) partial sum p_i, producing an updated partial sum p_{i+1} for the next iteration (or the accumulated sum of the multiplication pairs so far). This accounts for one MAC operation in one iteration. Since the final summation is a result of n iterations of MACs, we say it takes n MACs. As a result, computation energy depends on the number of MACs, giving

$$E_{comp} = \alpha c \quad (2)$$

where c is the number of MACs and α is hardware energy cost per one MAC operation.

3.1.2 Data Access Energy

For each computation, data of different types (e.g., input and output) need to be stored in the memory. In particular, as shown in Figure 3, each MAC performs four data accesses, three reads (i.e., two inputs w_i and x_i and one previous accumulated partial result p_i) and one write (i.e., new partial result p_{i+1}). Since energy spent accessing different levels of memory hierarchy are significantly different, data movement energy depends on how data moves in the memory hierarchy (Yang et al., 2018).

Let M be a memory hierarchy level, V be a set of data types (e.g., input, output, weight), β_m be a *hardware energy cost per data access* in the memory level m, $a_{v,m}$ be the *number of data accesses* for data of type v accessed at memory level m, and p be a precision in terms of number of bits for data representation (e.g., 8, 16). We can estimate the energy consumption corresponding to data movement based on the number of data accesses and access location in the memory as shown below.

$$E_{data} = \sum_{v\in V}\sum_{m=1}^{M}\beta_m a_{v,m}\, p \tag{3}$$

Note that we express β_{cache} and β_{DRAM} in terms of energy cost of a MAC operation α, resulting in $\beta_{cache} = 6\alpha$ and $\beta_{DRAM} = 200\alpha$, used in (Yang et al., 2018).

In this study, without loss of generality, we consider data moves between two memory levels: cache (m = 1) and DRAM (m = 2) with a cache hit rate h. Data are looked up in the cache first. If they are not found (cache miss), they will be fetched from DRAM and stored in cache. As a result, we can simplify data movement energy to be as follows.

$$E_{data}= \sum_{v\in V}(\beta_{cache}a_v+ \beta_{DRAM}(1\text{-}h)a_v)\, p \tag{4}$$

As seen in (4), in the best-case scenario (h = 1), all data are fetched from cache, whereas in the worst case (h = 0), all data have to be fetched from DRAM as expected.

3.1.3 Transmission Energy

Transmission energy (E_{trans}) of a computing unit can be calculated from transmission power p scaled by transmission time t (Mo & Xu, 2020; Z. Yang et al., 2021). The transmission time can be obtained from dividing the total number of bits to be transmitted s by the achievable rate r.

$$E_{trans} = pt = p\,(s/r) \tag{5}$$

Depending on communication protocols, the achievable rate r can be calculated differently. For example, in Frequency Division Multiple Access protocol (FDMA) (Z. Yang et al., 2021), r can be achieved by:

$$r = b\,\log\left(1+\frac{ph}{N_0 b}\right) \tag{6}$$

where b is bandwidth, p is transmission power of the edge node, h is channel power gain and N_0 is power spectral density of the Gaussian noise. Similarly, in non-orthogonal multiple access (NOMA) protocol (Mo & Xu, 2020), r can be found by:

$$r = B\,\log\left(\frac{\sigma^2+\sum_{i=1}^{n}p_i h_i}{\sigma^2+\sum_{i=1}^{n-1}p_i h_i}\right) \tag{7}$$

where B is bandwidth, p is transmission power, h is channel power gain, n is the number of edge nodes and σ^2 is a variance for the additive white Gaussian noise (AWGN).

3.2 System Energy Estimation

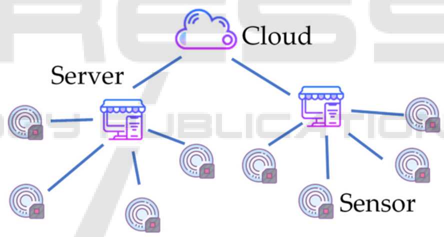

Figure 4: Sensor-based CPS network1

Once we quantify energy for each computing unit as in Section 3.1, this section combines the energy of all computing units in a system. Figure 4 shows an example of a sensor-based distributed system# consisting of two computing units, each is a network of sensors (or sensing nodes) and distributed server (or server or edge node). Total energy consumption of the system can be expressed by

$$E_{network} = N_{sense}\,(E_{sense})+N_{server}(E) \tag{8}$$

where N_{sense}, N_{server} is the number of sensors and servers, respectively. E_{sense} is energy consumed by each sensing node, which includes consumption during all sensor operations e.g., sensing, logging and transmission (Bouguera et al., 2018). Finally, E is energy consumed by each server obtained by modeling approach discussed in the previous section.

4 DEEP LEARNING MODELING

To further explain energy modeling of computing units in more details (i.e., to show how one can count the number of MACs and data access in the memory), we need to work on specific software units. Here we choose a relatively difficult computing unit of a popular Deep learning or deep neural network (DNN). DNN has been widely used in CPS for various tasks such as control, automation, detection, and monitoring. This section further describes the methodology in Section 3.1 to estimate energy of DNN computation. Specifically, we focus on energy consumption of computation and data access during the execution of the trained DNN model on one data instance. That is, we do not deal with energy usage for training DNN.

Background of DNN and how to assess the number of MACs and the number of data access from the DNN model are described in Subsections 4.1, 4.2, 4.3, respectively.

4.1 Background on DNN

Artificial neural networks (ANN) are a computational model consisting of layers of neurons. Each output is obtained by computing a weighted sum of all inputs, adding a bias, and (optionally) applying an activation function as shown in (9). Examples of activation functions are sigmoid function and Rectified Linear United (ReLU).

$$y = f\left(\sum_{i=0}^{n} w_i x_i + b\right) \qquad (9)$$

where y, x_i, w_i, b and n are the output, inputs, weights, bias and number of inputs, and $f(.)$ is an activation function (Sze et al., 2017).

A convolution neural networks (CNN) is a type of DNN that has been successfully applied to image analysis and computer vision (e.g., face recognition, object classification). Figure 5 shows a typical CNN architecture where multiple convolution (CONV) layers are used for feature extraction and fully connected (FC) layers are used for classification. Since CNN usually deals with images with high dimensions, pooling (POOL) layers are used to reduce the dimensionality using pooling operations (e.g., max, average). As shown in Figure 5, the POOL layer selects the maximum element of an input region and reduces dimension of a 4x4 input to a 2x2 output.

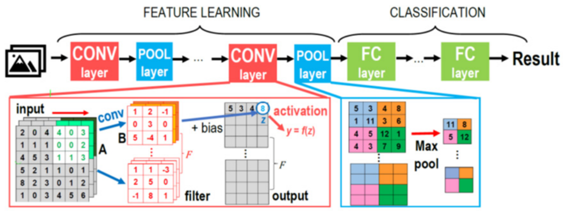

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Figure 5: A Convolutional Neural Network (CNN)1

The CONV layer, a building block of CNN, consists of high-dimensional convolutions. Equation (10) defines the computation of each CONV layer. For each layer, an input (also called input feature map) is a set of 2-dimensional matrices, each of which is called a channel. Each channel is convolved with a distinct filter channel (i.e., 2-dimensional weights). As seen at the bottom of Figure 5, a convolution starts with the 2-dim filter slides over a region of the 2-dim input of the same size, performing pointwise multiplication and summing the results into a single value. The convolution results are summed across all channels (3^{rd} dimension of input block). The bias b can be added to the result, yielding the single output value z (as shown in (10)).

$$z_{s,f,m,n} = \left(\sum_c \sum_i \sum_j w_{f,c,i,j} x_{s,c,m+i,n+j}\right) + b_f \qquad (10)$$

where $z_{s,f,m,n}$ is the output feature map of layer l, batch s, channel f and location (m, n), w is the weight of filter f, channel c and location (i, j), x is the input and b is bias. The filter repeats this process as it slides over all the input regions, yielding a filled output matrix. The process then repeats for all F filters. Each of the output values (LHS of (10)) then goes through an activation function and becomes an input to the next layer (Sze et al., 2017).

Since a DNN model consists of multiple layers of different types (e.g., convolution, pooling and fully connected), the total consumption of the DNN is the summation of computation and data access energy from all layers. Next, we provide a per-layer estimation of number of MACs (for computation energy) and data access (for data access energy)

4.2 Estimation of Number of MACs

Since different type of layers require different computation, we provide estimation of number of MACs for each layer as follows.

4.2.1 Fully Connected (FC) Layer

Consider Figure 6 representing a FC layer l of n neurons, each of which is connected with every neuron of an FC's input layer (or previous layer) of m neurons. (Note that if the FC's previous layer is a convolution or pooling layer whose output is represented in a stack of h 2-dimensional square planes, say $k \times k$ then the input layer of FC has $m = h \times k \times k$ neurons).

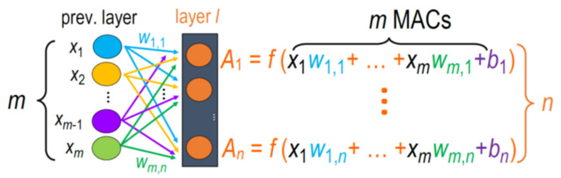

Figure 6: Computation and associated data in FC layer1

As shown in Figure 6, for each of n neurons in the FC layer, we compute m weighted sums (as in f's argument) and one activation (by function f). Thus, c, the total number of MACs in the FC layer is shown below in (11).

$$c = mn + c_{act}\, n \tag{11}$$

where c_{act} is the number of MACs used in the activation function which will be determined later.

4.2.2 Convolutional (CONV) Layer

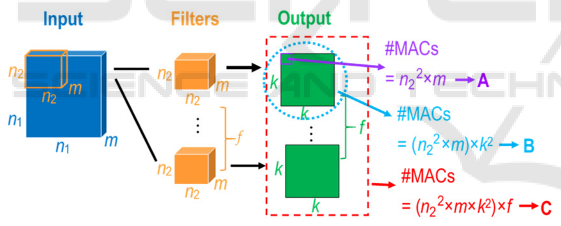

Figure 7: Computation and associated data in CONV layer.

The convolution layer aims to extract features by means of weights in filters. It results in a large number of computations and corresponding data movements. An input of n_1 width and height and m channels is convoluted with f filters, each of dimension n_2 x n_2 x m, and results in an output of size k x k x f.

As shown in Figure 7, the convolution process starts with a pointwise multiplication of a filter and an input region where the results are summed across all channels. To obtain this one output value (e.g., the top leftmost cell of the output), it takes $n_2^2 m$ MACs (A in Figure 7). The convolution process continues for the rest of the input region, yielding the output of size k by k yielding the number of MACs (B in Figure 7). The process then repeats for the rest of the f filters, ultimately producing f outputs and taking $n_2^2 mk^2 f$ MACs, shown as C. Note that the output value can go through to an activation function which takes another c_{act} MACs. In other words, to obtain each output value, it takes $n_2^2 m$ and c_{act} MACs. The operation repeats $k^2 f$ time for all output values giving the total number of MACs in the CONV layer as:

$$c = (n_2^2 m)(k^2 f) + c_{act}\,(k^2 f) \tag{12}$$

4.2.3 Pooling Layer

The energy consumption of a pooling layer depends on the type of the pooling operation. We consider the two popular types: max pooling and average pooling.

In max pooling, the filter slides over input region, the maximum element in the region is selected as an output value. Since no MAC operation is used, we obtain $c = 0$.

Similar operation is done in average pooling, but instead of selecting the maximum value of the input region, the operation averages the values in the region. Each operation is estimated to use one MAC. Since the number of pooling operations in a layer is equal to the size of the output, number of MACs operation can be expressed as:

$$c = n_2^2 m \tag{13}$$

4.2.4 Activation Functions

We estimate computation of different activation functions in terms of number of MACs to be used in the earlier layer-wise analysis. We denote c_{act} as number of MACs required to compute an activation function.

1. Linear function: $f(z) = z$ requires no MAC giving, $c_{act} = 0$.
2. Sigmoid function: $\sigma(z) = 1/(1+e^{-z})$ takes one MAC (for a division) with extra computation γ for exponential function. This gives $c_{act} = 1 + \gamma$.
3. ReLU function: $R(z) = max(0,z)$. It is a non-linear function and is widely used in both convolutional layer and fully connected layer. The computation does not require MAC, giving $c_{act} = 0$.
4. Softmax function: $S(z) = e^{z}/(\sum_{i=1}^{m} e^{z_i})$, where m is a number of classes. The function is typically used in the output layer for classification. We estimate the number of MACs to be m+1 (m for product sum and one for a division) with extra computation γm (i.e., γ for each of m computations of exponential function). As a result, we get $c_{act} = 1 + m + \gamma m$.

4.3 Estimation of Number of Data Access

Since computation in each type of layers differs, number of data access also varies. Therefore, we provide estimation of number of data access for each layer as follows.

4.3.1 Fully Connected (FC) Layer

For data movement energy in FC layer, we consider m input neurons, mn weights, n biases and n neurons in FC layer (or output layer). Let a_x be the number of data accesses for x. As shown in computation of A_i's in Figure6, each input x_i is read n times while each weight and each bias are each read once. Thus, a total number of data accesses for input, weight and bias would be mn, mn, and n, respectively. These results are shown in (14)-(16). As shown in Figure 6, each output A_i includes read/write accesses of m products, yielding $2m$ data accesses. Since there are n output neurons, a total of number of data accesses for output would be $2mn$ as given in (17).

$$a_{input} = m(n) \tag{14}$$

$$a_{weight} = m(n) \tag{15}$$

$$a_{bias} = n \tag{16}$$

$$a_{output} = n(2m) \tag{17}$$

Next section shows how to compute MACs and data movement energy in CONV layers.

4.3.2 Convolutional (CONV) Layer

Data movement energy in this layer involves input, filters (i.e., weights), biases and output. As shown in Figure 7, each input data is accessed at least once for each filter requiring $n_1^2\ m$ MACs. As the filter slides over the input, some of the input data are being accessed again (i.e., being reused). Let t be the maximum bound of the number of reuses and r_i be the number of data that are reused i times. Thus, for f filters, number of input data accesses is shown in (18).

Similarly, each weight in the filter and each bias is accessed once to calculate one output value. To complete the output for one filter of size k^2, as circled in blue in Figure 7., the weights and bias hence are accessed k^2 times. Since there are n_2^2m weights and 1 bias for one filter, with f filters, total number of weight and bias data access can be expressed in (19) and (20), respectively. As labeled as A in the Figure 7, each of the output value takes $n_2^2\ m$ iterations of MAC. This means the output value is being accessed $2\,n_2^2\ m$ times accounting for data read and write. Since there are k^2f output values, number of output data access can be expressed as shown in (21).

$$a_{input} = (n_1^2 m + \textstyle\sum_{i=2}^{t} r_i i) \cdot f \tag{18}$$

$$a_{weight} = n_2^2\ m\,f\,k^2 \tag{19}$$

$$a_{bias} = fk^2 \tag{20}$$

$$a_{output} = k^2 f\,(2n_2^2\ m) \tag{21}$$

4.3.3 Pooling Layer

Data movement energy for max pooling and average pooling involves only input and output. The input data access depends on the size of the filter (i.e., pooling size) and stride. Similar to how (18) is obtained, number of input data access can be determined by (22). In addition, stride is sometimes set to be equal to the size of the filter. As a result, the input region is not overlapped, causing each the input value to be accessed only once. In this case, the second term of (23) is zero. In this layer, each output data is accessed once, which accounts for data write.

$$a_{input} = (n_1^2 m + \textstyle\sum_{i=2}^{t} r_i i) \tag{22}$$

$$a_{output} = n_2^2 m \tag{23}$$

where n_1 is the width and height of the input, m is number of channels, n_2 is the width and height of the output. Note that, n_2 is derived from the input, pooling size k and stride s (i.e., $n_2 = (n_1 - k/s) + 1$).

5 ILLUSTRATIONS

This section illustrates how the model can be applied in practice to help the design and management of CPS, particularly in a smart agriculture system. Section 5.1 describes the system and the unit under study. Section 5.2 gives experiments and results.

5.1 Smart Agriculture Systems

Smart agriculture systems include smart farming and smart CPS for controlled environments for precision agriculture and food security supply (Rajasekaran & Anandamurugan, 2019). These systems typically employ sensors to collect data from the field and use them for various tasks (e.g., crop health monitoring, and management of soil nutrients, pesticides, fertilizer, and irrigation) to increase the crop yields. To sustain such a system, one needs to manage cost derived from energy consumption from computation in these units.

Consider a crop health monitoring subsystem of the smart agriculture CPS. The subsystem includes a disease detection unit that deploys a trained DNN model to analyze plant images sent from neighboring cameras (sensing nodes) in the field. The server in the disease detection unit executes the DNN model to detect if the plant has a disease or to classify the disease type. It then transmits those images with corresponding results to the cloud for backup and further analysis or to be alerted by another unit.

Suppose a farm owner wants to expand the farm to grow more plants, cover larger area with more sensors and disease detection computing units. This will lead to higher energy consumption. The farm owner or the smart agriculture system engineer needs to manage energy resource constraint as well as appropriate structures to maximize the overall net gain to the farm. Planning for resource management to make such a smart agriculture system sustainable can be challenging. In this paper, we limit the scope of our investigation to energy consumptions of computing units to identify appropriate scale and structure for a design of a sustainable future system.

5.2 Experiments and Initial Setup

We consider two CPS network structures: *star* and *mesh*. The left of Figure 8 shows two stars, each of which has four sensing nodes, where each directly connects to its assigned distributed server. The right of Figure 8 shows two meshes, each of which also has four sensing nodes, all of which are directly connected to one another. Sensing nodes sense and transmit their own data but also serve as repeaters that relay data from other nodes. For examples, sensing nodes that are not connected to the distributed server will send their data to their neighbors which will forward the data to the distributed server. Distributed servers in both structures connect to the cloud to store their data.

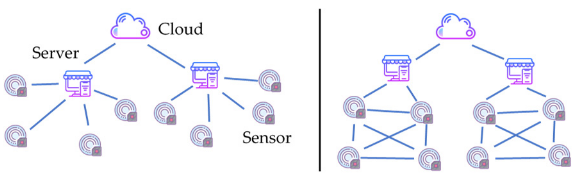

Figure 8: Star and Mesh Topology.

Since in each star or mesh 80% of nodes are sensing nodes and 20% of nodes are distributed server, we use the same ratio between sensing nodes and distributed servers when we scale total number of nodes from 100 to 10,000 nodes in our experiments. Note that each star or mesh maintains 4 sensing nodes and one distributed server. From this point on, we use *server* to mean *distributed server*, unless it is specified differently.

For a deep learning model deployed at the server of each structure, we choose Alexnet (Krizhevsky et al., 2017), a CNN model to be deployed at the server due to its popularity and successful use in many smart agriculture applications (Gikunda & Jouandeau, 2019). Alexnet's architecture contains 5 convolution layers with ReLu activation, 3 pooling layers and 3 fully connected layer with Softmax for classification.

In our illustration, data are fetched from cache and DRAM at 50% cache hit rate. Data precision is 16 bits. The energy consumption is expressed in terms of the number of MAC operations as it directly translates to energy usage. We also assume that each MAC operation consumes about 10 pJ (picojoules).

Table 1: Experimental Setup.

Variable	Type/Values
Structure	Star, mesh
DL model	Alexnet (CNN model)
Data Access	Cache (hit rate), DRAM
Communication Protocol	FDMA
% No. Servers	20%
% No. Sensors	80%
Bandwidth	500k Hz and 2M Hz

For a communication protocol, we use FDMA (Frequency Division Multiple Accesses) (Z. Yang et al., 2021). Bandwidth is set to 500k Hz and 2MHz to represent low and normal bandwidth scenarios. Transmission power for each central server is set to that of a standard laptop at 32 mW while the sensing node's is halved (16 mW). Distance between nodes is set to 100. For sensor energy consumption, the power and sensing time are 10.5 mW and 25 ms as reported by (Bouguera et al., 2018). The frequency of the operation (i.e., the sensing node captures picture and transmits the data) is set to be every hour. A summary of experimental setups is shown in Table 1.

Three sets of experiments are performed to help gain understanding of sources of energy consumption of the computing units of the smart agriculture system. The designer of the crop health monitoring units might ask the following: (1) Does different structure matter to energy consumption? (2) How does the number of sensors in each structure effect energy consumption? (3) Which of the task between computation or communication consumes more energy? (4) How much does the bandwidth effect total energy consumption? Our experiments aim to answer these questions with respect to scales (i.e., number of nodes) of the smart agriculture system.

6 EXPERIMENTAL RESULTS

The results of the experiments along with some explanations are discussed in three sections below. The results should help the farm owner or the smart agriculture system engineer in designing and selecting appropriate structures and scale to sustain energy usage of the new smart disease detection computing units.

6.1 Effects from Network Structures

We use our analytical energy model to estimate energy consumptions of two structures: star and mesh when scaling the number of nodes (i.e., sensors and distributed servers) up to 10,000 nodes.

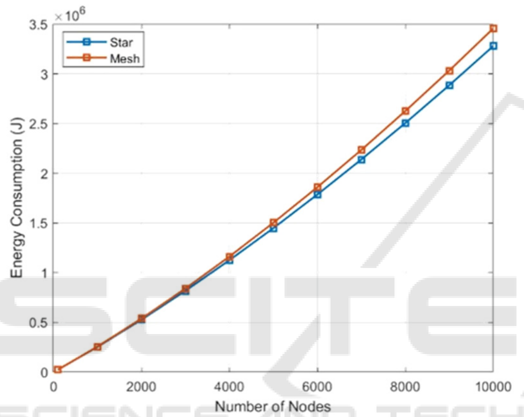

Figure 9: Energy consumption of star and mesh networks.

As shown in Figure 9, as we increase number of nodes, energy consumption linearly increases for both structures (or topologies) as expected as execution of each unit requires approximately the same energy usage in a normal situation (i.e., no transmission delays). However, the mesh structure consumes slightly higher energy consumption than the star structure. This is due to the differences in energy consumption by data transmissions to be investigated in more details below.

Figure 10 compares energy consumed by sensing nodes and (distributed) servers (or edge node) of both star and mesh structure. In both topologies, shown in Figure 10, the servers consume significantly higher energy than the sensors. This is mainly due to high energy consumption from deep learning execution. Moreover, as shown in Figure 10, energy consumption at the servers in both topologies are the same. This is because the servers in both topologies perform approximately the same amount of deep learning computation and transmit the same amount of data.

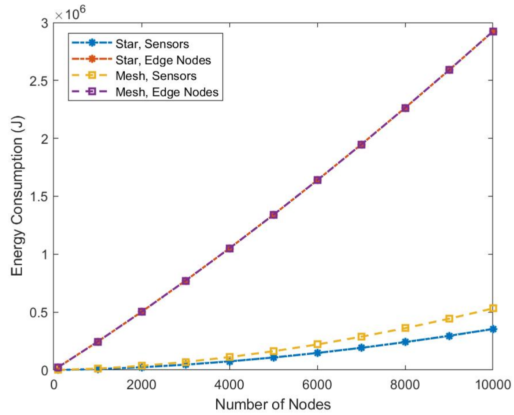

Figure 10: Energy consumption of sensors vs. distributed servers (edge nodes).

On the other hand, Figure 10 shows that the transmission (or communication) energy at sensing nodes of the mesh is higher than that of the star. As the number of nodes increases, the differences in transmission energy grow. This is because, as opposed to direct transmission in the star structure, sensing nodes in the mesh that are not connected to its designated server require multi-hop transmission. Since some nodes need to send not only their data but also data from other nodes, more energy is consumed. Consequently, the mesh structure has higher transmission energy and higher total energy consumption. In our experiments, we consider at most 2-hop data forwarding as depicted in Figure 8. If more hops are needed to reach the distributed server, even higher energy consumption is expected.

In general, despite being simple and cheaper in terms of energy, the star structure has limitation in the maximum transmission range between the sensing node and the server. Since sensing node and the server must be in transmission coverage of one another, having more sensing nodes may not mean increased coverage area. Using communication technology such as LoRa can overcome this issue as it enables long range transmission with low power consumption, but it has a low bandwidth. Mesh topology does not have the same issue as the sensing nodes can relay data from other nodes and hence can be anywhere as far as they are connected to another node. Moreover, it can provide better reliability since data can be rerouted using different paths in case a node fails. The smart farming designer has to take these tradeoffs into consideration along with energy consumption effects.

6.2 Effects from Bandwidths

This section explores impact of bandwidth to energy consumption by computing units. Since the results between star and mesh networks are similar, we only show the results from the star network here. We focus on energy consumption by the distributed servers rather than sensors since their energy consumption has much higher contribution to the overall system. Figure 11 and Figure 12 shows energy consumption of the distributed server with bandwidth capacity of 2MHz and 500kHz, respectively.

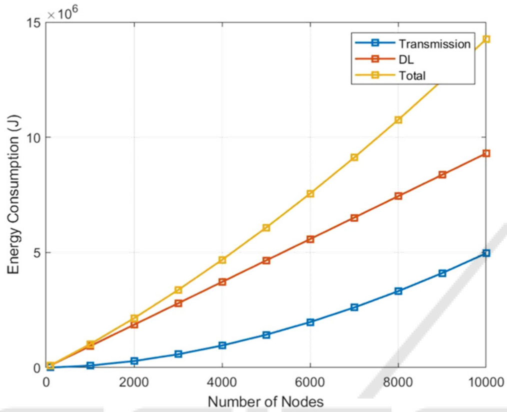

Figure 11: Energy consumption where bandwidth is 2MHz.

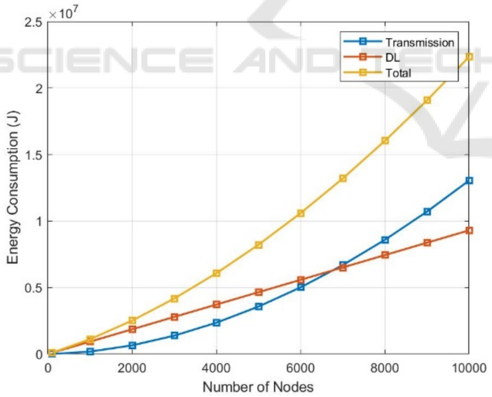

Figure 12: Energy consumption where bandwidth is 500kHz.

As shown in Figure 11, with a high bandwidth of 2 MHz, deep learning energy consumption dominates that of data transmission. Also, total energy consumption contributed by the DL computation and data transmission of the distributed server is scalable. However, this is not the case with a lower bandwidth.

As shown in Figure 12, when there are more than 7,000 nodes, transmission energy starts to dominate deep learning computation energy. This is because bandwidth is shared among the nodes. When there are nodes, higher traffic is expected. This results in longer transmission time and thus higher energy consumption. Thus, in the scenario of this experiment with low bandwidth, the system should not grow more than 7000 nodes, otherwise, more energy will be wasted on transmissions instead of actions to gain productivity (i.e., more images being analyzed). For the system designer, the ability to estimate energy consumption per computing units prior to implementation can give insights on the scale of the smart farm system to fit the energy budget constraint or to determine investment on bandwidth capacity.

6.3 Effects from Sensors and Servers Ratios

Results obtained in Section 6.1 indicate that structures (i.e., mesh, star) of the computing units do not appear to impact energy consumption that much. In our previous experiments, the number of sensors in each structure is set to be four. We want to investigate further the number of sensors in each structure impacts energy consumption. This section considers only the star structure as it is baseline energy consumption of the two structures.

We consider two sets of sensors, 10 and 100. Table 2 shows comparison of energy consumption between having ten and a hundred sensors sending data to one server. The ratio difference in the last column represents the ratio of energy consumption in the 100-sensor case over that in the 10-sensor case. Thus, it gives a multiplying factor of the former to the latter. As shown in the first line of Table 1, since the number of sensors increases 10 times, sensing energy consumption increases 10 times as expected. Similarly, at the distributed server, more number of sensors means more number of images being processed. Thus, the server has to do 10 times more image analysis and thus, the energy consumption of DL execution increases 10 times as it should be.

Table 2: Effect of number of sensors in a star-structured group.

Energy Consumption	10 sensors + 1 edge node	100 sensors + 1 edge node	Ratio Difference
Sensing	0.06	0.63	10.00
Sensor Transm.	173.06	2,376.75	13.73
Total at Sensor	173.13	2,377.38	13.73
DL execution	11,624.73	116,247.29	10.00
Edge Transm.	181.67	3,003.42	16.53
Total at Server	11,806.40	119,250.71	10.10

Nevertheless, transmission cost does not necessarily increase linearly. Transmission energy of the 100-sensor case is about 13.7 times more than that of the 10-sensor case. This is due to higher traffic which in turns increases the latency and energy. Similarly, the transmission cost at the server is over 16 times more expensive. Since the server transmits larger data size than the sensors, this causes heavier transmission traffic and results in much higher energy consumption. With the results shown here we make a conjecture that the number of sensors in each structure can lead to larger difference of energy consumption produced by mesh and star topologies.

Overall, our experiments and results aim to show methodology to help the farm owner or engineer design a sustainable smart farming system based on estimated energy consumption of computing units.

7 LIMITATION AND DISCUSSION

This paper focuses on a method for quantifying the energy consumption of software artifacts in CPS and illustrates its use for deep learning software. The evaluation of the resulting models of the deep learning software are limited to theoretical models. Proper evaluation of the resulting models requires further empirical work on real-world systems. This is beyond the scope of our work in this paper. However, we show initial findings of our theoretical evaluation of our resulting models below.

Table 3: Alexnet computation energy.

Method	CONV	FC	Total
Ours	666M	58.6M	724M
Sze et al., 2017	666M	58.6M	724M
T. J. Yang et al., 2018	528M	58.6M	586M

Specifically, we compared energy consumed by Alexnet and compared with published results in (Sze et al., 2017) as well as those obtained by an online analytical tool (T. J. Yang et al., 2018).

In Table 3, assuming that the data movement of the computation in all the three methods are the same, the energy consumptions are compared based on the number of MACs. As shown in Table 3, our results match those reported by Sze et al. The estimates from Yang et al., however, are about 21% less than those of ours and Sze et al.'s. This preliminary result gives a theoretical comparison of our models with existing work. However, to complete the theoretical evaluation, we need to relax the assumption on data movement. To fully evaluate our approach, we need to experiment our method with different software computation in CPS and obtain energy models to be compared with actual energy obtained by power measuring tools in real systems. These are potentials of our future work.

8 CONCLUSIONS

This paper presents an analytical approach to quantifying energy consumption of software artifacts in CPSs. For clarity and due to the increasing use of deep learning in CPSs, the approach is described using the deep learning computation process. While the model is specific to deep learning in distributed networks, the proposed approach provides a building block concept that is general in that it can be applied to any software computation (e.g., other machine learning or data analysis algorithms) in the CPS other than deep learning. The paper also illustrates how the resulting energy model can be applied in practice including methodology in analyses to help the design and management of CPS. This contributes to a fundamental approach towards the development of green computing CPS, particularly in the aspects of planning of energy resources.

Future work includes (1) applying the proposed approach to other real-world CPS software components, and (2) expanding the energy consumption modelling to manage CPS resources in multiple contexts (e.g., economy, energy, computation, quality of service, environment, and sustainability).

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